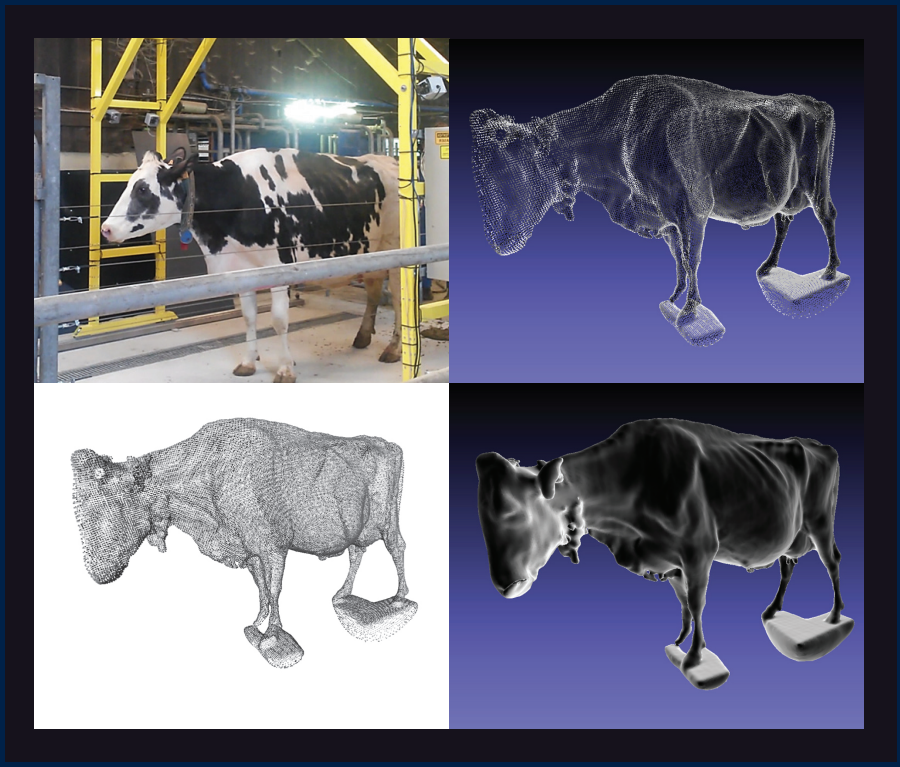


Precision Livestock Farming '17

Edited by D. Berckmans and A. Keita

Precision Livestock Farming '17

Edited by D. Berckmans and A. Keita

Papers presented at the 8th European Conference on Precision Livestock Farming

Nantes, France
12-14 September '17

International scientific committee responsible for the selection and review of the papers:

The oral and poster presentations were selected on the basis of abstracts. The abstracts and papers were reviewed by 73 invited reviewers. We would like to thank all these reviewers for their work and support.

Alberto Peña Fernández	Belgium
Alessia Diana	Ireland
Ali Youssef	Belgium
Amanda E. Stone	USA
Anatol Krozer	Sweden
Anders Herlin	Sweden
Andy Butterworth	United Kingdom
Barbara Tzschentke	Germany
Bart Sonck	Belgium
Bengt-Ove Rustas	Sweden
Bernadette Earley	Ireland
Bert Ipema	The Netherlands
Bjørn Steinar Sæther	Norway
Bruno Meunier	France
Cameron Clark	Australia
Callum Eastwood	New Zealand
Cees Lokhorst	The Netherlands
Chaoyuan Wang	Republic of China
Charlotte Hallen Sandgren	Sweden
Christian Manteuffel	Germany
Christina Umstätter	Switzerland
Claudia Arcidiacono	Italy
Claudia Kamphuis	The Netherlands
Claus Aage Grøn Sørensen	Denmark
Clément Allain	France
Daniel Berckmans	Belgium
Daniella Moura	Brazil
David Verde	Spain
Deborah Piette	Belgium
Dries Berckmans	Belgium
Emanuela Tullo	Italy
Ephraim Maltz	Israel
Erik Vranken	Belgium
Felix Adrion	Germany
Hadis Mahdavi	Spain
Harriet Wishart	United Kingdom
Harry Blokhuis	Sweden
Heiner Lehr	Spain
Ilan Halachmi	Israel
Ilana Richter	Israel
Ilaria Fontana	Italy
In-bok Lee	South-Korea
Isabelle Veissier	France
Jarissa Maselyne	Belgium
Jesus Pomar Goma	Spain
Jörg Hartung	Germany
Karen Helle Sloth	Denmark
Lenn Carpentier	Belgium
Li Rong	Denmark
Maciej Oczak	Austria
Marcella Guarino	Italy
Marie-Madeleine Mialon-Richard	France
Martin Føre	Norway
Mathieu Silberberg	France
Nathalie Quiniou	France
Nicole Kemper	Germany
Paolo Liberati	Italy
Parimal Rajkondawar	Sweden
Per Nielsen	Denmark
Rudi De Mol	The Netherlands
Se-Woon Hong	South-Korea
Sinead Quealy	Ireland
Stephanie Van Weyenberg	Belgium
Susanne Klimpel	Germany
Tami Brown Brandl	USA
Theo Demmers	United Kingdom
Thomas Jungbluth	Germany
Thomas Banhazi	Australia
Thomas Bartzanas	Greece
Tom Van Hertem	Belgium
Tomas Norton	Belgium
Tony Waterhouse	United Kingdom
Wilma Steeneveld	The Netherlands

Scientific Committee

Dr Gilles Salvat	France
Dr Nicolas Eterradossi	France
Dr Alassane Keita	France
Dr Isabelle Veissier	France
Prof. Daniel Berckmans	Belgium
Prof. Erik Vranken	Belgium
Prof. Tomas Norton	Belgium
Prof. Marcella Guarino	Italy
Prof. Jörg Hartung	Germany
Dr Kees Lokhorst	The Netherlands

Organising Committee

Nicolas Eterradossi	France
Alassane Keita	France
Françoise Pol	France
Jean-Erik Blochet	France
Emmanuelle Girard	France
Geneviève Clément	France
Anne Verbrugge	Belgium
Pauline Créach	France
Jean-Pierre Chanet	France
Michel Marcon	France
Clément Allain	France
Brigitte Landrain	France
Philippe Faverdin	France

European Committee for PLF

Daniel Berckmans (chair)	Belgium
Kees Lokhorst (secretary)	The Netherlands
Theo Demmers	UK
Marcella Guarino	Italy
Ilan Halachmi	Israel
Alassane Keita	France
Christina Umstätter	Switzerland
Sandra Rose-Meierhöfer	Germany

We thank Ms. Siân Jones for the professional language check of papers from non-native English speakers.

Table of Contents

Editorial

This is the 8th ECPLF conference and Precision Livestock Farming technology is now a daily reality for many farmers and researchers. From around 7.5 billion people today, the world's population is expected to reach 10 billion by 2050. This increase will occur mainly in developing countries. Consequently the worldwide demand for animal products is expected to increase by up to 70%.

Because the number of animals is increasing and the number of farms is decreasing, every farm will house more animals. In some regions it has become common to see farms with several hundred thousand pigs or broiler chickens or several tens of thousands of milking cows. Under these conditions it is very difficult, if not impossible, for farmers to monitor all their animals satisfactorily as they are housed in very big groups.

There are serious challenges to face in terms of the relationship between animal health and human health, as 60% and 80% of human pathogens and emerging diseases, respectively, are zoonotic and thus originate from animals. At the same time, concern for animal welfare is growing. Another area of enormous concern is the environmental impact of animal production; for example, the livestock sector in France generates about 300 million tons of organic effluents, producing up to 1.8 million tons of nitrogen every year. This environmental impact must be managed so that animal productivity can achieve its genetic potential. Major areas of interest in the coming years will therefore be continuous monitoring of animal health and welfare in farm animals, regardless of the scale of production, and the environmental impact of the global livestock sector.

PLF aims to provide real-time monitoring and management systems for farmers. PLF technology must therefore measure and analyse data continuously so that farmers can receive an alert when something goes wrong. Examples of research areas which have already been translated into reality include monitoring of some animal diseases, animal productivity, precision feeding, animal behaviour and welfare, and monitoring the physical environment of a livestock building (precision climate control).

Further development of PLF technologies must be achieved by integrating them into the livestock economy in the context of globalisation and international competition.
The ambition of this conference is to enable sharing of knowledge and experience and facilitate useful discussion in order to achieve significant progress in the field of PLF.

Alassane Keita

Session 1

Dairy

The usability of the suction method to measure teat skin elasticity

S. Demba[1], S. Rose-Meierhöfer[2], M. Neumerkel[3], C. Ammon[1], R. Brunsch[1]
[1]*Leibniz Institute for Agricultural Engineering and Bioeconomy (ATB), Department of Engineering for Livestock Management, Max-Eyth-Allee 100, 14469 Potsdam, Germany*
[2]*Hochschule Neubrandenburg, University of Applied Sciences, Department of agricultural machinery, Brodaer Str. 2, 17033 Neubrandenburg, Germany*
[3]*Humboldt-Universität zu Berlin, Faculty of Life Science, Thaer-Institute, Unter den Linden 6, 10099 Berlin, Germany*
sdemba@atb-potsdam.de

Abstract

The teat of a dairy cow is exposed to a large load during milking because it is the interface between the udder and the liner in the milking process. This results in a fatigue of the teat tissue, especially the teat skin, and can lead to teat damages. The aim of this study was to test the usability of the suction method for teat skin elasticity measurements to get a better understanding of the teat liner interface. The usability of the different measuring traits was analysed as well. The Cutometer® dual MPA 580 is a tool to detect the elasticity of the skin and several skin layers with the help of suction. It was used to investigate the teat skin elasticity of the right rear teats from 101 randomly selected cows. Measurements were carried out in a side-by-side milking parlour before and after milking using the measuring mode 1 of the Cutometer® dual MPA 580. Penetration depth of the skin, gross elasticity, net elasticity, ratio of immediate retraction to total distension and difference in maximal skin deformation between the last and the first suction were analysed. Descriptive statistics of all traits were calculated. Based on the results of our study we concluded that the Cutometer® dual MPA 580 is generally usable to measure teat skin elasticity. Further studies are needed to validate the method. The influence of anatomical, physiological, and technical factors on teat skin elasticity will be investigated as well.

Keywords: skin behaviour, teat damages, dairy cow, machine milking

Introduction

The teat skin is the outermost layer of the teat wall. It has a thickness of 1-2 mm, is hairless and usually slightly wrinkled. In addition, it contains a high ratio of elastic fibres, which allow a strong strain of the teat up to 30 % during milking (Hospes & Seeh, 1999). While the udder skin is composed of the epidermis, the dermis and

the hypodermis, the teat skin has no hypodermis (Ferdowsi *et al.*, 2013). Thus, a detaching of the skin from their base is impossible. The innervation of the teat is, compared with the udder, pronounced. In the teat skin, especially at the teat tip, many nerve fibres are located (Hospes & Seeh, 1999).
The property of the skin to change and recover shape when it is stretched or deformed is named skin elasticity (Clancy *et al.*, 2010). Skin viscoelasticity combines the elastic properties of the skin with the principle of viscosity, the resistance to flow when a force is applied to a fluid (Everett & Sommers, 2013). The mechanical properties of the skin can be influenced by age (Cua *et al.*, 1990; Ryu *et al.*, 2008; Krueger *et al.*, 2011; Luebberding *et al.*, 2014), gender (Fiedler *et al.*, 2012; Luebberding *et al.*, 2014) and body region (Ryu *et al.*, 2008; Krueger *et al.*, 2011). Teat skin elasticity can be influenced by milking as well (Kuchler, 2011; Krzyś *et al.*, 2011).

The Cutometer® dual MPA 580 (Courage and Khazaka electronic GmbH, Cologne, Germany) is a tool to detect the elasticity of the skin and several skin layers. It consists of a main unit and a measuring probe (Dobrev, 2014) and measures skin elasticity using suction and elongation (Woo *et al.*, 2014). The main unit contains a vacuum pump with pressure sensor and microelectronics to generate a consistent vacuum between 20 and 500 mbar during the measuring procedure. The measuring probe contains the suction head and an optical measuring system (Dobrev, 2014). This optical measuring system includes a light transmitter, a light recipient and two glass prisms (O'goshi, 2006). During the measurement the skin is drawn into the probe and its vertical deformation is measured (Ryu *et al.*, 2008). Depending on the depth of penetration in the probe the incoming light intensity differs. Thus, the ability of the skin to resist the suction (firmness) and to regress to its original condition after removal of the negative pressure is detected (Courage & Khazaka, 2012). There are four measuring modes available: measurement with constant negative pressure (mode 1), measurement with linear increase and decrease in negative pressure (mode 2), measurement with first constant and then linear decrease in negative pressure (mode 3), and measurement with a linear increase in negative pressure and then a sudden elimination of the negative pressure (mode 4). These differ in the combination and the meaning of their measurement parameters (Dobrev, 2014). The measurement mode 1 is most frequently used in the literature (Cua *et al.*, 1990; Hashmi & Malone-Lee, 2007; Ryu *et al.*, 2008; Krueger *et al.*, 2011; Ohshima *et al.*, 2013; Bonaparte & Chung, 2014; Luebberding *et al.*, 2014; Dykes, 2015;). To evaluate the elastic properties of the skin an output of various parameters is possible. These can be divided into three groups: the R-, F-, and Q-parameters and they are dependent on the mode. While R-parameters are frequently used in skin research (Cua *et al.*, 1990; Dobrev, 2002; Hashmi &

Malone-Lee, 2007; Fiedler *et al.*, 2012; Dykes, 2015), F- and Q-parameters are rarely used.
The measuring of teat skin elasticity may help to give information about the fatigue of teat skin during milking and can be a method to evaluate objectively the teat load during milking.

Material and Methods

Animals and study design

The study took place on a commercial dairy farm in Germany. On three days in July and August 2015, the teat skin elasticity of 101 randomly selected German Holstein cows was measured. The lactating cows were between their first and sixth parity, and the days in milk (DIM) were between 10 and 596 (median = 90 d). At the time of investigation, the herd had an average milk yield of 29.8 kg per cow per day, with a mean fat content of 3.85% and a protein content of 3.38%. The cows were milked three times a day in a 2 x 24 Side-by-Side milking parlour equipped with conventional milking clusters, and the machine vacuum was adjusted to 42 kPa. Alternate pulsation was used with a pulsation rate of 60 min^{-1} and a pulsation ratio of 60:40. The temperature and humidity for test day 1, 2 and 3 were 19.3°C and 59.5%, 24.8°C and 60.6% and 21.5°C and 77.4%, respectively.

Data collection

Teat skin elasticity was evaluated during milking using the Cutometer® dual MPA 580 by Courage and Khazaka electronics GmbH (Cologne, Germany). The opening of the measuring probe was 6 mm and the time-strain mode (mode 1) was used. For each measurement, a suction period about 1 second followed by a 1-second suction-off relaxation period was used with a setting of 450 mbar of suction. This measuring cycle was repeated ten times, so the measuring time was 20 seconds per measuring. Teat skin elasticity was taken before and after milking on the right rear teat (Figure 1). Before milking indicates after udder cleaning and after milking means directly after cluster removal and before dipping.

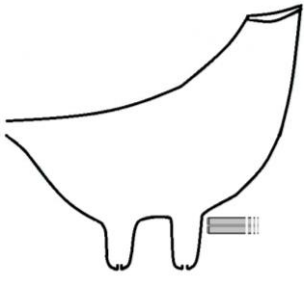


Figure 1: The measuring point on the right rear teat for teat skin elasticity detection

Statistical analysis

All statistical analyses were performed using the SAS 9.4 software package (SAS Institute Inc., Cary, NC, USA). The penetration depth of the skin (R0 in mm) and the gross elasticity (R2 in %) were used to evaluate the usability of the suction method to measure teat skin elasticity. The descriptive statistics was analysed using the UNIVARIATE procedure. T-tests of the differences were performed to determine differences in R0 and R2 before and after milking, respectively.

Results and Discussion

Penetration depth of the skin (R0)

R0 before and after milking ranged between 0.50 mm and 2.86 mm (1.87 mm ± 0.83) and 0.50 mm and 2.82 mm (2.10 mm ± 0.76), respectively. Table 1 shows the descriptive statistics of R0 before and after milking.

Table 1: The measures for location and variability of the penetration depth of the skin (mm) before and after milking (N = 105)

Measures for location			Measures for variability		
	before milking	after milking		before milking	after milking
Mean	1.87	2.10	Standard deviation	0.83	0.76
Median	2.43	2.56	Variance	0.68	0.57
Mode	0.75	2.67	Range	2.36	2.32
			Interquartile range	1.59	1.42
			Coefficient of variation	44.2	36.0

The values of R0 show a high variation and mean R0 was significant higher after milking than before (P = 0.0003). Figure 2 shows the related values of R0 before and after milking. The data points on the right side of the diagonal line illustrate that in some cases the values of R0 were lower after milking than before.

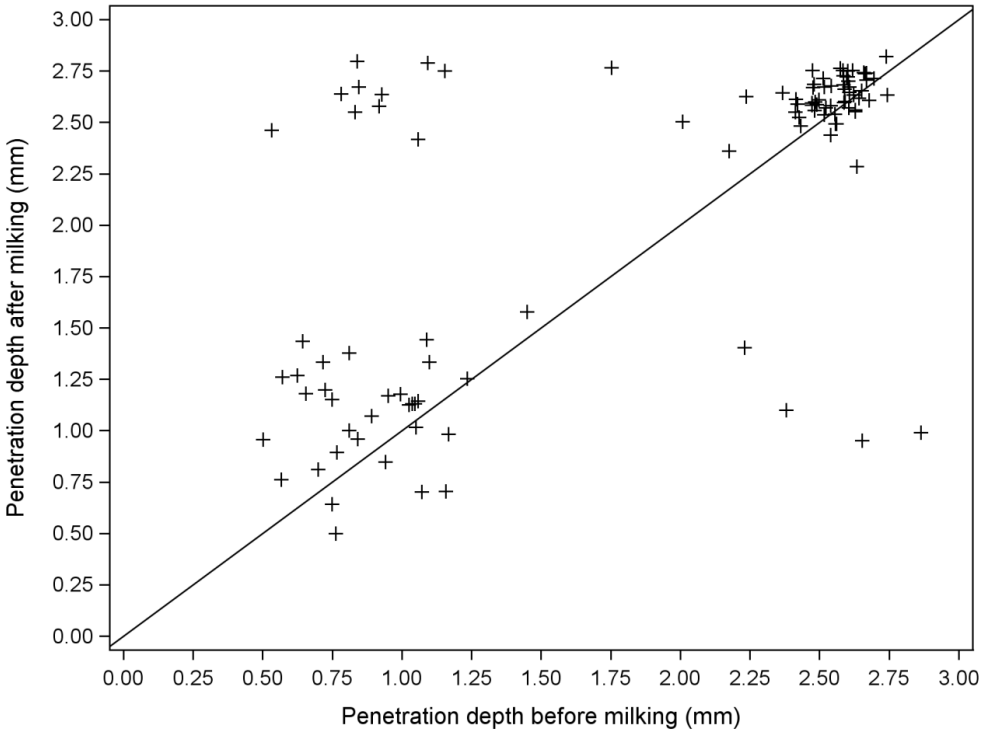


Figure 2: The related values of the penetration depth of the skin (mm) before and after milking with higher values after milking on the left side and higher values before milking on the right side of the diagonal line

Gross elasticity (R2)

R2 before and after milking was around 26% (± 24), respectively and ranges between 0.4% and 90.6% before milking and between 20% and 84% after milking. Table 1 shows the descriptive statistics of R2 before and after milking.

Table 2: The measures for location and variability of the gross elasticity of the skin (%) before and after milking (N = 105)

Measures for location			Measures for variability		
	before milking	after milking		before milking	after milking
Mean	26.3	26.1	Standard deviation	23.1	23.9
Median	15.8	15.8	Variance	5.3	5.7
Mode	12.0	-	Range	90.2	82.0
			Interquartile range	36.5	32.9
			Coefficient of variation	87.8	91.5

The values of R2 show a very high variation and no differences between mean R2 before and after milking could be found. Figure 3 shows the related values of R2 before and after milking. This figure illustrates that the values of R2 were higher after milking than before and the other way around.

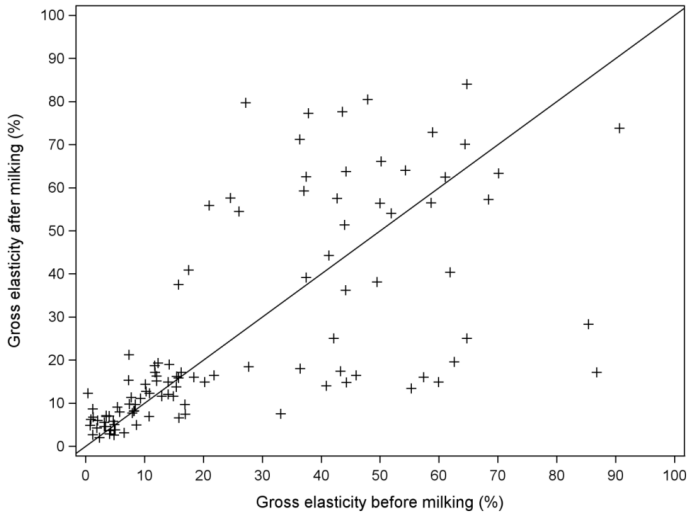


Figure 3: The related values of the gross elasticity of the skin (%) before and after milking with higher values after milking on the left side and higher values before milking on the right side of the diagonal line

In this investigation the mean penetration depth of the skin was 1.87 mm before and 2.10 mm after milking. For the penetration depth of human skin 0.03-0.08 mm (Krueger *et al.*, 2011), 0.09-0.13 mm (Luebberding *et al.*, 2014), 0.24-0.34 mm (Woo *et al.*, 2014) and 0.61-0.94 mm (Bonaparte & Ellis, 2014) were recorded. The measurements of teat skin were higher, so the teat skin penetrated deeper into the probe during measurements. The gross elasticity for teat skin found in this investigation was before and after milking 0.4-90.6% and 20-84%, respectively. The mean gross elasticity was 26% for both times of measurement. For human skin the gross elasticity is stated with 40.98-76.67% (Krueger *et al.*, 2011), 79.9-87% (Bonaparte & Chung, 2014), 57.11-57.33% (Luebberding *et al.*, 2014), 67-77% (Bonaparte & Ellis, 2014), 76-88% (Woo *et al.*, 2014) and 79-83% (Nam *et al.*, 2015). The differences in the anatomic structure between human skin and teat skin could be a possible reason for the lower firmness and elasticity of teat skin. Generally human skin is similar to teat skin, but in detail some differences can be seen. Teat skin shows more wrinkles than human skin and has a very high proportion of elastic fibres (Hospes & Seeh, 1999). This could be the reason for the higher R0 values. In contrast, Hibbitt *et al.* (1992) describe the teat skin as a firm surface which is able to tolerate mechanical shear

forces. This should result in a lower R0 of the teat skin. R2 of teat skin was lower than that of human skin. This disagrees with the anatomic differences regarding the higher proportion of elastic fibres (Hospes & Seeh, 1999). Another reason for the lower firmness and elasticity of teat skin could be the differences in skin thickness between teat and human skin, because the mechanical properties of skin are influenced of skin layer thickness (Krueger *et al.*, 2011). With 1-2 mm teat skin is thicker than human skin. Liang & Boppart (2010) found a thickness of 0.09-0.20 mm for human epidermis and stratum corneum. The measured values of teat skin have a high variation for all traits. In our investigation this variation could be explained with the experimental setup. The chosen measuring time of 20 s was very long and not all of the cows stood still for the whole time. Thus, air got into the probe and could have distorted the measurements. The use of different device settings regarding measuring mode, length of suction and relaxation and number of repetitions could reduce the variability. In some investigations the variation for human skin elasticity was high as well (Luebberding *et al.*, 2014; Bonaparte & Ellis, 2014). R0 seems to be an important trait to evaluate teat skin elasticity, because several parameters were calculated with the help of it. Ohshima *et al.* (2013) showed in their study that the parameter F3 is appropriate to evaluate cheek skin elasticity, because it is less influenced by environmental factors compared with the R-parameters. Perhaps the area parameters are suitable to detect teat skin elasticity as well. According to the manuals these parameters have no limiting values, which represent good or bad elasticity. This would be a problem to analyse the elastic properties of teat skin with the help of the F-parameters. The most important problem seems to be that there is no gold standard for measuring skin elasticity. Thus, it is not clear which parameter and experimental setup represents the real elastic properties of skin (Bonaparte & Chung, 2014). This discussion can be transferred to teat skin elasticity as well.

It can be concluded that the suction method is useful to measure teat skin elasticity. Nevertheless, the method has to be validated which requires further investigations.

Conclusions

Based on the results of the present study, the suction method is usable to measure the elasticity of teat skin. To reduce the high variability of the measured values, other device settings might be helpful. This should be investigated in further studies. A validation of the suction method to measure teat skin elasticity is necessary. It cannot be concluded that one of the tested traits is superior to the other regarding the detection of teat skin elasticity. Because several parameters were calculated with the help of the penetration depth of the skin, R0 seems to be

an important parameter. A combination of several parameters is most suitable to evaluate teat skin elasticity.

References

Bonaparte, J.P. and Chung, J. 2014. The effect of probe placement on inter-trial variability when using the Cutometer MPA 580. *Journal of medical engineering & technology* **38**(2) 85-89.

Bonaparte, J.P. and Ellis, D. 2014. Skin Biomechanical Changes after Injection of Onabotulinum Toxin A: Prospective Assessment of Elasticity and Pliability. *Otolaryngology-Head and Neck Surgery* **150**(6) 949-955.

Clancy, N.T., Nilsson, G.E., Anderson, C.D., and Leahy, M.J. 2010. A new device for assessing changes in skin viscoelasticity using indentation and optical measurement. *Skin research and Technology* **16**(2) 210-228.

Courage & Khazaka 2012. *User manual of the The Cutometer® dual MPA 580* Cologne, Germany: Courage+Khazaka electronic GmbH.

Cua, A.B., Wilhelm, K.P., and Maibach, H.I. 1990. Elastic properties of human skin - relation to age, sex and anatomical region. *Clinical Research* **38**(2) A681-A681

Dobrev, H. 2014. Cutometer. In *Non Invasive Diagnostic Techniques in Clinical Dermatology*, Vol. 1, Berardesca, E., Maibach, H. and Wilhelm, K.-P. (eds.), Springer, 315-338.

Dobrev, H.P. 2002. A study of human skin mechanical properties by means of Cutometer. *Folia medica* **44**(3) 5-10.

Dykes, P. 2015. Increase in skin surface elasticity in normal volunteer subjects following the use of copper oxide impregnated socks. *Skin Research and Technology* **21**(3) 272-277.

Everett, J.S. and Sommers, M.S. 2013. Skin Viscoelasticity: Physiologic Mechanisms, Measurement Issues, and Application to Nursing Science. *Biological Research for Nursing* **15**(3) 338-346.

Ferdowsi, H., Moradi, M.A., and Asadi, M. 2013. Histolocical Study on the Sensory Receptors of the Teat Skin in Sarabi Cattle. *International Journal of Basic Sciences & Applied Research* **2**(2) 168-171.

Fiedler, M., Gerhardt, L.C., Derler, S., Bischofberger, G., Hurny, C., and Munzer, T. 2012. Assessment of Biophysical Skin Properties at Different Body Sites in Hospitalized Old Patients: Results of a Pilot Study. *Gerontology* **58**(6) 513-517.

Hashmi, F.and Malone-Lee, J. 2007. Measurement of skin elasticity on the foot. *Skin Research and Technology* **13**(3) 252-258.

Hibbitt, K.G., Craven, N., and Batten, E.H. 1992. Anatomy, Physiology and Immunology of the Udder. In *Bovine medicine. Diseases and husbandry*

of cattle, Andrews, A.H., Blowey, R.W., Boyd, H., and Eddy, R.G. (eds.), Blackwell Scientific Publications, 922 pp.

Hospes, R. and Seeh, C. 1999. *Sonographie und Endoskopie an der Zitze des Rindes.(Sonography and endoscopy of the bovine teat)* Stuttgart: Schattauer Verlagsgesellschaft mbH.

Krueger, N., Luebberding, S., Oltmer, M., Streker, M., and Kerscher, M. 2011. Age-related changes in skin mechanical properties: a quantitative evaluation of 120 female subjects. *Skin Research and Technology* **17**(2) 141-148.

Krzyś, A., Luberański, A., Szlachta, J., and Wiercioch, M. 2011. Dependencies of elasticity changes and geometric parameters on tension force of liners used for milking. *Agricultural Engineering* **7**(132) 45-55.

Kuchler, K. 2011. *Der Einfluss des Melkens auf Durchblutung und Morphologie der Rinderzitze untersucht mittels Color Angiographie und B-Mode Sonographie. (The influence of milking on blood flow and morpholohy of bovine teats using color angiography and B-mode sonography).* Doctoral Thesis. Ludwig-Maximilian-Universität München.

Liang, X. and Boppart, S.A. 2010. Biomechanical properties of in vivo human skin from dynamic optical coherence elastography. *IEEE transactions on bio-medical engineering* **57**(4) 953-959.

Luebberding, S., Krueger, N., and Kerscher, M. 2014. Mechanical properties of human skin in vivo: a comparative evaluation in 300 men and women. *Skin Research and Technology* **20**(2) 127-135.

Nam, G.W., Baek, J.H., Koh, J.S., and Hwang, J.K. 2015. The seasonal variation in skin hydration, sebum, scaliness, brightness and elasticity in Korean females. *Skin Research and Technology* **21**(1) 1-8.

O'goshi, K.I. 2006. Suction Chamber Method for Measurement of Skin Mechanics: The Cutometer®. In *Handbook of Non-Invasive Methods and the Skin*, 2nd edn, (Eds. J Serup, GB Jemec & GL Grove). CRC Press, 579-582.

Ohshima, H., Kinoshita, S., Oyobikawa, M., Futagawa, M., Takiwaki, H., Ishiko, A., and Kanto, H. 2013. Use of Cutometer area parameters in evaluating age-related changes in the skin elasticity of the cheek. *Skin Research and Technology* **19**(1) E238-E242.

Ryu, H.S., Joo, Y.H., Kim, S.O., Park, K.P., and Youn, S.W. 2008. Influence of age and regional differences on skin elasticity as measured by the Cutometer®. *Skin Research and Technology* **14**(3) 354-358.

Woo, M.S., Moon, K.J., Jung, H.Y., Park, S.R., Moon, T.K., Kim, N.S., and Lee, B.C. 2014. Comparison of skin elasticity test results from the Ballistometer® and Cutometer®. *Skin Research and Technology* **20**(4) 422-428.

Maximising grazing with a mobile milking robot

E. Cloet[1], V. Brocard[2], F. Lessire[3] and S. Guiocheau[1]
[1] *Chambre d'agriculture de Bretagne, 2 allée Saint-Guénolé, CS 26032, 29322 Quimper Cedex, France*
[2] *V. Brocard, Institut de l'Elevage, BP 85225, 35652 Le Rheu Cedex, France*
[3] *F. Lessire, Service de Nutrition, Faculté de Médecine Vétérinaire, Université de Liège, Chemin de la ferme, 6 B, 4000 Liège, Belgium*
Estelle.Cloet@bretagne.chambagri.fr

Abstract

Recent development of milking robots (AMS) is often followed by a change in production systems with a decrease in grazing despite its numerous benefits. Because milking requires permanent access to the robot, cows cannot graze in paddocks which are a long way from the AMS or separated by roads. Moving the AMS might be a solution to maintaining grazing in these contexts. Therefore, two experimental farms, Liège in Belgium and Trévarez in Brittany, France, chose to design a mobile AMS by placing it on a trailer. This trailer is inside the cowshed during winter and on a grassland summer site during 6 months of the year. Two grass management systems were studied over 3 to 6 years, allocating two or three paddocks per 24h (systems AB and ABC). The impact of these different systems on animal performance, cow traffic, grass usage, working time and feeding costs was assessed.
These two experimental farms show that it is possible to use a mobile milking robot, with the moving time for the robot, cows and drafting gate limited to 15 man-hours in total, the AMS being out of use for just 3 to 4 hours. High grass usage and good traffic to the robot were obtained in both the AB and the ABC systems with limited human intervention. However, the investment cost of such solutions remains relatively high and must be balanced by decreased feeding costs.

Keywords: Dairy cows, automatic milking system, mobile milking robot, grazing, grass management

Introduction

Investment in a robotic milking system is becoming a common solution to reduce labour requirements in Europe. The number of farms with an AMS (automatic milking system) in France has doubled since 2010 with an AMS present on approximately 4,800 farms (Allain, 2016). However, after purchasing

the AMS, farmers usually increase concentrate usage in order to maximise milk production, and grazing is reduced or even eliminated. In France, only 50% of farms are still grazing after the arrival of an AMS (Poulet et *al*, 2013).
Although grazed grass has always formed the basis of the forage system in many west European regions because of its low production cost, grazing also has many positive impacts, e.g. on animal health (Burow *et al*, 2011), milk composition and the environment. French farms with AMS and grazing have higher profits per work unit than those without grazing (Caillaud et al, 2015).
The growth in farm size leads to land fragmentation and reduces the area of grazed grass per cow. Because milking with an AMS requires permanent access to the robot, cows cannot graze in paddocks which are a long way away or separated by roads. It is necessary to find ways of enabling those areas to be grazed. A mobile AMS might allow grazing of large blocks of paddocks which are not directly accessible from the barn.
This paper describes studies on two mobile AMS, the grass management systems in place during the grazing season and their impact on milking performance, cow traffic, grass usage, working time and feeding cost compared with the winter period when the AMS is located inside the cowshed.

Materials and methods

Design of the mobile system

The experimental farms of Trévarez (Chambre d'agriculture de Bretagne), located in a maritime climate in western France, and of the University of Liège, located in the Ardennes in Belgium, are in areas with good grass growth all year round. Grazed grass has always been the basis of the forage system in these areas but, as on many commercial farms, only part of the agricultural area of these farms can be grazed by the dairy herds. For example, in Trévarez, the land is split into four main blocks of fields by roads and neighbours. In Liège, a motorway separates the barn from the grazing area.
To allow grazing of areas which are not accessible from the barn, these experimental farms chose to design a mobile AMS by placing it on a trailer. The AMS on its trailer is located inside the cowshed during the winter and on a grassland summer site for 6 months of the year (Cloet et al., 2017).
In Trévarez, the system consists of two trailers, one with the robot and the second one with the milk tank. The trailer with the milking robot (a Delaval VMS milking robot) also carries the computer for data management and has an area for the technical equipment needed for the robot (compressor, vacuum pump, hot water tank and electrical installation).

During the winter, the trailer with the robot is located inside the shed but the trailer with the tank remains outside. Cows have access to grazing on the winter site during spring and autumn. From April to October, the trailers, drafting gate and cows are moved to the summer site. On the summer site, a platform was built to accommodate the trailers. The drafting gate is placed so that it directs cows towards the tracks to the paddocks. A waiting area was constructed with a slatted floor above a slurry pit. An isolation box, a concentrate silo, a small technical room and a surveillance camera were also added. The extra cost of the mobile system was € 95,000 for the trailers and the summer site facilities because all the services had to be installed (no water, no power, no internet, no tracks, no fences, no access road at the start).
In Liège, the system is similar and also consists of two trailers (with a Lely T4C milking robot). The summer site also had to be fitted out, with stabilisation of the area for the trailers, addition of a concentrate silo, a flexible tank to collect the effluent, and a slatted floor to stabilise the access for the cows. The total additional cost was € 75,000.

The mobile AMS was first transferred in 2011 in Liège and in 2014 in Trévarez. The mobile AMS is placed in a block of paddocks on the summer site where several grass management strategies can be tested.

Grass management strategies

In a situation where the diet is 100% grazed grass, the key to successfully limiting human intervention is to motivate the cows to go to the AMS voluntarily. To increase cow traffic without fetching the cows, providing the cows with an opportunity to reach a new paddock of grass after the AMS can be a motivation. The experiments conducted in Australia (Lyons et al., 2013) and Ireland (O'Brien et al., 2015), offering fresh grass two or three times per 24h to facilitate cow traffic to the AMS, were used to choose the grass management strategies in Liège and Trévarez.
During the grazing period, the herd only has a grazed grass diet with no buffer forage and little use of concentrate. The grazing system is rotational with a front fence.
In Trévarez, the pastures are ryegrass and white clover mixtures. The water points are located in the waiting area of the AMS and in the tracks. The 22 ha of the summer site are split in 27 paddocks of 0.7 to 1 ha.
In Liège, the summer site is composed of permanent grassland and the 24 ha are split into 14 paddocks. The maximum distance between the paddock and the AMS is 700 to 800 m on both sites.

In those conditions, different strategies were tested using 2 paddocks per 24 h (AB; day and night) or 3 paddocks per 24 h (ABC; morning, afternoon, night). Movement to the paddocks after the AMS was monitored by means of a drafting gate located in the waiting area.

In Liège, the paddocks in the day blocks were accessible at 6 a.m. and the paddocks in the night blocks were accessible at 6 p.m. In Trévarez, the two strategies were tested with different changeover times. In 2014, the 22 ha of the summer grazing site were divided into two blocks: a day block and a night block. The access times were 7 a.m. for the day paddocks and 5 p.m. for the night paddocks. In 2016 (ABC), the area was divided into 3 blocks: morning, afternoon and night blocks. The access times were 5 a.m. for the morning paddock, 12 a.m. for the afternoon paddock and 7 p.m. for the night paddock. The 2015 results were excluded from the study because severe summer drought limited the experiments.
The herd is composed of Holstein cows on both farms. On average 51 cows were milked in Liège in 2015 (calving all year). In Trévarez, 46 cows were milked on average in 2014 and 52 in 2016. The seasonal average hides an important variation in the number of cows between spring and summer. For example, in 2016, the number of cows milked per day varied from 61 to 35 cows, depending on the calving periods and grass availability.

Results and discussion

AMS transfer between winter and summer sites

The first transfer of the mobile AMS took place in 2011 in Liège and in 2014 in Trévarez.
In Liège, the summer site is only 100 m from the barn, but direct access is made impossible by a motorway, whereas in Trévarez, the summer site is 4.5 km from the winter site (Table 1).

Table 1: Mobile AMS transfers in Liège and Trévarez

	Liège	Trévarez
Distance from building to summer site	100 m but 4-track motorway to cross	4.5 km
Time required (human hour)	15h (4 people)	13-17h (3-4 people)
Transfer of	Cows, robot, tank	Cows, robot, tank, drafting gate
Robot stopped	4h	3h

The first step in the transfer is to close off the cows' access to the robot, stop the AMS and disconnect the connections between the two trailers and to the electricity and water supply. The second step is to move the trailers between the sites. Once installed on the site, the trailers have to be reconnected. During that time, the cows are transferred with a livestock truck. The robot starts again with the first cow to milk, after only 3 to 4 hours of interruption.
After 3 (Trévarez) and 6 (Liège) years of experience, the transfer is no longer considered a problem and is easily done, and there is no need for the AMS retailer to be present.

Animal performance in 100% grazing

The experiments in Trévarez and Liège between 2014 and 2016 kept the cows in a 100% grazed grass system for 150 to 200 days (Table 2). The grazed grass intake observed was over 2.5 t DM per cow per year in both situations, which is far above the common reference levels with an AMS in these regions. These results show that it is possible to integrate an AMS into a grass system with no buffer forage over a long period and with little use of concentrate (Table 2). The milk yield and milking frequency are also satisfactory in these conditions (Table 2).

Table 2: Principal results for the 100 % grazing period in Liège and Trévarez

	Liège	Trévarez	
	2015	2014 - AB	2016- ABC
Number of days 100% grazing in season	195	161	149
Grazed grass intake per cow (t DM yr^{-1})	2.5	2.6	2.5
Number of milking cows	51	46	52
Milk per AMS (kg d^{-1})	961	867	914
Milk per cow (kg d^{-1})	18.8	18.6	17.7
Av. lactation stage (month)		6.5	6.2
Milking frequency (d^{-1})	2.2	1.8	1.7
Concentrate (kg cow^{-1} d^{-1})	2.7	0.9	0.7

Feeding costs and working time

Thanks to grazing, the feeding cost (concentrate and forage cost) in summer is much lower than in winter: -45% in Liège and -75% in Trévarez (Table 3). This difference results in a higher margin over feeding cost and a greater profit for farmers.

Table 3: Comparison of feeding cost between winter and summer in Liège and Trévarez

€ per 1000 l	Liège	Trévarez
Feeding cost winter	145.5	86.3
Feeding cost summer	79.7	21.9

In Trévarez, the herdsman's time spent looking after the cows and the milking robot was compared for the situation during winter without any grazing and with 100% grazing during the summer (Table 4). The result shows a reduction in working time of 1 hour 40 minutes per day during the summer, which allows time for other activities. This is partly due to good cow traffic with, most of the time, no need to fetch the cows.

Table 4: Comparison of the working time between winter and summer in Trévarez

Hours per day, in Trévarez (2016)	100% grazing	100% in the barn
Time around robot	0:58	1:03
Time inside the barn	0:05	
Time for feeding		1:49
Time for grass management	1:04	
Total time	2:07	3:48

The comparison of the two grass management strategies, AB (2014) and ABC (2016) in Trévarez did not show a significant difference in milk production (Déprés, 2016); though it remains difficult to compare the situations: different grazing years, grass growth, herd composition, etc. In terms of milking frequency, the results show that the choice of milking permission parameters could have more influence than the number of paddocks allocated. Indeed, different permission parameters were tested in 2016 and the less restrictive one resulted in a significantly lower milking frequency than with the second one which was more restrictive and closer to the 2014 permission parameters (Brocard et al., 2017).

Conclusion

The experiences on the two experimental farms show that it is technically possible for an AMS to be mobile, and that it is easy to transfer the system between the winter and summer sites. The 100% grazing systems allow a high intake of grazed grass with limited use of concentrate and satisfying milking performance. The reduced intervention time and the high margin over feeding cost could compensate for the additional cost of the mobile system.
The grass management strategies tested offer practical observations to help farmers who want to integrate an AMS into a grass-based system.

References

Allain C., 2016. « Robots de traite, le déploiement continue ». Disponible sur www.idele.fr

Brocard V. et al., 2017. Pâturer avec un robot de traite : propositions de mode d'emploi. AFPF congress, Paris, march 2017, under press.

Burow E. et al., 2011. The effect of grazing on cow mortality in Danish dairy herds. *Prev.Vet. Med*., 100, p 237 - 241.

Caillaud D. et al., 2015. Résultats techniques et économiques de deux échantillons d'élevages français avec ou sans robot de traite. *Renc. Rech. Rum*, 22, p341-344

Cloet E. et al, 2017. Pâturer avec un robot de traite déplaçable pour lever la contrainte d'un parcellaire morcelé. *International RMT Congress « Bâtiments d'élevage de demain : construire l'avenir »* Lille, Febr. 17, under press.

Despres C., 2016. Impacts sur les performances techniques et les aspects socio-économiques d'un système de pâturage à trois parcelles par jour (ABC) par rapport à deux (AB). Master's thesis, *ISARA-Idele*, 98 p.

Lyons N.A. et al., 2013. Comparison of 2 systems of pasture allocation on milking intervals and total daily milk yield of dairy cows in a pasture-based automatic milking system. *J. Dairy Sci.*, 2013a, Vol. 96, 7, pp. 4494-4504.

O'Brien B. et al, 2015. Automatic milking within a grass based dairy farming system. Proc. of the EAAP congress, Warsaw. p334.

Poulet J.L. et al., 2013. Etat des lieux de la traite robotisée en France et en Europe. Disponible sur www.idele.fr

Prediction of dry matter intake of lactating dairy cows with daily live weight and milk production measurements

P. Faverdin[1], A. Charrier[1] and A. Fischer[1,2]
[1]*Agrocampus Ouest, INRA, PEGASE, F-35590 Saint-Gilles, France*
[2]*Institut de l'élevage, Department of animal husbandry techniques and environment, F-35650 Le Rheu, France*
Philippe.faverdin@inra.fr

Abstract

In dairy farming, monitoring tools are developing rapidly and the possibility of combining available data to generate additional information raises new questions. The high throughput body weight is a new and frequent phenotype on dairy farms. Feed intake monitoring in dairy cows remains largely absent, even though it is useful for herd management. The purpose of this work was to predict the dynamics of dry matter intake with a model using live weight, milk production and ration characteristics. This model is based on the assumption that changes in body weight are closely related to dry matter intake through two components: short-term changes in digestive content related to ingestion and long-term changes in body reserves, which are linked to the cumulative energy balance of the cow since calving. The energy balance results from the difference between the energy inputs from the ingested quantities and the energy requirements related to milk production. The model was tested in a trial with 65 cows receiving the same complete ration during the first 18 weeks of lactation. Observed individual intake was predicted well by the model, with average weekly errors of 2.3 kg, although the daily errors are still high (SD = 3.31 kg). Intake prediction during the first month of lactation showed a systematic bias and further investigation will be necessary to understand this bias and correct it.

Keywords: intake, dairy cow, body weight, dynamic model, digestive content, body reserves

Introduction

Precision livestock farming is booming, especially in the dairy sector where individual monitoring is most common. Data on milk production and animal weights are now widely available on commercial farms. However, feed intake monitoring in dairy cows remains largely absent, even though it is useful for herd management. Feed intake kinetics throughout the lactation appear to be closely correlated with body weight kinetics throughout the lactation (Figure 1)

and with milk yield kinetics. Combining daily body weight and milk yield measurements could therefore be a potential predictor of phenotypes which is still difficult to assess on the farm. The main purpose of the present study was to predict dry matter intake from daily changes in body weight and milk yield.

Recent studies have shown that a combination of changes in body weight and body condition scores is a good method of estimating energy changes in body reserves (Banos *et al.*, 2005, Friggens *et al.*, 2011, Thorup *et al.*, 2012). Changes in live weight are therefore an interesting and accessible phenotype for estimating changes in body reserves. Live weight is composed of four main components: “bone mass”, “lean mass” which is rich in water and protein, “fat mass” which is rich in lipids from reserves and poor in water, and “digestive contents” representing about one-quarter of live weight in lactating cows. Due to its different components, it is still difficult to relate the variation in live weight to variations in body reserves. The use of live weight to estimate body reserves therefore requires an estimate of digestive contents (Friggens *et al.*, 2011; Thorup *et al.*, 2012). At the beginning of lactation, digestive contents increase greatly because of the rapid increase in DMI and partially mask the loss of empty body weight related to the mobilisation of body reserves. To overcome the problem of missing intake data, the weight of the digestive contents was at best a function of the live weight used to calculate empty body weight (Friggens *et al.*, 2011).

The objective of this work was to better interpret live weight changes in relation to dry matter intake and energy balance in two steps:
- use of a simple live weight model to better estimate the importance of dry matter intake in the weight of the digestive contents and the importance of energy balance to explain variations in empty live weight
- extrapolation of these parameters from the live weight model to a dynamic mechanistic model using daily live weight and milk production data to predict dry matter intake.

The aim of this study was to achieve a proof of concept that the daily live weight will give interesting added value to milk yield data used to predict dry matter intake variations for monitoring dairy cows.

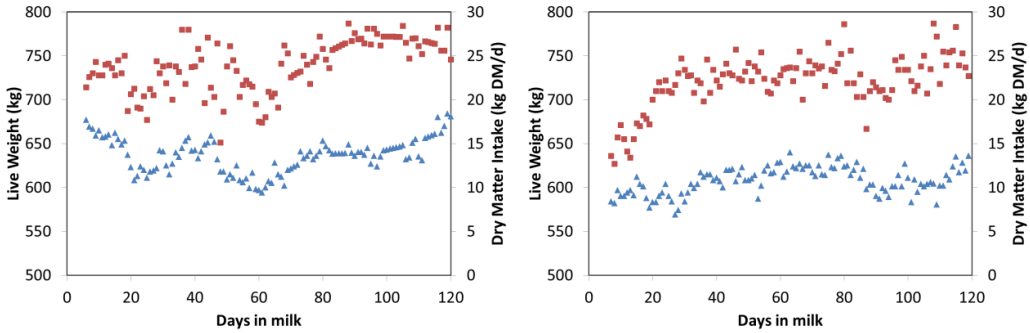


Figure 1: Example of daily intake (square) and live weight after morning milking (triangle) of two lactating cows during the first part of lactation.

Materials and methods

Experimental dataset

The data used are based on an experiment carried out at the INRA experimental farm in Méjusseaume (INRA URM PEGASE) to study the variability in feed efficiency of dairy cows during lactation. These data cover the first 120 days after calving in 65 Prim'Holstein dairy cows (from September 2014 to February 2015). The experimental group of cows was composed of 34 primiparous and 31 multiparous cows.

The cows were milked twice a day (7:00 and 16:00) and fed after each milking with an iso-protein and iso-energy ration based on maize silage. The maize-based diet was offered as a total mixed ration with 64.7% maize silage, 13.5% cereal based compound, 10.5% soyabean meal, 10% dried lucerne and 1.3% mineral, vitamin and ammonium sulphate mixture. The cows were fed individually ad libitum twice daily after milking with individual uneaten feed levels of 10% on average.

The amount of each feed offered was weighed at each distribution by the robot feeder ("roulimetre"). The uneaten feed was weighed and removed from the trough each morning before the next distribution. The dry matter (DM) content of each feed was measured once a week for concentrated feed and each day for silage. The amount of feed dry matter intake (DMI) was then calculated daily as the difference in DM between the amounts offered and refused for each cow. The feed value of each component of the diet was determined by means of chemical composition analysis (departmental analysis laboratory of the LDA, Saint-Brieuc, France) and equations from INRA feeding systems (INRA, 2010).

The cows were weighed every day after milking using a static automatic weighing platform W-2000®, a prototype developed by Delaval (Tumba,

Sweden). Milk production was measured at each milking and then cumulated daily. The fat and protein content of the milk were analysed four times a week (on two days, at the morning and evening milking) to calculate milk net energy output.

Data measured every day over long periods may contain either missing data or some aberrant data due to operational problems (identification, weighing error, failure of the measuring instrument). For this type of model, reliable daily data are required. These aberrant values were detected using Loess local regressions. This is particularly suitable for nonstationary time series, which is the case in this study. The Loess was adjusted to the data for live weight (LW), milk yield (MY), DMI, milk fat content (MFC) and milk protein content (MPC). Any value outside an interval of plus or minus two standard deviations around this Loess was considered aberrant and deleted.

Live weight model

The live weight model hypothesises that changes in live weight are mainly due to changes in digestive contents and body reserves (equation 1):

$$\Delta LW = \Delta digestive\_content + \Delta body\_reserves \qquad (1)$$

Throughout the study, only the morning LW was used, as it is less subject to variations due to meals as the first meal of the day starts just after weighing. In addition, weighing is carried out after milking when the udder is empty, which makes it possible to avoid the weight variations associated with milk production. The weight of the pregnant uterus and the foetus was disregarded because the study period was before 150 days of gestation when the gestation weight becomes truly significant (Ferrell et al., 1976).

The model assumes that changes in digestive contents are primarily related to changes in intake. For the component of body reserve changes in live weight variations, the model assumes that these variations are proportional to the energy balance (EB) of cows. This energy balance was calculated in terms of net energy (UFL) based on the INRA feeding system and tables 2010 (Faverdin et al., 2010) as the daily difference between the net energy intake (UFLi) and energy requirements (UFLreq) for milk production (function of MY, MFC and MPC) and maintenance (function of LW) (equation 2):

$$\mathrm{UFLreq_t} = \mathrm{MY_t} \times [0.44 + 0.0055 \times (\mathrm{MFC}_t - 40) + 0.0033 \times (\mathrm{MPC}_t - 31)] + (1.54 + 0.0066 \times \mathrm{LW}_t) \quad (2)$$

A positive EB indicates that the energy intake is higher than the energy required, this excess of energy being stored as body reserves. Conversely, a negative EB is interpreted as a deficit in energy; this lack of energy is covered by mobilisation of body reserves. The cumulative EB (cumulated energy balance, CEB) throughout the lactation thus reflects changes in body reserves after calving.

Daily live weight can thus be considered as a function of the previous day's DMI for digestive contents and of CEB since calving for body reserve changes. This assumption is modelled in equation 3. The live weight at calving (LW_0) represents the initial situation and is useful when the average body size of the cows is considered:

$$LW_t = \alpha \times CEB_{t-1} + \delta \times DMI_{t-1} + \gamma \times LW_0 \qquad (3)$$

This model was simply estimated by linear regression of the available dataset, considering the coefficients α, δ, γ to be identical for all the cows because they were all fed with the same ration every day. The coefficient α can be used to convert the mobilisation of body reserves into UFL per kg of live weight and the coefficient δ represents the changes in digestive content, corresponding to a change in intake of one kg of DM. These coefficients were then reused in the intake model.

Dry matter intake model

In equation 2 above, intake is used to calculate the CEB (medium and long term effect) and digestive contents (short-term effect). The idea was to construct a deterministic model from a mathematical sequence of DM intake defined by recursion at daily time intervals starting at calving and using the high throughput data for live weight and milk production (to calculate the animal's energy requirements). The variation in daily LW between two days (t and t-1) can be simply estimated using equation 4:

$$LW_t - LW_{t-1} = \alpha(UFLi_{t-1} - UFLreq_{t-1}) + \delta \times (DMI_{t-1} - DMI_{t-2}) \quad (4)$$

The daily energy intake, UFLi is theoretically the product of energy density (UFLration UFL/kg DM) of the ration and intake (kg DM/d). The UFLration is calculated as the weighted sum of the feed energy values. However, due to digestive interactions, the energy density of the ration per kg of DM is not constant. To simplify the model, a simple regression correction (equation 5) was used based on simulation of the densities calculated with the INRA reference method (Faverdin et al., 2010):

$$UFLi = 0.863 \times (DMI \times UFLration) + 1.35 \qquad (5)$$

This UFL correction model is only valid for a ration similar to the one used in this study and must be adjusted for different rations. By combining equations (4) and (5), DMI_{t-1} can be isolated from equation (6):

$$DMI_{t-1} = \frac{(LW_t - LW_{t-1} - 1.35 \times \alpha + \delta \times DMI_{t-2} + \alpha \times UFLreq_{t-1})}{\delta + 0.86 \times \alpha \times UFLration_{t-1}} \quad (6)$$

To simulate the DMI with the model, it is therefore sufficient to estimate an initial value of DMI at t=0 and to have continuous monitoring of the LW and the MY. The predicted DMI values are compared with those measured in the experiment. To test the validity of the prediction, the root mean square error (RMSE) was estimated as the sum of the squared differences between the measured and predicted values divided by the number of values. Model calculations and statistical analyses were performed on version 3.1.2 of the R® statistical software (R Core Team, 2015).

Results and discussion

The linear regression to predict LW gives the following equation:

$$LW_t = 35.4 + 0.206\ (\pm 0.004) \times CEB_{t-1} + 4.62\ (\pm 0.09) \times DMI_{t-1} + 0.818(\pm 0.005) \times LW_0$$

where n=7466, RSE = 25.2 kg and R^2=0.875

The coefficients obtained in this model are very consistent with the literature. The coefficient 0.206 related to the energy balance means that the loss of one kg of live weight corresponds approximately to an energy value of 5 UFL, which is very close to the interval of 4 to 6 UFL/kg LW proposed by Chilliard et al. (1987) for the mobilisation of reserves. It is likely that the energy value of one kg LW mobilised is less than the energy required to store one kg LW. Because the experimental period focused on the start of lactation (1-120 days), the coefficient of CEB may only reflect the energy value of one kilogram of mobilisation. Similarly, the coefficient of 4.62 digestive content per 1 kg of ingested DM is close to that proposed by Pithon (1975) and slightly higher than that proposed by Rémond (1988). These two coefficients are used in the intake model (equation 6b):

$$DMI_{t-1} = \frac{(LW_t - LW_{t-1} - 1.35 \times 0.206 + 4.62 \times DMI_{t-2} + 0.206 \times UFLreq_{t-1})}{4.62 + 0.86 \times 0.206 \times UFLration_{t-1}} \quad (6b)$$

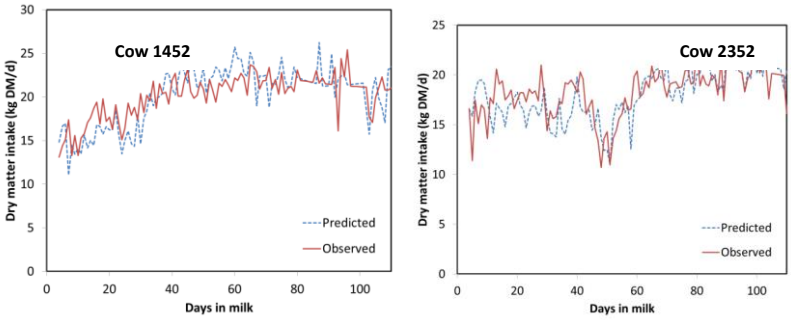


Figure 2: Evolution of observed (──) and estimated (- - -) dry matter intake using the intake model for two cows 1452 (normal) and 2352 (with drop in the middle) during the first 120 days of lactation.

Comparison of simulated DMI values from equation (5) and observed values gives an average RMSE of 3.31 kg DM, the standard deviation of DMI being 3.85 kg DM. This large error is reduced when average values are compared at a weekly level (2.3 kg DM). This is due to the fact that large daily variations in the DMI model are not synchronous with the day to day observations. Nevertheless, this quality of prediction varies greatly from one cow to another. Figure 2 shows a good fit between the kinetics and the model based on observation date, with an RMSE of 2.3 and 2.1 kg DM, respectively, for the two cows 1452 and 2352. The trace for cow 2352 (Figure 2) shows that the model is capable of estimating short-term decreases in DMI and simulating "non-standard" curves. On the other hand, the DMI of other cows is a poor match, with significant biases. Two main phenomena explain these biases: the stage of lactation and the differences in feed efficiency between cows.

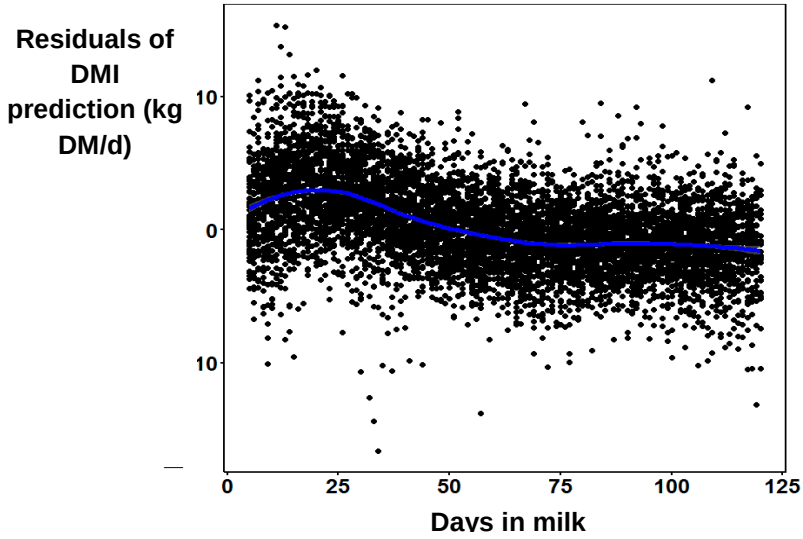


Figure 3: Evolution of the dry matter intake residuals model for 65 cows during the first 120 days of lactation. The line indicates the average value for residuals obtained with Loess smoothing. It clearly indicates a bias in the model in early lactation.

The residues are higher during the first 40 days in milk and present a bias with underestimation of DMI. This early lactation bias is present for the majority of cows (Figure 3), and is more or less pronounced for some individual curves (Figure 2). This lack of adjustment suggests that the model is unable to take account of important phenomena in early lactation, which leads to underestimation of DMI after calving. A first hypothesis relates to the stability of the coefficients used with the stage of lactation. It is possible that the variation of one kg of weight does not correspond to the same energy value, depending on

the stage (Moe et al., 1971, Doreau and Rémond 1982, Faverdin et al. 2006). A second hypothesis, based on the results of Doreau and Rémond (1982) and Doreau et al. (1988), is that feed digestibility is lower in early lactation than in the rest of lactation. According to Doreau and Rémond (1982) and Doreau et al. (1988), digestibility decreases until 4 to 6 weeks after calving, when the average residuals in the DMI model are highest. It would be interesting to correct the energy inputs in early lactation in the EB calculation, although this is not currently taken into account by feeding systems.

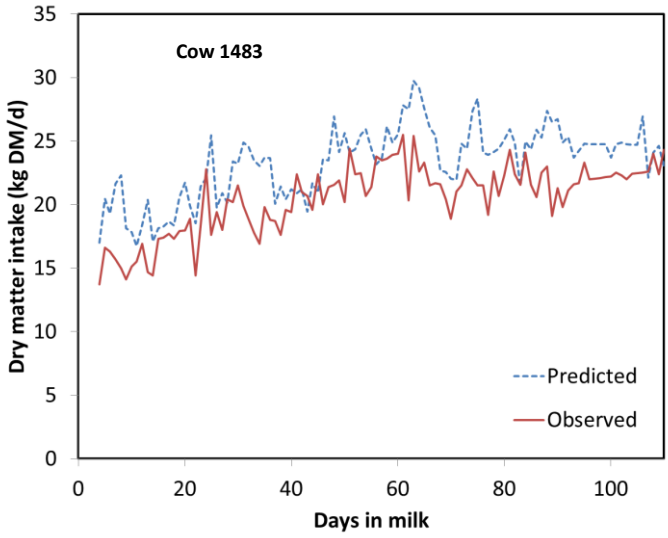


Figure 4: Observed (──) and estimated (- - -) evolution of dry matter intake during the first 120 days of lactation for a very efficient cow. The model does not simulate the level of feed intake during the whole period (RMSEP = 3.4 kg DM/day), but simulates the variations satisfactorily.

Another bias present for some cows appears to be related to differences in feed efficiency between cows. The bias sometimes appears systematically over the entire period. Figure 4 illustrates this situation. The DMI estimated by the model has a similar pattern to the observed DMI, but systematically shifted upwards. A cow with poor feed efficiency will present the opposite trend. In practice, this bias is probably less important because it does not mask the kinetics of DMI.

Finally, the model is very sensitive to the initial conditions. Since the model is constructed as a series in which DMI tests a DMI_{t-1} function, the initial data in the series plays an essential role in terms of the quality of the estimates. Initial live weight or intake values which differ too much from the trend will generate biased estimates during a large part of the simulation.

Conclusions

High-throughput live weight measurements are a useful means of estimating individual intakes. Changes in this weight are due both to changes in medium and long-term energy balance reserves and to shorter-term changes in digestive contents, which account for one-quarter of the live weight of the cow. These two components are sensitive to variations in dry matter intake. A simple model based on variations in live weight and production can simulate short- and medium-term variations in dry matter intake and make it possible to detect abnormal evolutions. However the energy models used suffer from significant biases at the beginning of lactation which must be better understood before we can estimate changes in individual dry matter intake during this critical period.

Acknowledgements

The authors thank the “GIS Elevage Demain” for supporting the study and all the staff of the INRA experimental farm at Méjusseaume (UMR PEGASE) for their management of the experiment.

References

Banos, G., Coffey, M. P. and Brotherstone, S. 2005. Modeling daily energy balance of dairy cows in the first three lactations. *Journal of Dairy Science* **88** (6) 2226–37.

Chilliard, Y., Rémond, B., Agabriel, J., Robelin, J. and Vérité, R., 1987. Variations du contenu digestif et des réserves corporelles au cours du cycle gestation - lactation. *Bulletin Technique du Centre de Recherches Zootechniques et Vétérinaires de Theix* **70** 117-131.

Doreau, M., Rémond, B. 1982. Comportement alimentaire et utilisation digestive d’une ration de composition constante chez la vache laitière en fin de gestation et début de lactation. *Reproduction Nutrition Développement* **22** (2) 307–24.

Doreau, M., Adingra, K., Rémond, B., and Chilliard, Y. 1988. Effets respectifs des Quantités ingérées et du stade physiologique sur la digestibilité d’une même ration chez la vache laitière. *Reproduction Nutrition Développement* **28** (Suppl.1) 63–64.

Faverdin, P., Delagarde, R., Delaby, L., and Meschy F. 2010. Alimentation des vaches laitières. In *Alimentation des bovins, ovins, caprins*. Quae Editions, Versailles. 23-58.

Ferrell, C.L., Garrett, W.N., and Hinman, N. 1976. Growth, development and composition of udder and gravid uterus of beef heifers during pregnancy. *Journal of Animal Science* **42** 1477-1489.

Friggens, N.C., Thorup, V.M., and Edwards, D. 2011. Estimation à la ferme du bilan énergétique des vaches laitières à l'aide des mesures fréquentes de poids vif et de note d'état corporel. *Rencontres Recherches Ruminants* **18** 39–42.

INRA, 2010. *Alimentation des bovins, ovins et caprins. Besoins des animaux – Valeurs des aliments.* Quae Editions, Versailles, 312pp.

Moe, P. W., Tyrrell, H. F., and Flatt, W. P. 1971. Energetics of body tissue mobilization. *Journal of Dairy Science* **54** (4) 548–53.

Piton, J. 1975. Intérêt et importance de la mobilisation des réserves corporelles des vaches laitières au début de la lactation : analyse de quelques facteurs de variation. *Thèse Université des Sciences et Techniques du Languedoc*. Montpellier. 57pp.

R Core Team, 2015. R® statistical software. http://www.R-project.org.

Rémond, B. 1988. Evolution du poids du contenu du réticulo-rumen chez les vaches laitières au cours des deux premiers mois de la lactation.," *Reproduction Nutrition Développement* **28** (Suppl.1) 109-110.

Thorup, V. M., Edwards, D., Friggens, N. C. 2012. On-farm estimation of energy balance in dairy cows using only frequent body weight measurements and body condition score. *Journal of Dairy Science* **95** (4) 1784–93.

Change to new AMS - Effect on milk delivery and milk quality

Sandra Rose-Meierhöfer[1], Sandra Gündel[2], Susanne Demba[3], Christian Ammon[3]
[1]*Hochschule Neubrandenburg, University of Applied Sciences, Department of agricultural machinery, Brodaer Str. 2, 17033 Neubrandenburg, Germany*
[2]*Universität Hohenheim, Faculty of Agricultural Sciences, Schloss Hohenheim 1, 70599 Stuttgart, Germany*
[3]*Leibniz Institute for Agricultural Engineering and Bioeconomy (ATB), Department of Engineering for Livestock Management, Max-Eyth-Allee 100, 14469 Potsdam, Germany*
rose@hs-nb.de

Abstract

In the last 20 years the number of dairy farms milking with automatic milking systems (AMS) increased continuously. Thus, AMS have been developed steadily regarding technical terms and the used software. The aim of the present study was to investigate whether an AMS of the newest generation with improved sensor technique and new algorithms had advantages in terms of efficiency and animal health compared to a previous model of the same manufacturer. Over a period of ten months, the data of 50 dairy cows were analysed. All cows were milked by a Lely Astronaut A2 as well as by a Lely Astronaut A4. As traits that could be influenced by the change of the milking system milkings per cow and day, milking intervals, time in AMS, milking time, milk yield and milk flow were investigated. All traits under consideration were tested for differences between AMS with generalized linear mixed models. The results of this investigations showed significant influences with the change to the new AMS regarding milking time, time in AMS, milk flow and milking intervals. Milking time and time in AMS decrease whereas milk yield, milk flow and milking interval increase in the new AMS. For milkings per cow and day no significant differences between both systems could be found. In conclusion, the purchase of an AMS of the newest generation could bring advantages regarding time for milking, milk flow and milking interval. However, changes in udder health and efficiency cannot be achieved with technical innovations, exclusively.

Keywords: automatic milking system, new generation, milking time, milk flow, milking intervals

Introduction

The increasing demand for milk and dairy products leads to a new challenge for global dairy production. Therefore, automatic milking systems (AMS) have been developed and used in practice since the 1990s. As a consequence, farms with AMS are faced with the question whether or not an investment in a new AMS is efficient. To estimate the efficiency of AMS, information about behaviour, milk delivery and milk quality are important. The technical design and the functionality of an AMS could influence behaviour and milking characteristics of dairy cows directly and indirectly.

The time in AMS can directly be influenced by the teat-cleaning and cup attachment of the AMS. The cleaning and stimulation of the teats results in oxytocin release and milk ejection (Bruckmaier *et al.*, 2001). A proper teat preparation leads to a better milking performance with higher milk yields per milking, shorter milking time and less bimodality (Sandrucci *et al.*, 2007). According to Berry *et al.* (2013), the milking time contributes to costs in dairy production systems. The milk flow can be influenced by the stimulation technique of the AMS as well. Kolbach *et al.* (2013) found positive effects of the stimulation treatment on peak milk flow. Sandrucci *et al.* (2007) found out that the milk flow is affected by the premilking operations. On the other side, the milk flow is influenced by milkings per cow and day and milking interval as well (Tremblay *et al.*, 2016, Hogeveen *et al.*, 2001). The milk yield per AMS and day is used to evaluate the efficiency of an AMS (Castro *et al.*, 2012). It depends on the individual milk yield per cow, which is influenced by milkings per cow and day, milk flow and time in AMS (Tremblay *et al.*, 2016). Hart *et al.* (2013) found, that cows which are milked three times a day produce more milk than cows which are milked twice a day. On the other side, the length of milking intervals had a significant influence on milk production (Hogeveen *et al.*, 2001). The milk yield per AMS is influenced by the number of cows and the milk flow. This milk yield could be maximized by milking the maximum number of cows per AMS and on average 2.4-2.6 milkings per cow and day (Castro *et al.*, 2012). Thus, the milkings per cow per day play an important role regarding the efficiency of an AMS. Milkings per cow and day depend on the traffic system of the AMS. Bach *et al.* (2009) detected more visits to AMS with forced traffic systems compared with free traffic systems. Gygax *et al.* (2007) compared two AMS from different manufacturers regarding milk yield, milking frequency, milking interval, teat-cup attachment success rate and length of milking procedure. They found differences in teat-cup attachment success, duration of several milking phases and milking frequency regarding different AMS. It cannot be said whether these results can be transferred to the comparison of two AMS of the same manufacturer. Therefore, the aim of this investigation was to

determine whether an AMS of the newest generation with improved sensor technique and new algorithms has advantages in milk delivery and milk quality compared with a previous model of the same manufacturer.

Material and Methods

Animals, milking equipment and study design

The study took place in a commercial dairy farm in Germany. From a total of approximately 220 milking Holstein cows, 50 healthy cows, which moved in a new barn with different housing conditions, were investigated over a period of ten months. The lactating cows were between their first and seventh parity and the days in milk were between 10 and 346. All investigated cows were milked by an Astronaut A2 (Figure 1) as well as by an Astronaut A4 (Figure 2). Both automatic milking systems are produced by Lely (Lely Holding S.à r.l., Maassluis, the Netherlands). The two AMS mainly differ in their design and in their software. The control unit of the A4 is not installed in the milking box like the A2 one. The two AMS differ regarding their dimensions, the type of animal entrance, the motor of the attachment arm and the detection of the animal position inside the box. Furthermore, the number of possible different concentrates and the collected milking data are different between both AMS. On the other side, the cleaning system, the dimensions of the silicone liner and the teat detection system are the same for both AMS. The teat cleaning, premilking and dipping are identical as well.

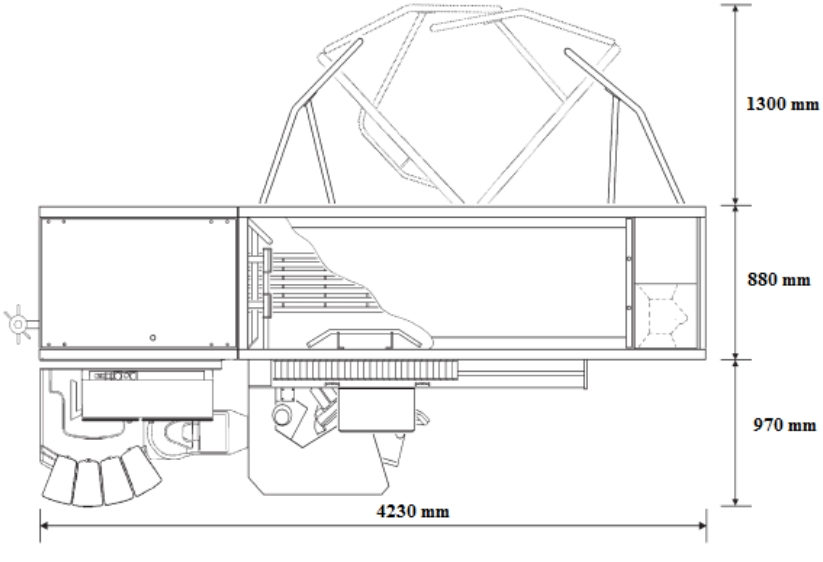


Figure 1. Dimensions of the Lely Astronaut A2 (Lely, 2004)

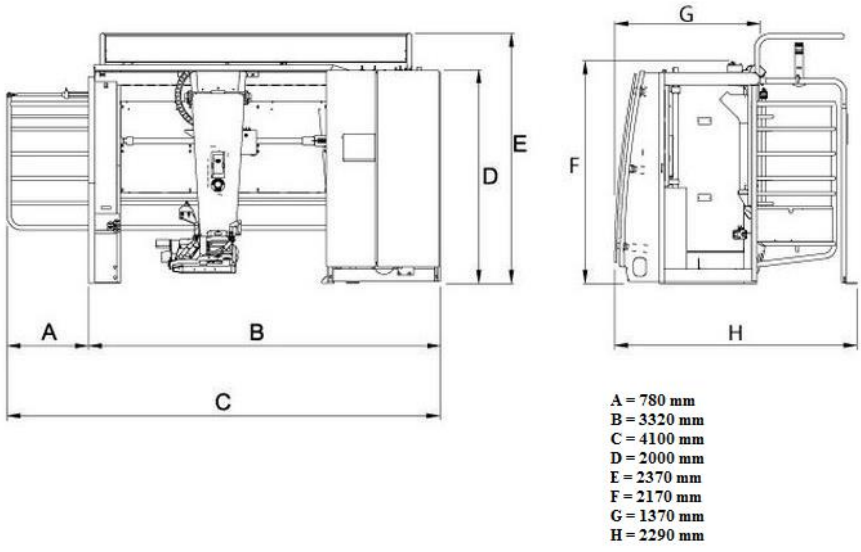


Figure 2. Dimensions of the Lely Astronaut A4 (Lely, 2012)

Both AMS used alternate pulsation with a pulsation rate of 60 min^{-1} and the pulsation ratio was 60:40 in the A2 and 65:35 in the A4. The vacuum was adjusted to 42.5 kPa in the A2 and 44 kPa in the A4. The number of cows per AMS varied between 45 and 50. The cow traffic of the A2 was semiforced, whereas the traffic system of the A4 was free. The housing conditions of the cows changed from slatted floor and cubicles with mats to partially slatted floor and deep bedded cubicles. The group of cows were milked in the A2 first and changed at the beginning of 2015 to the A4. The traits milkings per cow and day, milking interval, time in AMS, milking time, milk yield and milk flow were investigated regarding their dependence of an AMS changeover.

Statistical analysis

To show the effect of the changeover to an AMS of a new generation, a total of 25,522 records were analysed using the SAS software package 9.4 (SAS Institute Inc., Cary, NC, USA). All animals in the third or higher parity were pooled into a single group. For each cow a period of three weeks was set as changeover period. The data from this period were not included in the calculation. The GLIMMIX procedure with logit link function and Poisson distribution was used to analyse the traits milkings per cow and day and milking interval.

The model to analyse the influence of the change on milkings per cow and day was the following:

$$y_{ijk} = \mu + CH_i + P_j + x_1 DIM + C_{jk} + \varepsilon_{ijk} \quad (1)$$

Where y_{ijk} is the observed number of milkings per cow and day; μ is the overall mean; CH_i is the fixed effect for time of changeover (i = 1 to 2);P_j is the fixed effect of parity j (j = 1 to 3); x_1DIM is the regression coefficient for days in milk x; C_{jk} is the random effect for cow k (k = 1 to 50) within parity j (j = 1 to 3); and ε_{ijk} is the independent residual.

The interaction between the time of changeover and the parity was added to the model, to calculate the milking interval. This resulted in the following model:

$$y_{ijk} = \mu + CH_i + P_j + x_1 DIM + x_1(DIM \times P)_i + C_{jk} + \varepsilon_{ijk} \qquad (2)$$

Where y_{ijk} is the observed milking interval; μ is the overall mean; CH_i is the fixed effect for time of changeover (i = 1 to 2); P_j is the fixed effect of parity j (j = 1 to 3); x_1DIM is the regression coefficient for days in milk x; $x_1(\text{DIM} \times \text{P})_i$ is the regression coefficient for day in milk x_1 at the time of changeover i; C_{jk} is the random effect for cow k (k = 1 to 50) within parity j (j = 1 to 3); and ε_{ijk} is the independent residual.

The MIXED procedure was used to analyse the influence of the changeover on milk yield, milk flow, milking time and time in AMS.

The daily milk yield was used to analyse the influence of changeover on the milk yield. The Wilmink approach (Wilmink, 1987) was used to estimate regression coefficients for day in milk in order to achieve lactation curve shapes. This resulted in the following model:

$$y_{ijkl} = \mu + CH_i + P_j + TD_l + x_1 W_1 + x_2 W_2 + x_1(W_1 xDIM)_j$$
$$+ x_2(W_2 xDIM)_j + C_{jk} + x_1 W_{1k} + x_2 W_{2k} + \varepsilon_{ijkl} \qquad (3)$$

Where y_{ijkl} is the observed milk yield; μ is the overall mean; CH_i is the fixed effect for time of changeover (i = 1 to 2); P_j is the fixed effect of parity j (j = 1 to 3); TDl is the fixed effect of test day l (l = 1 to 299); x_1W_1 is the regression coefficient for day in milk x_1; x_2W_2 is the regression coefficient x_2=EXP(-0.05 days in milk); x_1(W_1 x DIM) is the regression coefficient for day in milk x_1 within parity j; x_2(W_2 x DIM) is the regression coefficient x_2=EXP(-0.05 days in milk) within parity j; C_{jk} is the random effect for cow k (k = 1 to 50) within parity j (j = 1 to 3); x_1W_1 is the regression coefficient for day in milk x_1 within the cows; x_2W_2 is the regression coefficient for x_2=EXP(-0.05 days in milk) within the cows; and ε_{ijkl} is the independent residual.

To calculate the influence of the changeover on the milk flow, the following model was used:

$$y_{ijk} = \mu + CH_i + C_{jk} + \varepsilon_{ijk} \qquad (4)$$

Where y_{ijk} is the observed milk flow; μ is the overall mean; CH_i is the fixed effect for time of changeover (i = 1 to 2); C_{jk} is the random effect for cow k (k = 1 to 50) within parity j (j = 1 to 3); and ε_{ijk} is the independent normally distributed residual.

With the following model the influence of the changeover on milking time and time in AMS was calculated:

$$y_{ik} = \mu + CH_i + MY + MF + (MY \times MF) + C_k + MY_k + MF_k + (MY \times MF)_k + \varepsilon_{ik} \quad (5)$$

Where y_{ik} is the observed milking time and time in AMS; μ is the overall mean; CH_i is the fixed effect for time of changeover (i = 1 to 2); MY is the mean milk yield; MF is the mean milk flow; (MY x MF) is the interaction between milk yield and milk flow; C_k is the random effect for cow k (k = 1 to 50); MY_k is the random regression coefficient for milk yield within cow k; MF_k is the random regression coefficient for milk flow within cow k; $(MY \times MF)_k$ is the interaction between milk yield and milk flow within cow k; and ε_{ik} is the independent normally distributed residual.

Results and Discussion

The mean values of both AMS regarding milkings per cow and day, milking interval, time in AMS, milking time, milk yield and milk flow are shown in Table 1.

Table 1. Means and 95% confidence intervals (CI) for milkings per cow and day, milking interval, time in AMS, milking time, milk yield and milk flow in the Lely Astronaut A2 and the Lely Astronaut A4

Trait	A2	CI		A4	CI	
		Lower	Upper		Lower	Upper
milkings per cow and day	2.9	2.64	3.16	2.9	2.52	3.45
milking interval (hh:minmin ± min)	07:49	07:30	08:10	08:10	07:49	08:31
time in AMS (minmin:ss ± s)	06:36	05:18	07:48	06:24	05:06	07:36
milking time (minmin:ss ± s)	04:30	03:12	05:48	04:30	03:12	05:48
milk yield (kg per cow and day)	37.7	35.7	39.7	41.0	38.9	43.1
milk flow (kg min^{-1})	2.7	2.5	2.9	3.1	2.9	3.3

The milking time differed significantly between both AMS ($p = 0.0199$). Cows were milked in average 270 s (4 min 30 s) in the A2 and 269 s (4 min 30 s) in the A4. The time in AMS was significant shorter ($p < 0.0001$) for the A4 as well. It was for A2 6 min 36 s and A4 6 min 24 s. Both AMS differed significantly regarding daily milk yield ($p < 0.0002$). The milk yield increased by 3.3 kg with the changeover of the AMS. The differences between both AMS regarding milk flow were significant as well ($p < 0.0001$). The milk flow was 2.7 kg min^{-1} in the A2 and 3.1 kg min^{-1} in the A4. The milk flow increase with the change of the AMS. The milking interval was 7 h 49 min and 8 h 10 min for the A2 and for the A4, respectively. It differed significantly between both AMS (< 0.0001). The milking interval was longer for the A4 than for the A2. For milkings per cow no significant differences between both systems could be found.

One of the key factors influencing the decision of new investment is the economic gain a producer will achieve with a new milking system (Hogeveen *et al.*, 2004). Therefore, the efficiency of a milking system play an important role. The milk yield per AMS and day is used to evaluate the efficiency of an AMS. This depends on individual milking time, because longer milking times reduce the milking capacity of an AMS (Castro *et al.*, 2012). In this investigation the milking time as well as the time in AMS was significantly less in the Astronaut A4 compared with the Astronaut A2. Although the milking time differed significantly between both AMS, from a practical point of view a shortening of the milking time to a second can be neglected. The high number of records resulted in the significant differences of the milking time during the present investigation. Regarding the time in AMS, it could be assumed that the technical development had improved the functionality of the cleaning brush and the teat cup attachment, with the help of faster imaging software and laser technology. The milking capacity is influenced by the attachment technology (Kaufmann *et al.*, 2001). The whole milking process is optimized by finding the teats quickly and accurately. This leads to a shorter milking time with better milk delivery. Sandrucci *et al.* (2007) confirm the importance of the time between stimulation and milking for the milk flow. Besides the technical equipment, the milk flow influences the milking time (Sandrucci *et al.*, 2007). Therefore, the milk flow is an indicator for the efficiency of a milking system. An increasing milk flow reduces the milking time without influencing the milk yield (Köhler, 2002). In this investigation the milk flow was higher in the A4 than in the A2. A reason could be a better stimulation of the udder, because it influences decisively the milk delivery (Bruckmaier and Blum, 1996, Sandrucci *et al.*, 2007, Kolbach *et al.*, 2013). The different milking vacuum of both AMS could be a reason for the increasing milk flow as well. The vacuum of the A4 is higher and according to Bade *et al.* (2009) a higher vacuum increases the milk flow. The teat-end

vacuum of both AMS should be compared. An important indicator for the efficiency of a milking system is the milk yield (Castro *et al.*, 2012). With the changeover to the A4 the milk yield of the herd increases from 37.7 kg to 41.0 kg per cow and day. The milk yield is influenced by the milking technique as well as the management or the genetics (M'Hamdi *et al.*, 2012). In this study the same cows were milked with both AMS so the influence of genetics can be excluded. With the changeover of the AMS, the housing conditions changed as well. The lying cubicles changed and the herd size decreased. It could be assumed that this had a higher influence on the milk yield than the milking technique. This should be tested in further investigations. In this investigation the milking interval increases by 21 min with the changeover of the AMS. This reduces the efficiency of the A4 because an increasing milking interval leads to decreasing milkings per cow and day. The milkings per cow and day influence the efficiency of an AMS as well (Gygax *et al.*, 2007). It is influenced by the number of AMS in the barn (Tremblay *et al.* 2016) as well as by cow traffic (Jacobs and Siegford, 2012). The more AMS are in the barn, the higher is the number of milkings per cow and day. Free cow traffic results in more milkings per cow and day compared with forced traffic. In this investigation neither the number of AMS per barn nor the traffic system influences the milkings per cow and day.

The results of the present study show that a purchase of an AMS of the newest generation could have advantages, but changes in milk delivery and efficiency cannot only be realized with technical development.

Conclusions

It can be concluded, that the change to an AMS of the newest generation could influence milk delivery and milk quality positively. The results of this investigations showed significant influences with the change to the new AMS regarding milking time, time in AMS, milk flow and milking intervals. Milking time and time in AMS decrease whereas milk yield, milk flow and milking interval increase in the new AMS. For milkings per cow and day no significant differences between both systems could be found. The decrease of milkings per cow and day with simultaneous increasing milk yield suggests a better efficiency of the A4. The purchase of an AMS of the newest generation could bring advantages regarding time for milking, milk flow and milking interval. However, changes in milk delivery and efficiency cannot be achieved with technical innovations, exclusively. In this investigation, the change of the barn environment, along with the changeover of the AMS, might have had a higher influence on the examined traits.

References

Bach, A., Devant, M., Igleasias, C., and Ferrer, A. 2009. Forced traffic in automatic milking systems efficiently reduces the need to get cows, but alters eating behavior and does not improve milk yield of dairy cattle. *Journal of Dairy Science* **92** (3), 1272-1280.

Bade, R.D., Reinemann, D.J., Zucali, M., Ruegg, P.L., and Thompson, P.D. 2009. Interactions of vacuum, b-phase, and liner compression on milk flow rates in dairy cows. *Journal of Dairy Science* **92** (3), 913-921.

Berry, D.P., Coughlan, B., Enright, B., Coughlan, S., and Burke, M. 2013. Factors associated with milking characteristics in dairy cows. *Journal of Dairy Science* **96** (9), 5943-5953.

Bruckmaier, R.M., Macuhova, J., and Meyer, H.H.D., 2001. Specific aspects of milk ejection in robotic milking: a review. *Livestock Production Science* **72** (1-2), 169-176.

Bruckmaier, R.M., and Blum, J.W. 1996. Simultaneous recording of oxytocin release, milk ejection and milk flow during milking of dairy cows with and without prestimulation. *Journal of Dairy Research* **63** (2), 201-208.

Catsro, A., Pereira, J.M., Amiama, C., and Bueno, J. 2012. Estimating efficiency in automatic milking systems. *Journal of Dairy Science* **95** (2), 929-936

Gygax, L., Neuffer, I., Kaufmann, C., Hauser, R., and Wechsler, B., 2007. Comparison of Functional Aspects in Two Automatic Milking Systems and Auto-Tandem Milking Parlors. *Journal of Dairy Science* **90** (9), 4265-4274.

Hart, K.D., McBride, B.W., Duffield, T.F., and DeVries, T.J. 2013. Effect of milking frequency on the behavior and productivity of lactating dairy cows. *Journal of Dairy Science* **96** (11), 6973-6985.

Hogeveen, H., Heemskerk, K., and Mathijs, E. 2004. Motivations of Dutch farmers to invest in an automatic milking system or a conventional milking parlour. In *Automatic milking: a better understanding.*, Meijering, A., Hogeveen, H., and de Koning, C.J.A.M. (eds.), Wageningen Academic Publishers, 56-61.

Hogeveen, H., Ouweltjes, W., de Koning, C.J.A.M., and Stelwagen, K., 2001. Milking interval, milk production and milk flow-rate in an automatic milking system. *Livestock Production Science* **72** (1-2), 157-167.

Jacobs, J.A. and Siegford, J.M. 2012. Invited review: The impact of automatic milking systems on dairy cow management, behavior, health, and welfare. *Journal of Dairy Science* **95** (5), 2227-2247.

Kaufmann, R., Ammann, A., and Hilty, R. 2001. Influence of technical capacity and construction on the economic efficiency of the AMS. In *5th*

Conference Construction, Engineering and Environment in Livestock Farming. Stuttgart, Germany , 248-253.

Köhler, S.D. 2002. Nutzung von Prozessparametern automatischer Melksysteme für die Erkennung von Eutererkrankungen unter Verwendung der Fuzzy Logic. Doctoral Thesis, Faculty of Agriculture and Horticulture, Humboldt University Berlin, Berlin, Germany.

Kolbach, R., Kerrisk, K.L., and Garcia, S.C. 2013. Short communication: The effect of premilking with a teat cup-like device, in a novel robotic rotary, on attachment accuracy and milk removal. *Journal of Dairy Science* **96** (1), 360-365.

LELY, 2004. *Astronaut – Konstruktionsbeschreibung Links- und rechtsseitige Modelle. (Lely Astronaut A2 Operator Manual.)*. Lely Industries N.V. (Eds.), 28.

LELY, 2012. *Lely Astronaut A4 Operator Manual*. http://www.lely.com/uploads/unzipped/Lely_Astronaut_A4_Operator_EN/#35469 Lely Holding S.à r.l., Accessed April 10, 2017.

M'hamdi, N., Bouallegue, M., Hamouda, M.B., Frouja, S., Brar, S.K., and Ressaissi, Y. 2012. Effects of Environmental Factors on Milk Yield, Lactation Length and Dry Period in Tunisian Holstein Cows. In *Milk Production – An Up-to-Date Overview of Animal Nutrition, Management and Health,* Chaiyabutr, N. (Ed.), 153-164.

Sandrucci, A., Tamburini, A., Bava, L., and Zucali, M. 2007. Factors Affecting Milk Flow Traits in Dairy Cows: Results of a Field Study. *Journal of Dairy Science* **90** (3), 1159-1167.

Tremblay, M., Hess, J.P., Christenson, B.M., McIntyre, K.K., Smink, B., van der Kamp, A.J., de Jong, L.G., and Döpfer, D. 2016. Factors associated with increased milk production for automatic milking systems. *Journal of Dairy Science* **99** (5), 3824-3837.

Wilmink, J.B.M., 1987. Comparison of different methods of predicting 305-day milk yield using means calculated from within-herd lactation curves. *Livestock Production Sciences* **17**, 1-17.

Why not investing in sensors is logical for dairy farmers

W. Steeneveld[1], C.J. Rutten[1], A.G.J.M. Oude Lansink[2] and H. Hogeveen[1,2]
[1]*Faculty of Veterinary Medicine, Utrecht University, Yalelaan 7, 3584 CL Utrecht, the Netherlands*
[2]*Chair group Business Economics, Wageningen University, Hollandseweg 1, 6700 EW Wageningen, the Netherlands*
w.steeneveld@uu.nl

Abstract

There are many claims regarding the potential of sensors for dairy farming, but in general the adoption on farms is still low. For sensor manufacturers, it is important to realize that uncertainty about future technological progress may influence the adoption of sensors. The aim of the current study was to explain why dairy farmers do not (yet) adopt sensors on their farms. To explain this, the uncertainty of the investment decision for highly adopted sensors (automated estrus detection) and recently released and thus hardly adopted sensors (automated body condition scoring (BCS)) was illustrated. The illustration makes use of the real options theory to analyze the timing of investment decisions. The results indicated that investing now in automated estrus detection resulted in higher economic returns than investing 5 years from now, while for the automated BCS postponing the investment resulted in higher economic returns compared to investing now. These results show that farmers indicating that they did not (yet) invest in sensors because they are waiting for improved versions made rational decisions. Based on the illustration it is economically worthwhile to postpone investments in sensors for which there is much uncertainty. Also, the current high adoption of automated estrus detection sensors is logical because the net present value of investing now is higher than the net present value of investing in 5 years. This study illustrated that uncertainty about the benefits of a sensor system, potential future improvement of sensor technology, and expected better management information from a sensor system, form rational economic reasons to postpone investment in sensor systems.

Keywords: adoption, sensors, dairy, investment, economics

Introduction

The adoption of sensors on dairy farms in general is low (Steeneveld and Hogeveen, 2015). Activity meters or pedometers are an exception to this general

trend and are moderately adopted for detection of estrus in the Netherlands (Steeneveld and Hogeveen, 2015), and the US (Borchers and Bewley, 2015). Other sensors are adopted much less frequently (e.g., walk over weighing platforms), or not adopted at all (e.g., automated body condition scoring (BCS)) (Steeneveld and Hogeveen, 2015). For the Netherlands, it was reported that economic considerations and waiting for improved versions, which provide better interpretable data or information, are important reasons for not adopting sensors on dairy farms (Steeneveld and Hogeveen, 2015).

Waiting for improved versions is probably a rational reason for not adopting when one realizes that estrus detection performance improved considerably over the last 20 years. Frost *et al*. (1997) found a sensitivity of 70% with a specificity of 60%, while Kamphuis *et al*. (2012) found a sensitivity between 62-75% at a specificity of 99%. This means that sensors for estrus detection have undergone significant technological progress, and that limited further improvement in detection performance can be expected. Therefore, postponing the investment in estrus detection sensors is expected to have minimal advantage, and this may explain the current high adoption rate. In contrast, sensors such as the automated BCS are still in the phase of a technique measuring parameters of the cow (Rutten *et al*., 2013). Interpretable information with clear decision support on what to do with BCS is still lacking with automated BCS. Therefore, technological progress and more informed decision support, and thus a gain of postponing the investment, can be expected. The expected gain of postponing the investment may explain the current low adoption rate.

For sensor manufacturers it is important to realize that uncertainty about future technological progress influence the adoption of sensors, and thus ultimately sales. The uncertainty about future technological progress can by structured by using the real options theory, which describes the problem structure, timing, linkage of decisions, and underlying uncertainties (Trigeorgis and Reuer, 2017). The aim of the current study was to explain why dairy farmers do not (yet) adopt sensors on their farm. To explain this, the effects of uncertainty about future technological progress for sensors which are highly adopted (sensors for estrus detection) and are hardly adopted (automated BCS) was illustrated by using the real options theory. This illustration can help especially manufacturers to understand the effect of uncertainty of future technological progress on the adoption of sensors by dairy farmers.

Material and methods

Real options theory

The real options theory is a method of option pricing from financial theory (Buhl *et al*. 2016). In corporate investment decisions and strategic management under uncertainty, real options theory can be used to clarify the problem structure (e.g. the different options, management decisions, and their timing), to appraise the options (i.e. estimating the net present value of each option) and to plan the implementation (i.e. a strategic timeline that defines at which moment what option should be executed) (Trigeorgis and Reuer, 2017). Previously, the real options theory was used to determine the timing of investment in information technology solutions. The real options theory was well suited for this problem because future information technology developments are highly uncertain, and therefore timing of investment is complex (Buhl *et al*., 2016). Investing in sensors on dairy farms can be seen as a specific example of information technology investment decisions. Also for sensors, the future technological progress is uncertain, and this makes timing of investment a difficult decision. Therefore, the real options theory was used to illustrate the effects of uncertainty about future technological progress in sensor systems on investment decisions of dairy farmers.

In the real options theory, different investment options are compared quantitatively. In the current analysis, the net present value (NPV) was estimated for "investment now" and investment in five years' time ("postponed investment") for both sensors (automated estrus detection and automated BCS). For the estimation of the NPV the additional cash flow that resulted from improved operational management on a dairy farm was calculated. This additional cash flow was estimated by the difference is gross margin between a simulated average dairy herd with and without a sensor. A life time of 10 years was assumed for both the estrus sensor (Rutten et al., 2014) and the BCS sensor. It was assumed that the investment was incurred and paid in year 0 and that revenue and costs of using the sensor system were incurred and paid in the ten subsequent years. For each year the average additional cash flow was discounted under an assumed discount rate of 5%. The discounted additional cash flows were summed up over the life time of the sensor to estimate the NPV. The NPV's of postponed investments were discounted under an assumed discount rate of 5%. The NPV of "investment now" was then compared to the discounted NPV of "postponed investment".

Simulation model

The simulation model simulates an average Dutch dairy cow with a production level of 8573 kg/305 days (CRV 2016), a base conception rate of 50%, who starts her estrus cycle at 35 DIM, with an interval of 21 days and a gestation length of 280 days. A herd of 100 average dairy cows was simulated by the simulation model. The simulation model was a deterministic discrete event model.

Estrus is simulated as the occurrence of ovulation in 21 days intervals starting at 10.5 days after the end of the voluntary waiting period. Subsequently, the occurrence of estrus, metritis and early embryonic death were modeled. The methodology of Inchaisri *et al*. (2010) was used, in which the probability of insemination success was milk yield dependent. For simulation of estrus it was assumed that the estrus cycle length was 21 days. Each subsequent insemination is assumed to occur at on average 21 days after the previous one and that 5% of the cows would skip one full estrus cycle. Based on the sensitivity of estrus detection, the probability that a cow being in estrus is detected was calculated per day in lactation. This probability of detection was corrected for the relative day in lactation to the peak milk yield of the lactation. The conception rate was estimated on each day in lactation for an average lactation. This included a base conception rate adjusted with a day in lactation dependent factor, corrected for disease effects, the fertility difference between primi- and multiparous cows and the occurrence of early embryonic death and metritis (Inchaisri et al., 2010). The overall conception rate of an average cow at each day in lactation was the product of the base conception rate, probability of estrus detection and probability of conception.

The prevalence of hyperketonemia was reported to range from 0-80% with a mean of 11.2% (Van der Drift *et al*., 2012). For the duration of disease it was assumed that hyperketonemia occurred once per lactation. For milk production, Van der Drift *et al*. (2012) reported a decrease in milk production of 2 kg/day at an average of 35.8 kg/day (5.587%). It was assumed that this decrease lasted for 125 days. The decrease in milk production was assumed to develop and cure gradually over time, therefore a gradual decrease over 5 days was assumed at the start of hyperketonemia and a gradual return to normal milk production over 15 days at the end of hyperketonemia. Furthermore, for hyperketonemia the conception rate was assumed to be 0.2% lower. Higher incidences of mastitis (3.33 times higher) and displaced abomasum (1.61 times higher) were assumed for cows with hyperketonemia.

Sensors and their performance

It was assumed that the sensors for estrus detection are mature developed sensors and they do not make much technological progress anymore. This means that the gains of "postponed investment" are only marginally higher than the gains of "investment now" (Figure 1A). For automated estrus detection, it was assumed that for "investment now" the sensitivity would be 80% and the specificity 95% (e.g., Rutten *et al*., 2014). Moreover, it was assumed that the integration of sensor outcomes with operational farm management is clear. For "postponed investment", a little technical improvement of the system was assumed (an increase of specificity to 99%). Both situations were compared with a farm where the farmer applies visual estrus detection with a sensitivity of 50% and a specificity of 100%. It was assumed that automated BCS is a sensor for which much technological progress can be expected in 5 years' time (Figure 1B). There is no data available on the use of BCS data. One of the application could be to use it for ration adjustment. In the current study it was assumed that data from automated BCS can be used to adjust the ration when the number of cows with hyperketonemia increase. When an increased number of cows had hyperketonemia the intervention would be an adjustment of the feed ration. It was assumed that using the BCS sensor can result in three situations. Either the BCS sensor does not detect the increased number of cows with hyperketonemia (situation 1), the BCS sensor does detect the increased number of cows with hyperketonemia but the measure taken is not effective (situation 2) or BCS sensor does detect the increased number of cows with hyperketonemia and the measure taken is effective (situation 3). For "investment now" it was assumed that each situation was equally likely to occur. For "postponed investment" it was assumed that BCS measurements become more reliable and that better integration with management is possible. Therefore, it was assumed that the likelihood of situation 1, 2 and 3 are 30%, 20% and 50% respectively.

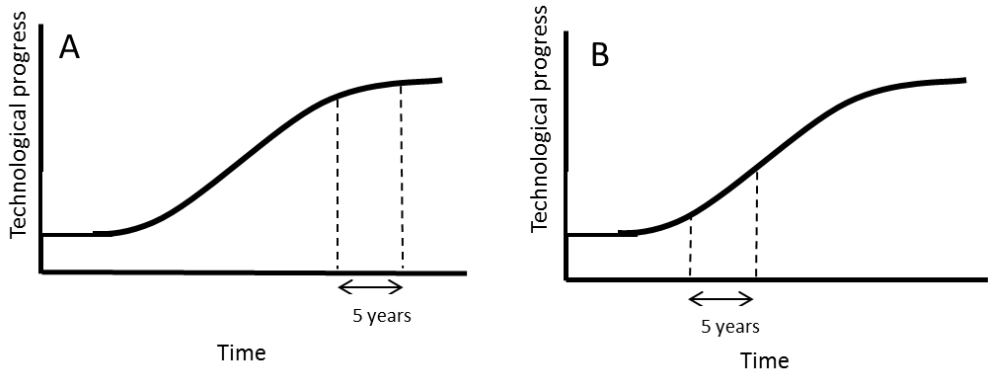


Figure 1: Graphical representation of the improved technological progress over time and its higher gains when the investment is postponed for 5 years for estrus detection sensors (A) and for automated BCS sensors (B).

Economic estimations

The herd simulation model estimated average technical herd performance per year in terms of milk production, number of inseminations, calves born and culled cows. The technical results were used to estimate annual milk revenues, feed costs, insemination costs, revenues from calve sales, costs of calving management, revenues of slaughtered cows and purchase costs of replacement heifers. Prices (Table 1) for inseminations, labor, slaughtered cows and purchase of heifers were based on the assumptions of Rutten *et al*. (2014). Additionally, it was assumed that a farmer checks the alerts generated by the estrus detection sensor. Costs for checking were assumed to be 1.5 € per alert (Rutten *et al*., 2014). For the automated BCS sensor it was assumed that the farmer spends half an hour per week on interpreting BCS data. For hyperketonemia additional assumptions were made. It was assumed that adjustment of the feed ration as intervention for a high incidence of cows with hyperketonemia costs € 2 per cow per intervention (Bewley *et al*., 2010). Cows with hyperketonemia have increased risk of mastitis and displaced abomasum. As the model already accounted for milk production losses due to hyperketonemia it was assumed that no additional losses for mastitis and displaced abomasum occurred. Annual farm gross margin was estimated as the difference between revenues and costs. The additional cash flow of applying a sensor was estimated by the difference in annual farm gross margin between the situation with a sensor and the situation without a sensor.

Table 1: Economic input variables and their sources of origin for variables in the model.

Variable	Value	Unit	Source
Prices			
Milk	0.345	€/kg	Wageningen Economic Research, 2016
Feed	0.112	€/kg	Wageningen Economic Research, 2016
Insemination	30	€/insemination	Rutten *et al*., 2014
Calving management	152	€/calving	Inchaisri *et al*., 2010
Calf	100	€/calf	Rutten *et al*., 2014
Heifer price	919	€/heifer	Rutten *et al*., 2014
Slaughter value	747	€/ cow	Adapted from Rutten *et al*., 2014
Labour			
Hourly rate	24	€/h	Blanken *et al*., 2016
Confirmation estrus	5	Min/alert	Authors' expertise

alerts			
Interpreting BCS data	0.5	h/week	Bewley *et al*., 2010
Costs for estrus detection sensor			
System	3600	€/herd	Rutten *et al*., 2014
Sensors	108	€/cow	Rutten *et al*., 2014
Maintenance	88	€/cow	Rutten *et al*., 2014
Equipment replacement	45	€/year	Rutten *et al*., 2014
Costs for automatic BCS			
System	8000	€/herd	Personal communication
Maintenance	5	€/cow/year	Personal communication
Other economic input			
Discount rate	5	%	Authors' expertise
Technical life time	10	year	Authors' expertise
Additional feed costs after ration adjustment	2	€/cow/year	Bewley *et al*., 2010

Results and Discussion

The overall aim of the current study was to explain why dairy farmers do not (yet) adopt sensors on their farm. To explain this, the effects of uncertainty about future technological progress for sensors which are highly adopted (sensors for estrus detection) and are hardly adopted (automated BCS) was illustrated. This illustration can help especially manufacturers to understand the effect of uncertainty of future technological progress on the adoption of sensors by dairy farmers.

The illustration indicates that investment now in automated estrus detection resulted in a higher NPV (€15,043.68) than postponing the investment (€12,350.07) (Table 2). For the automated BCS postponing the investment resulted in a higher NPV (€3,139.28) compared to investment now (€-1,015.20) (Table 2). Results from the model suggest that the limited adoption of sensors by farmers is due in part to uncertainty. Therefore, farmers indicating that they did not (yet) invest in sensors because they are waiting for improved versions (Steeneveld and Hogeveen, 2015) made rational decisions. Also, the current high adoption of automated estrus detection sensors (Steeneveld and Hogeveen, 2015) is rational because the NPV of investing now is higher than the NPV of investing in 5 years. The results indicate that farmers behave economically rational in their

sensor investment decisions, and it confirms that uncertainty about future sensor performance and uncertainty about whether improved informed decision support will become available play an important role in investment decisions.

Table 2: Results of the investment analysis of a sensor for estrus detection and for a BCS sensor. The additional cash flow is the financial gain that results from the use of a sensor. The net present value (NPV) for investment now was estimated over a ten-year period and the option to postpone investment was estimated over a ten year period five years from now.

	Investment now	Postpone investment	Δ
Automated estrus detection			
Additional cash flow (€/year)	3,946.09	4,039.14	93.05
NPV (€)	15,043.68	12,350.07	-2,693.61
Automated BCS			
Additional cash flow (€/year)	1,404.56	2,054.91	650.35
NPV (€)	-1,015.20	3,139.28	4,154.48

The current study was built upon the assumption that there is considerable uncertainty for the hardly adopted sensors. This assumption was valid as for many input variables on hyperketonemia and the performance of the BCS sensor no scientific literature was available, and therefore authors expertise had to be used. For instance, a prevalence of 11.2% was assumed while there is debate and uncertainty about the prevalence and severity of hyperketonemia (e.g., Van der Drift *et al*., 2012; McArt *et al*., 2015). Also, assumptions on the benefit of the BCS sensor were used while the magnitude of improvement in feed ration adjustments by using a BCS sensor is unknown as well as the effectiveness of an adjustment in the feed ration.

Many assumptions were made. First, the simulation model was deterministic and therefore the stochastic nature of for instance hyperketonemia incidence, effect of ration adjustments and detection of hyperketonemia were ignored. For these factors the input values will in practice vary between farms and will in reality be described by a probability distribution rather than by a fixed value. For a stochastic model, however, the probability distribution for a input variable are needed. As these probability distributions are unknown, stochastic modelling was not possible at this moment. Secondly, technical progress was considered at two fixed (now

and 5 years from now) points in time. Therefore, technological progress in the period between these two time points was ignored. For some aspects of technological progress this assumption was realistic. For instance, improved camera technology for the BCS sensor would become available on the market at some moment, but the exact point in time on which the improvement becomes available is unknown. For other aspects of technological progress the assumption of two fixed moments in time is not realistic. For instance, improvement in detection algorithms may become available as part of a software update for a sensor system. So, technological progress over the five year period as assumed in the current study will develop in practice in a number of steps overtime.

Because of all the uncertainties and assumptions made it cannot be concluded whether investment in a BCS sensor is profitable now or in the future. The current study merely illustrates that the uncertainties are there and that it is difficult to predict whether investment is profitable when so many uncertainties are involved. Dairy farmers who are interested in a BCS sensor will face the same issues as they cannot estimate what a BCS sensor will gain them.

This study illustrated that it can be economically worthwhile to postpone investments in sensors for which there is much uncertainty. The results indicate that farmers behave economically rational in their sensor investment decisions, and it confirms that uncertainty about future sensor performance and uncertainty about whether improved informed decision support will become available play an important role in investment decisions. Informed decision support, or advises relevant for operational management, as part of the sensor system is often lacking (Rutten *et al*., 2013). Estrus is an exception to this observation because the sensor produces a clear output (estrus alert), which has a clear management decision attached to it (breed or not). This difference in development, namely a clear link to and value for operational management versus an unclear link and value, between estrus sensors and other sensors may well be a reason for the difference in adoption. Until now most research on sensors is on the detection of diseases or estrus and not on decision support possibilities based on the available data (Rutten *et al*., 2013). Therefore, adding decision support to sensor data would be helpful in improving the value of sensor for operational management and would be a topic for future research (Rutten *et al*., 2013).

The illustration in the current study helps to understand the effect of uncertainty of future technological progress on the adoption of sensors by dairy farmers, and thus explains why dairy farmers do not (yet) adopt sensors on their farm. Uncertainty is thus a key driver in the adoption of technology. Of course, there are many more aspects of adoption (e.g., Pannell et al., 2006; Douthwaite et al., 2001). The

availability of support, seeing other farmers using the tools and integration with the farm system are also important factors in adoption. For instance, a way to reduce uncertainty can be offering support or demonstration of how the sensor can be used. Also the guarantee of (software) updates during the lifetime of the sensor can help to reduce the benefits that postponing investment has for farmers. Proper support could be used to help farmers to use sensor technology and gain more benefits from the sensor system and therefore reduce their uncertainty about the technology (Eastwood et al., 2016).

Conclusions

This study illustrated that uncertainty about the benefits of a sensor system, potential future improvement of sensor technology, and expected better management information from a sensor system, form rational economic reasons to postpone investment in sensor systems. The uncertainty associated with benefits of an automated BCS and the lack of inputs for our estimations were large and prohibited conclusions on the profitability of such a system. The concepts and considerations presented in this paper can be used for further development of sensor systems and enhancing adoption by farmers.

Acknowledgements

This research was supported by NWO (Netherlands Organisation for Scientific Research,
The Hague, the Netherlands).

References

Bewley, J.M. M.D. Boehlje, A.W. Gray, H. Hogeveen, S.J. Kenyon, S.D. Eicher, M.M. Schutz. 2010. Assessing the potential value for an automated dairy cattle body condition scoring system through stochastic simulation. *Agricultural Finance Review* 70: 126–150.

Blanken, K., F. de Buisonje, A. Evers, W. Ouweltjes, H. van Schooten, J. Verkaik, I. Vermeij, and H. Wemmenhove. 2016. Livestock Research, Wageningen UR. Kwantitatieve Informatie Veehouderij 2016-2017. Wageningen, the Netherlands.

Borchers, M. R. and J. M. Bewley. 2015. An assessment of producer precision dairy farming technology use, prepurchase considerations, and usefulness. *J. Dairy Sci.* 98:4198-4205.

Buhl, H. U., B. S. Hackel, F. Probst, and J. Schosser. 2016. On the Ex Ante Valuation of IT Service Investments. Bus Inform Syst Eng+ 58:415-432.

CRV. 2016. Annual report 2016. CRV (cattle breeding company), Arnhem, the Netherlands.

Douthwaite, B., J. D. H. Keatinge, and J. R. Park. 2001. Why promising technologies fail: the neglected role of user innovation during adoption. *Research Policy* 30(5):819-836.

Eastwood, C. R., J. G. Jago, J. P. Edwards, and J. K. Burke. 2016. Getting the most out of advanced farm management technologies: roles of technology suppliers and dairy industry organisations in supporting precision dairy farmers. *Animal Production Science* 56(10):1752-1760.

Frost, A. R., C. P. Schofield, S. A. Beaulah, T. T. Mottram, J. A. Lines, and C. M. Wathes. 1997. A review of livestock monitoring and the need for integrated systems. *Comput.Electron.Agric.* 17:139-159.

Inchaisri, C., R. Jorritsma, P. Vos, G. C. van der Weijden, and H. Hogeveen. 2010. Economic consequences of reproductive performance in dairy cattle. *Theriogenology* 74:835-846.

Kamphuis, C., B. DelaRue, C. R. Burke, and J. Jago. 2012. Field evaluation of 2 collar-mounted activity meters for detecting cows in estrus on a large pasture-grazed dairy farm. *J. Dairy Sci.* 95:3045-3056.

McArt, J.A., D.V. Nydam, and M.W. Overton. 2015. Hyperketonemia in early lactation dairy cattle: a deterministic estimate of component and total costs per case. *J. Dairy Sci.* 98: 2043-2054.

Pannell, D. J., G. R. Marshall, N. Barr, A. Curtis, F. Vanclay, and R. Wilkinson. 2006. Understanding and promoting adoption of conservation practices by rural landholders. *Australian Journal of Experimental Agriculture* 46:1407-1424.

Rutten, C. J., W. Steeneveld, C. Inchaisri, and H. Hogeveen. 2014. An ex ante analysis on the use of activity meters for automated estrus detection: To invest or not to invest? *J. Dairy Sci.* 97:6869-6887.

Rutten, C. J., A. G. J. Velthuis, W. Steeneveld, and H. Hogeveen. 2013. Invited review: Sensors to support health management on dairy farms. *J. Dairy Sci.* 96:1928-1952.

Steeneveld, W. and H. Hogeveen. 2015. Characterization of Dutch dairy farms using sensor systems for cow management. *J. Dairy Sci.* 98:709-717.

Trigeorgis, L. and J. J. Reuer. 2017. Real Options Theory in Strategic Management. *Strategic Manage J* 38:42-63.

van der Drift, S. G. A., R. Jorritsma, J. T. Schonewille, H. M. Knijn, and J. A. Stegeman. 2012. Routine detection of hyperketonemia in dairy cows using Fourier transform infrared spectroscopy analysis of beta-hydroxybutyrate and acetone in milk in combination with test-day information. *J. Dairy Sci.* 95:4886-4898.

Wageningen Economic Research. 2016. www.agrimatie.nl.

Session 2

Cattle behaviour

Behaviours recognition using neck-mounted accelerometers in dairy barns

S. Benaissa[1,2], F.A.M. Tuyttens[2,3], D. Plets[1], T. De Pessemier[1], J. Trogh[1], E. Tanghe[1], L. Martens[1], L. Vandaele[1], A. Van Nuffel[5], J. Wout[1], B. Sonck[2,4]
[1]*Department of Information Technology, Ghent University/iMinds, iGent-Technologiepark 15, 9052 Ghent, Belgium*
[2]*Institute for Agricultural and Fisheries Research (ILVO)-Animal Sciences Unit, Scheldeweg 68, 9090 Melle, Belgium*
[3]*Faculty of Veterinary Medicine, Ghent University, Salisburylaan 133, 9820, Merelbeke, Belgium*
[4]*Department of Biosystems Engineering, Faculty of Bioscience Engineering, Ghent University, Coupure links 653, B-9000 Ghent, Belgium*
[5]*Institute for Agricultural and Fisheries Research (ILVO)- Technology and Food Science Unit, Burgemeester van Gansberghelaan 115 bus 1, 9820 Merelbeke, Belgium*
Said.Benaissa@ugent.be

Abstract

In large-sized farms, automated measurement of cows' behaviours by data loggers saves time and labour. The aim of this study is to propose methods for measuring three behaviours (lying, standing, and feeding) of dairy cows in barns using neck-mounted accelerometers. Lying, standing, and feeding behaviours of 16 lactating dairy cows were logged for 6 hours with 3D-accelerometers attached to the collar of the cows. The behaviours were simultaneously recorded using visual observation and video recordings as a reference. Different features were extracted from the logged raw data and classification algorithms (K-nearest neighbours, naïve Bayes, and support vector machine) were used to classify the cows' behaviours. The models allowed excellent classification of the feeding behaviour (precision 93%, sensitivity 98%), followed by lying (precision 83%, sensitivity 96%). Standing was the most difficult behaviour to classify with a maximum precision and sensitivity of 75% and 65%, respectively. These results suggest that neck-mounted accelerometers are promising tools to automatically monitor cows' behaviours such as feeding time, lying time and lying bouts. Such monitoring could be useful for automatically alerting farmers of cows that need attention, e.g. in order to prevent welfare, health or production problems.

Keywords: Accelerometer, dairy cows, machine learning, behaviors classification, feature extraction.

Introduction

Analysing behaviours (e.g., lying, feeding) has widely been considered as an interesting approach to monitor the reproduction status, health, and overall well-being of dairy cows. In large size farms, traditional methods based on direct observation or analysis of video recordings have become labour-intensive and time-consuming (Müller and Schrader, 2003). Thus, automatic behaviour recognition systems using, for example accelerometers in combination with machine learning algorithms, become increasingly important to continuously and accurately quantify cows' behaviours (Martiskainen et al., 2009; Müller and Schrader, 2003; Robert et al., 2009; Vázquez Diosdado et al., 2015). Robert et al. (2009) used a three-dimensional leg-mounted accelerometer to monitor and classify three behaviour patterns (i.e., lying, standing, and walking). However, feeding behaviour was not considered in this work. Another study (Mattachini et al., 2013) compared two accelerometer technologies [HOBO Pendant G (Onset Computer Corporation, Pocasset, MA) and IceTag (IceRobotics, Edinburgh, UK)], with video recording to measure lying and standing of dairy cows. The classification was based on the static components of the accelerometer axes, which is impractical in real situations where a slight movement of the cow could change the static components within the same behaviour. A recent study (Vázquez Diosdado et al., 2015) used a simple decision-tree algorithm to detect lying, standing, and feeding behaviours with a neck-mounted accelerometer. The proposed algorithms required a high sampling rate (50 Hz) and also used the static component of the Y-axis to distinguish between standing and lying.
To reduce the energy consumption and maintenance requirements associated with recharging batteries, a relatively low sampling rate was used (1 Hz) in the present study to classify three behaviours (i.e., lying, standing, feeding). Also, the classification was based on the three accelerometer axes (i.e., X, Y, Z) simultaneously, instead of just one or two axes only. This makes the monitoring system independent on where the logger is attached (above, behind, or below the cow's neck).

Materials and methods

Animals and housing

Measurements were carried out between March and July 2016 in a state-of-the-art dairy cattle research barn of the Institute for Agricultural and Fisheries Research (ILVO) in Melle, Belgium. The cows (n=31) were housed in an area of 30 m long and 13 m wide with individual cubicles and concrete slatted floor. The cubicles (n = 32) were bedded with a lime-straw-water mixture. A total of 16 different second parity Holstein cows (parity 2.7 ± 1.4, milk yield 33.6 ± 5.6

kg/d; mean ± SD) were used for this study. The cows had access to a milking robot via the feeding area and a smart selection gate (feed-first cow traffic system). The cows were fed roughage ad libitum, the amount of protein rich and balanced concentrate was fixed depending on lactation stage and production level. The concentrates were supplied both in the milking robot and by computerized concentrate feeders. Drinking water was available ad libitum. The cows had free access to a rotating cow brush.

Reference data

Observations on the behaviour of the cows were made directly in the barn and with video recordings at the same time as data from the sensors were collected. Table 1 lists the considered behaviours in this study with their descriptive definitions. The methodology of the observation was as follows. Every minute time window was assigned 0, 1 or 2 to refer to lying, standing, and feeding behaviours, respectively, based on the behaviour that was present during the largest proportion of that minute. We note that walking was not considered as a behavioural class apart, because it was observed less frequently and for shorter durations (on average, 8 to 12 minutes per cow). However, due to its importance in detecting health and welfare status, future studies should consider this behaviour apart by logging data for long time periods, so enough samples can be collected for the analysis.

Table 1: Ethogram for the classification of behaviours registered during observations.

Behaviour	Description
Lying	The cow is in a lying position (main body area contact with floor)
Standing	The cow is standing in the alleys, the milking robot, or while brushing on at least three legs with no movement to another place
Feeding	Eating: Intake, chewing, and swallowing of feed Drinking: Putting mouth in water bowl and swallowing water

Sensor data

Two cows were monitored simultaneously using an accelerometer attached to each cow from 10 AM to 4 PM. The accelerometer was attached to the neck collar (right side) as shown in Figure 1. The acceleration data were logged with a sampling rate of 1 Hz (1 sample each second) using HOBO loggers (Onset Computer Corporation, Pocasset, MA). The HOBO logger is a waterproof 3-channel logger with 8-bit resolution, which can record up to approximately 21,800 combined acceleration readings or internal logger events. The logger uses an internal 3-axis accelerometer with a range of ± 3 g (accuracy ± 0.075 g at

25°C with a resolution of 0.025 g) based on micro-machined silicon sensors consisting of beams that deflect with acceleration. The orientation of the accelerometers is shown in figure 1. The same orientation was respected for all cows. The clocks of the observer, the video recording system, and the sensors were synchronized at the start and at the end of the observation period so that observation data could be aligned accurately with the tri-axial accelerometer data retrieved from the sensors. In total, 96 hours of data (i.e., 16 cows*6 hours) were recorded and used for classification of the behaviours.

Figure 1. Position and orientation (X, Y, and Z axes) of the accelerometer

Data processing and features extraction

Raw time series collected from 16 individual cows were uploaded to a laptop for processing. From the accelerations along X, Y, and Z axes, the acceleration sum vector (A_{sum}) was calculated as follows:

$$A_{sum} = \sqrt{{a_X}^2 + {a_Y}^2 + {a_Z}^2} \quad (1)$$

Where, a_X is the acceleration along the X-axis, a_Y is the acceleration along the Y-axis, and $a_Z$is the acceleration along the Z-axis. Figure 2 shows an example of the time series acceleration sum vector (A_{sum}). When a cow is feeding, large variations were registered in comparison with standing and lying. This is an important characteristic that should be exploited in the feature extraction phase.

Using Octave software, the data were segmented into equal time intervals of 1 min (60 samples). Features extraction is then performed for each data segment. The purpose of feature extraction is to find the main characteristics of the raw data segments. In this study, time- and frequency-domain features were used. Time-domain features are directly derived from the time-dependent raw acceleration data for each time interval. These features include eight basic signal statistics (minimum, first quartile, median, third quartile, maximum, mean, root mean square, and standard deviation) and the overall dynamic body acceleration (ODBA) (Gleiss et al., 2011). Frequency-domain features include the periodic

characteristics of the signal, such as coefficients derived from Fourier transforms. In frequency domain, the spectral energy and spectral entropy were used (Wang et al., 2005) in this study.

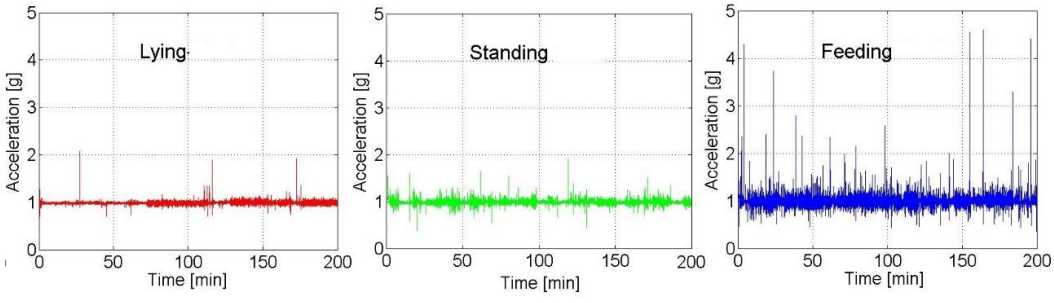


Figure 2. Example of the acceleration sum vector (A_{sum}) from leg- and neck-mounted accelerometers for the considered behaviours.

Classification and performance evaluation

In our classification approach of the cows' behaviours, three supervised machine learning algorithms were used (i.e., K-nearest neighbours, naïve Bayes, and support vector machine) (Martiskainen et al., 2009; Vázquez Diosdado et al., 2015). K-nearest neighbours and the naive Bayes classifiers are possible options because they are fast, simple and well understood. Support vector machine (SVM) is better at handling complex classification tasks, but requires more computational costs, especially in the training phase. To make a fair comparison, the same datasets (number of samples and features) were used as input to the considered algorithms.

To measure the performances of the classification approaches, the precision, the sensitivity, and the overall accuracy were used (Chawla, 2005). Since data were collected on 16 cows, the leave-one-out cross validation strategy was used. Therefore, data collected on 15 cows were used to train the system and then the system was tested by classifying the data of the sixteenth cow accordingly. This was repeated 16 times until data from all the cows was classified and the average precision, sensitivity and overall accuracy were considered.

Results and discussion

The precision and sensitivity are listed in Table1. Feeding was the best classified behaviour with a sensitivity between 95% and 98% and a precision between 84% and 92%. Standing was the most difficult behaviour to classify with a sensitivity lower than 66% for all classifiers. This could be explained as follows. The frequent neck movements during feeding, make this behaviour easy to distinguish from both other behaviours. (Martiskainen et al., 2009). However, the

neck generally moves little during both standing and lying, which makes it hard to differentiate these two behaviours. Similar conclusions were drawn also in (Martiskainen et al., 2009; Mattachini et al., 2013). In (Martiskainen et al., 2009), a neck-mounted accelerometer with a sampling rate of 10 Hz was used to classify cows' behaviours based on the SVM algorithm. In their study, standing and lying behaviours were mostly confused with each other (30% of the cases) and feeding was misclassified less often (14% of the cases) as standing. Consequently, neck-mounted accelerometers are better suited for monitoring feeding behaviour.

Table 2. Precision (Pr) and sensitivity (Se) [%] for each behavioural class and classification approach. K-NN: K-nearest neighbours, NB: Naïve Bayes, SVM: support vector machine.

	SVM		NB		K-NN	
	Pr	Se	Pr	Se	Pr	Se
Standing	75	66	67	47	64	56
Feeding	92	98	84	95	88	96
Lying	83	96	82	94	82	95

For the overall accuracy, SVM was the best classifier followed (91%) by K-NN (86%) and Naïve Bayes (84%). SVM algorithm is more suitable for complex classification tasks and it requires more computation capabilities than Naïve Bays and K-NN (Douglas et al., 2011), especially in the training phase. However, after the classification model is developed, SVM classifies the new data without looking to the training set, which would save the memory of the monitoring system, in contrast to Naïve Bays and K-NN, where the training set is always required to classify the new instances. Therefore, the selection of the best classification algorithms is a trade-off between performance and computation/memory capabilities.

More data would be needed especially from other herds to validate the findings of this research. Furthermore, other positions (e.g., leg, ear) should be addressed in order to investigate the best position for the behaviours' classification. Also a combination of the data from different positions could enhance the classification performances. Finally, the data logging time per cow (i.e., 6 hours) was not sufficient to collect enough data for some behaviours such as walking. These behaviours could be set in separate behavioural classes when much more samples would be available.

Conclusions and future work

In this research, measurements with neck-mounted accelerometer have been performed to automatically classify cows' behaviours (i.e., lying, standing, and feeding) based on machine learning algorithms. Feeding was the best classified behaviour followed by lying behaviour. Standing was the most difficult behaviour to classify. Moreover, SVM algorithm performed better than the other algorithms (Naïve Bays and K-NN). These results suggest that the accelerometers are promising tools to automatically monitor cows' behaviours. Such a behaviour monitoring system would enable determination of relevant information about the cows' behaviour patterns (e.g., feeding time, lying time, lying bouts), which offers new potential technologies for the automated detection of health and welfare problems in dairy cows.

Acknowledgments

This work was executed within MoniCow, a research project bringing together academic researchers and industry partners. The MoniCow project was co-financed by imec (iMinds) and received project support from Flanders Innovation & Entrepreneurship. E. Tanghe is a Postdoctoral Fellow of the FWO-V (Research Foundation – Flanders). The authors would like to thank Thijs Decroos and Sara Van Lembergen for their help during the measurements.

References

Chawla, N. V, 2005. Data Mining for Imbalanced Datasets: An Overview. Data Min. Knowl. Discov. Handb. 853–867. doi:10.1007/0-387-25465-X_40

Douglas, P.K., Harris, S., Yuille, A., Cohen, M.S., 2011. Performance comparison of machine learning algorithms and number of independent components used in fMRI decoding of belief vs. disbelief. Neuroimage 56, 544–553. doi:10.1016/j.neuroimage.2010.11.002

Gleiss, A.C., Wilson, R.P., Shepard, E.L.C., 2011. Making overall dynamic body acceleration work: On the theory of acceleration as a proxy for energy expenditure. Methods Ecol. Evol. 2, 23–33. doi:10.1111/j.2041-210X.2010.00057.x

Martiskainen, P., Järvinen, M., Skön, J.-P., Tiirikainen, J., Kolehmainen, M., Mononen, J., 2009. Cow behaviour pattern recognition using a three-dimensional accelerometer and support vector machines. Appl. Anim. Behav. Sci. 119, 32–38. doi:10.1016/j.applanim.2009.03.005

Mattachini, G., Riva, E., Bisaglia, C., Pompe, J.C.A.M., Provolo, G., 2013. Methodology for quantifying the behavioral activity of dairy cows in

freestall barns. J. Anim. Sci. 91, 4899–4907. doi:10.2527/jas2012-5554
Müller, R., Schrader, L., 2003. A new method to measure behavioural activity levels in dairy cows. Appl. Anim. Behav. Sci. 83, 247–258. doi:10.1016/S0168-1591(03)00141-2
Robert, B., White, B.J., Renter, D.G., Larson, R.L., 2009. Evaluation of three-dimensional accelerometers to monitor and classify behavior patterns in cattle. Comput. Electron. Agric. 67, 80–84. doi:10.1016/j.compag.2009.03.002
Vázquez Diosdado, J.A., Barker, Z.E., Hodges, H.R., Amory, J.R., Croft, D.P., Bell, N.J., Codling, E.A., 2015. Classification of behaviour in housed dairy cows using an accelerometer-based activity monitoring system. Anim. Biotelemetry 3, 15. doi:10.1186/s40317-015-0045-8
Wang, S.W.S., Yang, J.Y.J., Chen, N.C.N., Chen, X.C.X., Zhang, Q.Z.Q., 2005. Human activity recognition with user-free accelerometers in the sensor networks. 2005 Int. Conf. Neural Networks Brain 2, 1212–1217. doi:10.1109/ICNNB.2005.1614831

Automated measurement of dairy cow grooming behaviour from real-time location system

B. Meunier[1*], E. Delval[1], C. Cirié[2], M.M. Mialon[1], P. Pradel[2], Y. Gaudron[1], D. Ledoux[1], I. Veissier[1]
[1] *INRA, VetAgro Sup, UMR1213 Herbivores, Site de Theix, 63122 Saint-Genès-Champanelle, France*
[2] *INRA, UE1414 HERBIPOLE, Site de Marcenat, 63122 Saint-Genès-Champanelle, France*
*bruno.meunier@inra.fr

Abstract

It has been reported that grooming behaviour may be related to status (calving, stress), health (mastitis) and production (milk yield). Consequently, accurate long-term monitoring of grooming behaviour could advantageously serve as a PLF solution to provide alarms or well-being indicators. The main activities of dairy cows (resting, moving, eating, etc.) can be monitored indoors 24/7 using a real-time location system (RTLS). During the EU-PLF project (2012-16), the CowView RTLS (GEA) was assessed on 160 cows, equipped with tags, in our freestall barn enhanced with mechanical swinging brushes (Delaval). From the large positioning dataset collected (1 location/animal/s), we extracted grooming behaviour (scratching using the brush) with good sensitivity (80%) and a suitable positive predictive value (60%). The accuracy of our grooming detection algorithm was evaluated by comparing the results obtained against video analyses. Subsequently, 23 dairy cows were monitored for 32 days, and patterns of grooming activity were analysed to study variations between cows and between days. 24-h video recording was re-visualised to explain the false detections observed, i.e. a cow detected in the brush area without grooming or a cow classified as grooming but not localised in the area. The kinetics of daily time spent grooming showed high day-to-day and inter-individual variations. Noisy tags appeared to be responsible for most of the false detections. Once smoothed, the kinetics modelled offer promising applications for detecting alterations in cow grooming behaviour patterns.

Keywords: monitoring, behaviour, RTLS, grooming, cow

Introduction

Grooming is a natural and essential (Bolinger et al, 1997) behaviour for dairy cows. Grooming behaviour is reported to be potentially related to physiological

status (calving (Newby et al, 2013), stress (Mandel et al, 2013) and health (mastitis, Fogsgaard et al, 2012). Equipping freestall barns with mechanical brushes may help cows to self-groom more body regions, thus reducing boredom, stress and dirt. Cows may only use brushes for a few minutes a day, e.g. 6 min/d spread over 7 daily visits (DeVries et al, 2007), but with large variations, e.g. 31 min/d (±18) in pre-calving cows (Newby et al, 2013). A monitoring device which is capable of measuring grooming behaviour automatically could therefore help detect such states and better serve precision livestock farming (PLF) approaches.

In a previous study (research paper submitted in March 2017) performed during the EU-PLF project (2012-16), we demonstrated, using a real time location system (RTLS) versus video and a dedicated algorithm, that we could monitor grooming behaviour – specifically, scratching using a mechanical brush – with good sensitivity (nearly 80%) and a suitable positive predictive value (PPV) of 60%. Since the cows were localised (x, y) at the 1 Hz datarate, we were able to continuously detect even short visits to the brush area. Nevertheless, this validation work was only carried out at herd level and for a short period of time (24h).

Here we focussed on how this approach to monitoring grooming – already applied and validated for more basic and major behaviours such as resting in the cubicle (Tullo et al, 2016) – can be used to detect more precise behavioural patterns, at individual level and over the long term. To this end, we first reanalysed the video used as the "gold standard" for our first study in order to understand the technical reasons why we had so many false detections (PPV=60%), and to investigate a filtering strategy. We then extracted the individual kinetics of grooming patterns over a longer period from our big RTLS dataset and proposed a dedicated data mining approach in order to assess the relevance of the measurement tools from a biological point of view.

Materials and methods

The study was conducted at the INRA Herbipole experimental unit, in a freestall barn equipped with the CowView RTLS (GEA Farm Technologies, Germany). In one of the rearing pens equipped with a mechanical swinging brush (Delaval, Sweden), the (x, y) positions of 23 cows (8 lactating cows, 10 dry cows, 5 heifers), each fitted with an active ultra-wideband tag, were collected continuously (1 location/animal/s) from 5 January 2016 to 6 February 2016. We also recorded 24 h of video film of the brush area between 22 and 23 January 2016 to determine whether or not cows used the brush.

A 3.6 m² area around the brush was empirically defined, and cows localised by the RTLS in this area were considered as "using the brush" (Figure 1). An

algorithm developed under ImageJ v1.50c image processing software (Schneider et al, 2012) allowed automatic extraction of a continuous profile of individual grooming behaviour. These profiles were first compared with the 24-h video to explain the false detection qualitatively using The Observer V11.5 software (Noldus, The Netherlands). These profiles were then summarised on a daily basis, visualised, and smoothed with a moving average filter to remove the false detections. Finally, the smoothed profiles were subjected to hierarchical clustering analysis, using Euclidean distance and the Ward's aggregation method bundled with XLStat software (Addinsoft, France), to blindly sort the cows and evaluate the relevance of the biological information contained in such data.

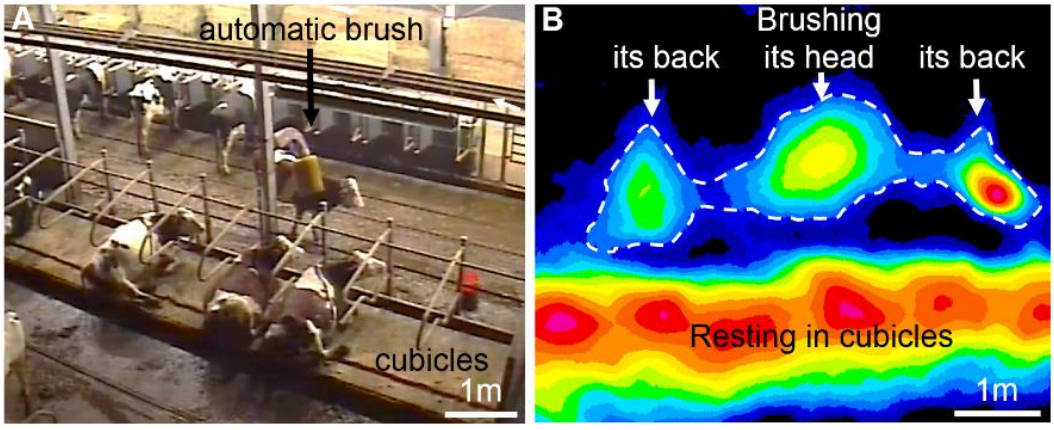


Figure 1. Snapshot of the video (A) and the corresponding heat map representation of density of occupancy processed from the RTLS data (B). Hot colours are associated with high levels of occupancy by the cows. The 3.6 m² area with the dashed outline was empirically drawn to be more probably associated with the use of the brush.

Results and discussion

The RTLS data were collected for 23 cows and 32 consecutive days with less than 5% missing values.

According to the video analysis, 23 cows used the brush for 8.3 h/d, i.e. 21.6 min/cow/d spread over 6.6 daily visits. These values are mid-range between those obtained in the studies by DeVries et al, 2007 and Newby et al, 2013. For the same 24-h period, the cows were detected in the brushing area for 10.0 h (+21% compared to video evidence), and for an average 10.3 h/d (±1.4 h) over the full 32-d period. This leads to the conclusion that our measure is quite stable and that the pressure on the brush is potentially high (10h/24h).

Comparison of the RTLS profile with the video profile found that most false-positive detections were due to cows standing in the area without using the brush and, to a lesser extent, cows standing in a very near area (e.g. the neighbouring cubicles) which were incorrectly located due to the positioning noise. In terms of the false-negatives, we observed very few individuals using the brush differently from the majority, i.e. body parallel to the cubicles when brushing its back (Figure 1-B). False-negatives were due firstly to the limited area of interaction, which could be enlarged, and secondly to the positioning noise due to tags which were badly positioned on the neck or tags masked by their environment. It is reasonable to assume that detection performance would have been better if we had restricted the area to a circle around the axis of the brush, although in that case we would only have detected cows brushing their head and neck, which accounts for only 29% of total brush-use time (De Oliveira et al, 2015).

Figure 2 shows the raw and smoothed daily duration of brush use (or, more precisely, presence in the brush area) for the two major and the two minor users. The plot reveals high day-to-day variation (potentially as much as 400 percent) as a consequence of both inter-individual biological variability (unknown) and technical variability (to recap, sensitivity was nearly 80% and PPV was 60%). This justified smoothing the data with the smallest window, which we considered to be 5 consecutive days, which does not induce a substantial phase-shift in the time-series. The dashed curves in Figure 2 reveal cyclical variation in the behavioural pattern between cows, which may potentially be biologically relevant (e.g. oestrus cycle, calving, days in milk) for long-term analysis, and between periods, which may potentially be explained by external events (e.g. temperature and humidity levels (Mandel et al, 2013).

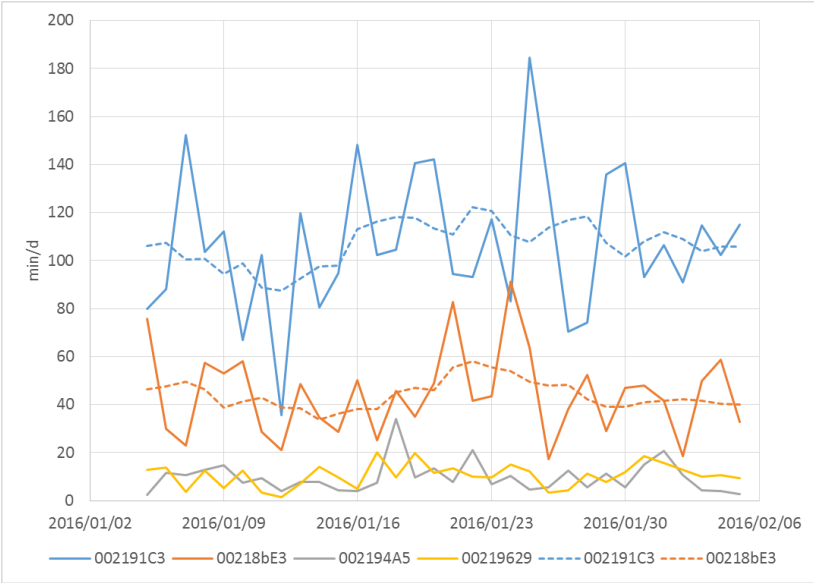


Figure 2. Daily duration (min/d) of presence in the brush area for the two major and two minor brush-user cows (distinguished by their tag numbers). The smoothed profiles (dashed line) are more informative as they potentially filter out the false (positive and negative) detections.

Figure 3-A depicts the dendrogram resulting from the clustering analysis. The automatic classification, without a priori information, revealed 4 groups of cows whose daily times spent in the brush area were uniform, relatively stable during this long time-period (32 d) and spread over a large range of brush use, from 10 to 110 min/d as depicted in Figure 3-B. This means that our automatic measurements are not only noise (found by chance), and also act, to a certain extent, as a validation process. The real hierarchy in this group was not evaluated but is not known to be expressed with this type of resource (Val-Laillet et al, 2008) if there is little pressure on it. In fact, we found no correlation between brush use and cow's weight, for instance, even though the major user (C1) was declared by the farmer to be the "big mamma" in the herd. Furthermore, the five heifers were mainly found (4/5) in the C2 cluster (one in C3), with all showing a relatively high level of brush use. Health may explain a part of clustering, for instance if cows are suffering from different levels of external parasite infestation.

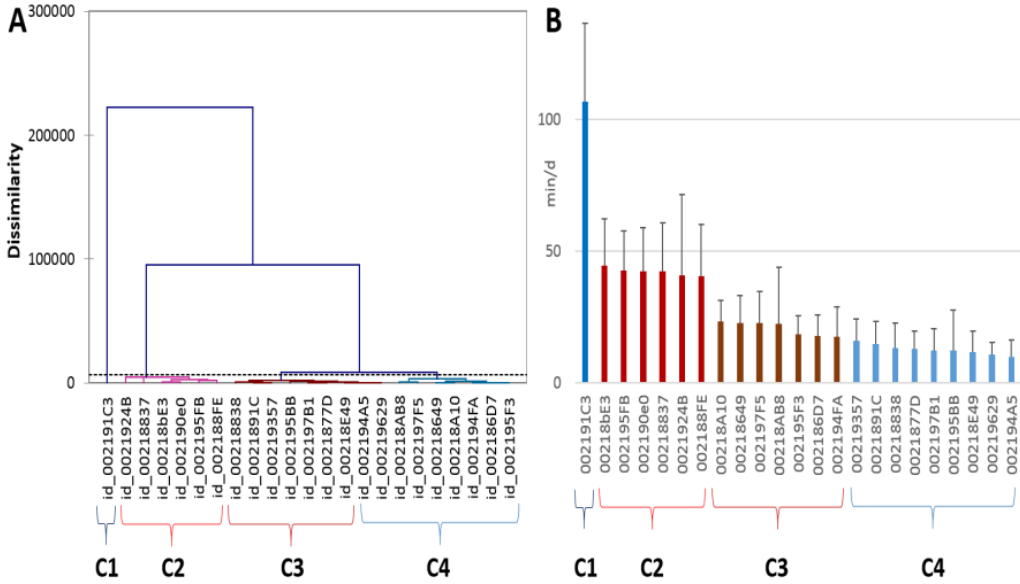


Figure 3. Dendrogram (A) resulting from the hierarchical clustering of the 23 cows, and histogram (B) of their mean (+ standard deviation) daily duration (min/d) of being in the brush area, ranged in descending order. The automatic classification (dashed horizontal line on the tree - A) revealed four significantly different groups of cows (C1 to C4) presenting different levels of brush use (B).

Conclusions

To our knowledge, this is the first study to describe brush use at individual level and over the long term. The kinetics of daily time spent grooming showed high day-to-day and inter-individual variations. The approach employed here revealed interesting cow behaviour profiles, which may be potentially associated with phenotype or physiological status as this grooming behaviour can be considered to be more or less freely expressed (i.e. without farming constraints) by each individual. The high range of "brush use" observed here could be compared with other factors such as dominance, health status or well-being indicators.

Noisy tags appeared to be responsible for most of the false detections. Once smoothed, the kinetics modelled offer promising applications for detecting alterations in cow grooming behaviour patterns. Nevertheless, omitting to consider sensor performance in the interaction with the individual could lead to misinterpretations, which further underlines how these new PLF devices must always be assessed at individual level, in each set of conditions, using robust approaches.

This monitoring approach could be easily implemented in real time to develop a PLF strategy or added to other time-budget information approaches to enrich the study of animal behaviour.

Acknowledgements

The European Community provided valuable financial participation in Collaborative Project EU-PLF KBBE.2012.1.1-02-311825 under the 7th Framework Programme. The authors thank Dominique Pomiès and the staff of the INRA experimental unit Herbipole (UE1414), especially Olivier Troquier, Florence Fournier and Christiane Espinasse. We also thank Karen Helle Sloth and Karsten Kristensen from GEA.

References

Bolinger, D. J., Albright, J. L., Morrow-Tesch, J., Kenyon, S. J., Cunningham, M. D. (1997). The effects of restraint using Self-locking stnachions on dairy cows in relation to behavior, feed intake, physiological parameters, health, and milk yield. *J. Dairy Sci.* 80, 2411-2417

De Oliveira, D., Franko, M. A., Keeling, L. J. (2015). A sequential analysis of body regions and body positions during mechanical brush use by dairy cattle, *Third DairyCare Conference*, Zadar, p. 28

DeVries, T. J., Vankova, M., Veira, D. M., von Keyserlingk, M. A. (2007). Usage of Mechanical Brushes by Lactating Dairy Cows. *J. Dairy Sci.* 90,

241‑2245. doi:10.3168/jds.2006-648

Fogsgaard, K. K., Røntved, C. M., Sørensen, P., Herskin, M. S. (2012). Sickness behavior in dairy cows during Escherichia coli mastitis. *J. Dairy Sci.* 95**,** 630–638

Mandel, R., Whay, H. R., Nicol, C. J., Klement E. (2013). The effect of food location, heat load, and intrusive medical procedures on brushing activity in dairy cows. *J. Dairy Sci.* 96, 6506-6513

Newby, N. C., Duffield, T. F., Pearl, D. L., Leslie, K. E., Leblanc, S. J., von Keyserlingk, M. A. (2013). Use of a mechanical brush by Holstein dairy cattle around parturition. *J. Dairy Sci. 96*(4), 2339-2344. doi: 10.3168/jds.2012-6016

Schneider, C. A., Rasband, W. S., Eliceiri, K. W. (2012). NIH Image to ImageJ: 25 years of image analysis. *Nat. Methods, 9*(7), 671-675

Tullo, E., Fontana, I., Gottardo, D., Sloth, K. H., Guarino, M. (2016). Validation of a commercial system for the continuous and automated monitoring of dairy cow activity. *J. Dairy Sci. 99*(9), 7489-7494. doi: 10.3168/jds.2016-11014

Val-Laillet, D., Veira, D. M., von Keyserlingk, M. A. (2008). Short communication: dominance in free-stall-housed dairy cattle is dependent upon resource. *J. Dairy Sci. 91*(10), 3922-3926. doi: 10.3168/jds.2008-1332

Determining learning and behavioural response to a virtual fence for dairy cows

S. Lomax[1], P. Colusso[1], J. Gargulio[1], C. Clark[1]
[1]*Dairy Science Group, Faculty of Science, University of Sydney, Australia*
sabrina.lomax@sydney.edu.au

Abstract

Virtual fencing (VF) has the potential to revolutionise control of livestock movement. Cattle can associate an audio cue with a mild electrical shock. This study investigates individual animal learning with VF collars, and if training time can be reduced using a visual cue (VC). The experiment utilised dog training collars fitted in Moo Monitors. 12 non-lactating dairy cows were subjected to one of 2 treatments: 1) Virtual Fence (VF) only 2) visual cue with VF (VC). Habituation to the laneway, pellets and manual collars occurred 2 x per day for 4 days prior to testing. Testing was performed in a laneway for 4 days. A VF line was set before a feed trough with pellets at the end of the laneway, and moved 10m closer to the holding yard each day for 3 days. Cows received an audio cue for 1 sec at the fence line. If they kept moving forward they received a mildly aversive electric shock. After 3 tests the VC was removed and the test repeated. Animal behaviour, and number of cues received was recorded. The visual cue reduced the number of times cows tested the fence line, with VC cows receiving less cues (mean 2.13) than VF cows (mean 4) overall ($P=0.007$). The number of cues reduced with each test ($P<0.001$), however increased with removal of the VC. The VC group received the most cues when the VC was removed ($P<0.001$). There is variation in response and learning of a VF, and results indicate that a visual cue is does not improve learning of associated cues.

Keywords: virtual fencing; learning; behaviour; cues

Introduction

Virtual fencing and herding technology involves the control of an animal's movement, positioning and groupings without ground-based fencing. This can be achieved by altering the animal's behaviour through sensory cues, electric shock, and the establishment of associative learning administered by radio-controlled collars. The commercial application of this technology in livestock is still a work in progress with research underway for its future use, as the management of free-ranging animals is an essential part of the agriculture systems (Anderson, 2007, Lee, Prayaga, et al., 2007). Cattle have been trained by associative learning to

avoid an area, feed attractant, and or group, when paired with an audio cue and electrical stimuli delivered by radio-controlled collars (Lee, Henshall, et al., 2009). Research has demonstrated these learning capabilities in respect to VH technology (Lee *et al*. 2007; 2009). Cattle have the ability to learn and be trained in VH technology, with the most effective method being associative training of using the paired audio cue and shock stimuli of the VH collars (Lee, Henshall, et al., 2009, Lee, Prayaga, et al., 2007). There is a need to gather information on the variation in individual response to and learning of these virtual fencing cues, to determine the need for training for practical and commercial applications. The objectives of the current study were to determine animal variation in learning and behavioural response to a virtual fence, and to evaluate the effect on training of the inclusion of a visual cue.

Materials and methods

Animals and housing

Eight non-lactating, multiparous Holstein-Friesian (HF) dairy cows, were used in the study. For the duration of the test period cows were housed in a large 100m x 80m paddock adjacent to the test site (Figure 1). Animals will have ad lib access to mixed pasture, supplemented with lucerne hay. The trial was conducted at The University of Sydney farm "Mayfarm", Camden, NSW. Three treatments were examined: 1) Virtual Fence only (VF n=4) and 2) Virtual Fence + visual cue (VC, tape across laneway, n=4).

Habituation

Cows were habituated to the virtual fence collars, yards, test laneway and feed attractant (pellets) twice daily for 4 days prior to testing. This involved moving the cows from their holding paddock into the race where they were fitted with manual collars to habituate them to wearing the devices. The collars were switched off so as not to impart any sound or electrical stimulus. The collars were fitted in the morning and removed in the afternoon each day for 4 days of habituation. Cows were trained to access and eat pellets at the end of the laneway during habituation. Pellets were provided in a feed trough at the far end of a laneway (50m) that was used for testing. Each morning the cows were released into the individually for 2 minutes and allowed to eat pellets for 30 seconds (approx. 1kg).

Virtual fence collars The collars were manual versions of the commercial prototype virtual fence devices (Agersens "eShepherd"). They incorporated a modified electric shock dog training device (ET300 mini Educator, E-Collar Technologies Inc, USA) in a commercial cattle health monitor collar (Moo Monitor, Dairymaster, Ireland).

Experimental procedure

The experiment was performed in a laneway (50m x 4m, Figure 1). Each morning prior to commencement of testing, cows were moved from the holding paddock into the yards (Figure 1), and fitted with the collars in the race. Each animal was tested individually daily (morning or afternoon) for 3 days. Individual testing was conducted out of sight of the other cattle. A virtual fence (VF) line was applied 5m in front of the feed trough, and moved 10m toward the entry gate each day of testing (Figure 1). A visual cue (non-electrified electric fence tape) was applied 3m from the VF shock line for the visual cue group. For testing each cow was released into a small holding area before the gate to the laneway test arena (Figure 1). Once the cow entered the entry gate to the test arena, testing commenced. Each cow was allowed a maximum of 3 minutes to approach the feed trough. Upon conclusion of the individual test the cow was walked back to the yards. Each afternoon after testing concluded, cows were let into the laneway individually to access feed without and cues or stimuli. The collars were removed at the end of each day and the cows returned to the holding paddock. After 3 tests, the visual cue was removed from treatment group 2 (VF + visual cue) and the test repeated (Test 4) to evaluate the effect on learning of the visual cue.

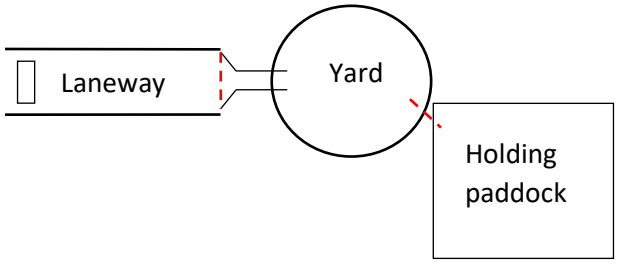


Figure 1 - Test setup – holding paddock, yards and laneway

The virtual fence was simulated using manual control of audio cue and electric shock. Administration was via a remote device with separate buttons for audio cue and electric shock. When the animal approached the audio cue line, an audio cue was administered for 1 second. If the animal continued toward the feed trough, a mild electric shock was administered for less than 1 sec. If the animal continued toward the feed trough and reached the feed trough, it was allowed to consume the pellets and the test period concluded. Each test period was videotaped and animal behavioural responses described as per Lee *et al* (2009).

Statistical analysis

Data was subjected to a restricted maximum likelihood logistic regression (REML, Genstat Version 18, VSNi UK). Number of audio cues, number of

shocks and total number of stimuli were assessed against treatment and test number.

Results and Discussion

There was no interaction between treatment and test. There was significant effect of treatment on the number of audio cues and total stimuli received by the cows (P<0.01) (Figure 2). Cows that did not have the visual cue during testing, received more cues overall. The cows used in the study were multiparous dairy cows. These cows are accustomed to the electrified tape that was used in the study as a visual cue. This indicates that the association of the tape, even though it was non-electrified, presented a barrier to accessing the feed reward. Cows in this group did not access the feed reward at all while the visual cue was present.

Treatment	**Visual Cue + Virtual Fence**	**Virtual Fence only**	**P-value**
Number of audio cues	1.25 ± 0.23^{a}	2.63 ± 0.23^{b}	0.006
Number of shocks	0.875±0.16	1.38±0.16	0.071
Total stimuli	2.13 ± 0.34^{a}	4.0 ± 0.34^{b}	0.007

Figure 2 - mean number of cues received across all tests (n=4 per treatment). Means within a row with different superscripts (^{a,b}) are significantly different There was a significant difference in number of cues received by all cows between each test (P<0.001, Figure 3). Between tests 1 and 3, the number of cues reduced with each test, indicated cow learning of the fence and the cues. When the VC was removed, the number of cues received increased significantly, indicating that cows had not learned to associated the visual cue with the virtual fence cues.

Test	**1**	**2**	**3**	**4-VC removed**
Number of audio cues	2.88 ± 0.48^{a}	1.125 ± 0.48^{b}	0.125 ± 0.14^{b}	3.625 ± 0.48^{a}
Number of shocks	1.375 ± 0.25^{a}	0.25 ± 0.1^{b}	0.125 ± 0.14^{b}	2.75 ± 0.25^{c}
Total stimuli	4.25 ± 0.61^{a}	1.375 ± 0.61^{b}	0.25 ± 0.61^{b}	6.375 ± 0.61^{c}

Figure 3 - mean number of cues received in each test, across all treatments. Means within a row with different superscripts (^{a,b}) are significantly different at P < 0.001.

These results indicate that the visual cue presented a visual and physical barrier to accessing the feed reward for cows in the VC group. The previous negative

association of the electric tape, though non-electrified in the study, stopped cows in this group from moving down the laneway toward the fence line. Tests 1 to 3 indicate a reduced interaction with the virtual fence, with a reduction in all cues received. As there was no interaction with treatment and test, it is difficult to assess whether this was due to the visual cue group not testing the fence line due to the barrier, or if the VF group of cows were negatively associating the laneway with the shock cues. Once the VC was removed, these cows no longer had the familiar barrier, and therefore tested the fence line in Test 4. The increase in number of stimuli in test 4 indicates there was no association made by the VC group with the visual cue and virtual fence cues.

Positive reinforcement is important. Cows were allowed to move down the laneway to access the pellets without any stimuli once per day. It was evident that as testing continued cows were less inclined to move down the laneway and required encouragement. This is an area for future study – to increase positive associate, and randomise it with testing so that animals do not learn a sequence.

Conclusion

The results from this pilot study present important data on the ability of animals to learn and respond to virtual fence cues. Results indicate that learning of the virtual fence cues is complex. Spatial memory is strong in cows, and there is a need to continue positive reinforcement to break the association of the laneway with negative VF cues. Furthermore, individual animal variation is evident, and with further study to increase sample size, we will be able to quantify this variation. It was evident that the inclusion of a known visual cue was not effective and improving learning, or association with the virtual fence cues. Further study on pasture, or using different visual cues that do not present a physical barrier, is necessary to determine a training protocol.

References:

Anderson, D.M. 2007. Virtual fencing past, present and future<xref ref-type="fn" rid="FN1">1</xref>. The Rangeland Journal 29: 65-78. doi:https://doi.org/10.1071/RJ06036.

Lee, C., J.M. Henshall, T.J. Wark, C.C. Crossman, M.T. Reed, H.G. Brewer, et al. 2009. Associative learning by cattle to enable effective and ethical virtual fences. Applied Animal Behaviour Science 119: 15-22. doi:10.1016/j.applanim.2009.03.010.

Lee, C., J.M. Henshall, T.J. Wark, C.C. Crossman, M.T. Reed, H.G. Brewer, et al. 2009. Associative learning by cattle to enable effective and ethical virtual fences. Appl. Anim. Behav. Sci. 119: 15-22. doi:10.1016/j.applanim.2009.03.010.

Lee, C., K. Prayaga, M. Reed and J. Henshall. 2007. Methods of training cattle to avoid a location using electrical cues. Applied Animal Behaviour Science 108: 229-238 doi:http://dx.doi.org/10.1016/j.applanim.2006.12.003.

Quantifying behavior of dairy cows via multi-stage Support Vector Machines

S. L. Madsen[1], H. Karstoft[1], R. N. Jørgensen[1], M. Nørremark[1], Y. Khokhar[2], J. S. Gómez[2], S. pier van Gosliga[2], K. Jaakkola[3]
[1]*Department of Engineering – Signal Processing, Faculty of Science and Technology, Aarhus University, Finlandsgade 22, DK-8200 Aarhus N, Denmark*
[2]*Connecterra B.V., Singel 542, 1017AZ Amsterdam, The Netherlands.*
[3]*Teknologian tutkimuskeskus VTT Oy, P.O. Box 1000, FI-02044 VTT, Finland*
slm@eng.au.dk

Abstract

The product portfolio of sensor based monitoring of animal behavior is increasing. The technology is attractive for reasons of resource management and animal welfare in dairy production. The objective of the present study was to support this technology in terms of methodologies for automated classification of behaviors that are essential for detection of lameness, estrus, emissions, and feed and water consumption. A multistage support vector machine (MSVM) classification model was constructed to recognize the behavioral patterns of three dairy cows based on 44 features reflecting the dynamics in data. Each cow was fitted with a neck collar comprising a combination of a three-axis accelerometer with a measure range of ±2 g, and a three-axis magnetometer with a measuring range of ±1.3 gauss. The recognized behavioral patterns were: '*Lying*', '*Upright'* and '*Ruminating*', with upright divided into the subclasses: '*Standing'*, '*Walking*', '*Feeding*', '*Drinking*'. The classification model achieved recognition of the main classes: '*Lying*' (89% sensitivity, 86% precision), '*Upright'* (81%, 84%). and '*Rumination*' (98%, 97%), The classification model achieved recognition of the subclasses: '*Standing'* (86%, 86%), '*Walking*' (14%, 53%), '*Feeding*' (91%, 84%) and '*Drinking*' (17%, 64%). Limited number of observations and uncertain annotation of the classes: '*Walking*' and '*Drinking*', resulted in poor performance for these classes. The transitions between '*Lying*' and '*Upright*' were also registered, but omitted in the analysis, since the duration of these resulted in very few observations. This study introduced a multistage SVM classification model and refined the features compared to previous and similar studies using SVM.

Keywords: multi-stage classification, behavior monitoring, accelerometer, dairy cows, support vector machines, resource management

Introduction

Assessment and classification of behavior of animal husbandry is a field in constant development. The motivation is to timely detect animals in need of attention from the farm managers. Seamless and accurate detection of for example estrus, lameness, illness, feed intake, water intake and other interference with animal health status is essential from an economical point of view, for maintaining milk and meat production, reproduction, and other functional traits of dairy cows.

With increasing farm size, the available time per cow for observation of behavior and health will obviously decrease. Making use of sensor data might support the management in the daily and long term management, investments and strategies (e.g. breeding program and improvements of stable interior).

The commercial development of advanced animal activity sensors are escalating rapidly. Alongside with increasing life cycle of batteries the activity sensors becomes a device that follows a dairy cow throughout its whole life. Recent commercialized systems is said to improve the automatic estimation of a multiple range of specific animal activities (duration of eating, lying, standing and walking), position and reproduction (estrus) derived from a single data logger and transmitter.

Data from three-axis accelerometers have been widely used in research and commercialized activity estimation systems to monitor dairy cattle activity, behavior and health e.g. (GEA Group 2017; Clark et al. 2015; SCR 2017; Thorup et al. 2015; Martiskainen et al. 2009; Nedap livestock management 2017). The common aim is to achieve as detailed and 100% reliable estimation of all dairy cow activities and characteristics. The problem of translating these measurements to distinct behavioral categories to create an ethogram is not overcome yet. Challenges to the accuracy of the behavioral information includes missing values, uncertainty in time, and embedded software interpretation/classification errors (Silper et al. 2015; Thorup et al. 2015; Martiskainen et al. 2009; Hokkanen et al. 2011). The objective of this study is determined on reduction of the interpretation/classification errors using accelerometers.

Different approaches for machine learning approaches to the interpretation of data from three-axis accelerometer or Kinect depth sensor data on animals have been published (Martiskainen et al. 2009; Behmann et al. 2016; Lee et al. 2016; Gerencsér et al. 2013; Gao et al. 2013; Hokkanen et al. 2011). From these studies the machine learning method, Support Vector Machine (SVM), are commonly adopted.

Sometimes it is preferable to partition the data into subgroups with similar features and derive the classifier parameters separately. This process results in a

multi stage SVM (MSVM) or hierarchical SVM, which can produce greater generalization accuracy and reduce the likelihood of overfitting as shown by (Stockman & Awad 2010). With a multistage approach, different kernel and tuning parameters can be optimized for each stage separately. The objective in this study is that the first stage SVM can be trained to distinguish between lying and upright posture of the cow independent of the remaining behavior classes. At the second stage, another SVM is trained to distinguish among the remaining classes.

The present study was aiming at developing a method for estimating multiple activity patterns of dairy cows by introducing the MSVM classifier method on three-axis accelerometer data.

Materials and Methods

Data were recorded from July 1st to August 5th 2015, at the research facility at the Danish Cattle Research Centre in Foulum, Denmark (56°29'17.5" N, 9°35'22.3" E).

Facilities, animals and measurements

Recordings of the dairy cow behavior by the data loggers were available for a total of 3 dairy cows over periods of varying time length and with a varying number of measuring sequences within the whole five week recording period. A measuring sequence is here defined as the time period in which a data logger has been continuously attached to a cow. Transfer of data from the data logger to a computer was done by manually removing the micro SD card of the data logger and reading data to the laptop. Data loggers were reattached to cows within a couple of hours. The manual data transfer was required with 7 days intervals due to device storage limits and battery life span.

The three cows was a part of a herd of 24 Holstein dairy cows in a stable section with 24 feeding boxes, four drinking boxes and 24 bedding cubicles. Total mixed rations (TMR) were available ad libitum in Insentec RIC feeder boxes (Insentec, Marknesse, The Netherlands). Observations of the cows feeding and drinking behavior were recorded for each of the feeding and drinking boxes, produced by Insentec RIC system. The feeding boxes identify each cow that puts its head into a feeding and drinking box and register time for arrival and departure as well as consumed weight/volume for each visit. The recordings of feeding and drinking behavior as well as milk production data were available throughout the whole recording period of five weeks.

The data logger was placed over the neck by using a collar that was passed through and fixed within the brackets of a polycarbonate micro case. The data logger casing comprised a Pelican micro case (Pelican Products, Inc., Torrance,

CA, USA). The data logger electronics and two 1.5V batteries were mounted inside the dust, moisture and ruggedized case in order to withstand the environmental conditions. A counterweight was added at the bottom of the collar to prevent the data logger from rotating. The collar was tightening sufficiently such that the collar moves together with the cow body, however it was not always sufficient to prevent the data loggers from tilting or turning upside down.
A GoPro Hero4 Black edition digital camera (GoPro, Inc., San Mateo, CA, USA) was mounted under the loose housing ceiling. The camera field of view covered all 24 bedding cubicles and alleys between bedding area and the feeding and drinking boxes. The frame rate was approximately 1.5 frames/s. Digital video were transmitted periodically in packages via Wi-Fi communication between the GoPro camera and a laptop located in a nearby office environment. Twice a day the cows left the section by walkways to a separate milking stable. In the period of walking to and from the milking stable and during milking the cows were outside the camera field of view.

Collection of data

The data logger was based on the OLIMEX MSP 430-CCRF development board (OLIMEX Ltd., Plovdiv, Bulgaria). The logger used an LSM303DLHC eCompass module (STMicroelectronics, Geneva, Switzerland) to collect three-axis accelerometer data with a measure range of ±2 g. The data was sampled with a 12-bit A/D converter with 1 mg/LSB sensitivity at a rate of 200 Hz. However, the data logger was configured to follow a periodic 200 ms cycle, where it samples 32 consecutive acceleration measurements and then writes the data onto a SD memory card, see Figure 1. The data logger was not sampling the acceleration during writing of the data, which introduces non-linearity in the data. To remove the non-linearity, the data was down-sampled, by selecting four samples each cycle resulting in an effective sampling rate of 20 Hz. The logger also included a three-axis magnetometer with a measuring range of ±1.3 gauss. The magnetometer data was not used in the following data analysis.

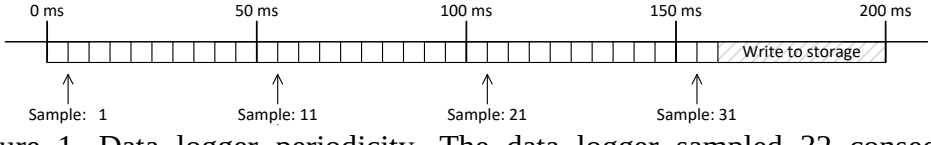


Figure 1. Data logger periodicity. The data logger sampled 32 consecutive samples (white boxes) and wrote data to the storage (gray) each 200 ms. The arrows denotes the selected samples resulting in a down-sampling to 20Hz.

Data Annotation

The behavioral actions of the cows were divided into three main categories: '*Lying*', '*Upright'* and '*Ruminating*'. The '*Upright'* category was again divided into four subclasses describing behavioral actions that only occurred when the cow was standing in an upright position. The behavioral categories are described in Table 1. Annotation of category no. 1 and 2 was carried out using video recordings. Software was specifically developed for annotating the video recordings frame-by-frame in order to register the start and end time for each animal behavioral pattern. The behavioral annotations were manually synchronized with the accelerometer data through identification of distinct patterns and transitions between these in the latter.

'*Ruminating*' was analyzed separately but in parallel since this action can occur in both while '*Lying*' and '*Upright'*. It was not possible to observe '*Ruminating*' from the video recordings, so the behavioral annotation of ruminating were carried out through identification of the distinct ruminating pattern (Nørgaard, 2003) directly from visual inspection of the accelerometer data.

Table 1. Description of behavioral action categories and subcategories.

Category No.	Behavior category	Definition
1	*Lying*	The cow lies in a bedding cubicle or floor
2	*Upright*	The cow is in an upright position standing on all four feet
2a	*Standing*	The cow stands still without feeding or drinking.
2b	*Walking*	The cow walks forward
2c	*Feeding*	The cow places its head in the feeding box
2d	*Drinking*	The cow places its head in the drinking box
3	*Ruminating*	The cow ruminates.

Additionally the transitions from '*Lying*' to '*Upright*' and from '*Upright'* to '*Lying*' were also registered as complete behavioral patterns. These observations were omitted in the analysis due the relative low amount of observations.

3D to 2D projection of acceleration data

The measured acceleration consisted of three components, corresponding to each axis in a three-dimensional coordinate system (eq. 1). The measured acceleration can also be decomposed into a vertical and horizontal component (eq. 2).

$$\boldsymbol{a}_t = \left(a_{x,t}, a_{y,t}, a_{z,t}\right) \qquad \text{(eq. 1)}$$

$$\boldsymbol{a}_t = \boldsymbol{a}_{v,t} + \boldsymbol{a}_{h,t} \qquad \text{(eq. 2)}$$

The decomposition into horizontal and vertical acceleration was better suited for analysis, since the sensors tend to displace themselves and thereby may charge alignment with the cow during the experiments. The vertical acceleration, $\boldsymbol{a}_{v,t}$, can be determined by projecting the instantaneous acceleration $\boldsymbol{a}_t$ onto the gravitational vector, $\hat{\boldsymbol{g}}$, and equivalent for horizontal acceleration, $\boldsymbol{a}_{h,t}$, is equal to the vector rejection.
Assuming that seen over time the cow was approximately stationary, the sensor will only be affected by the gravitation. An estimate for the gravitational vector, $\hat{\boldsymbol{g}}_t$, can thereby be determined by averaging the three channels (x, y and y), over a time window of a specific duration, for each time step. In this study the duration was chosen as 3 hours (±1½ hours with respect to the time, *t*). The vertical and horizontal accelerations were calculated by eq. 3 and 4. The vertical acceleration corresponding to the cows movement and was calculated by subtracting the gravitational contribution, eq. 5.

$$\boldsymbol{a}_{v,t} = \hat{\boldsymbol{g}} \frac{\boldsymbol{a}_t \cdot \hat{\boldsymbol{g}}_t}{\hat{\boldsymbol{g}}_t \cdot \hat{\boldsymbol{g}}_t} \qquad \text{(eq. 3)}$$

$$\boldsymbol{a}_{h,t} = \boldsymbol{a}_t - \boldsymbol{a}_{v,t} \qquad \text{(eq. 4)} \qquad \boldsymbol{a}_{m,t} = \boldsymbol{a}_{v,t} - \hat{\boldsymbol{g}}_t \qquad \text{(eq. 5)}$$

The decomposition of the acceleration vector is also visualized in Figure 2.

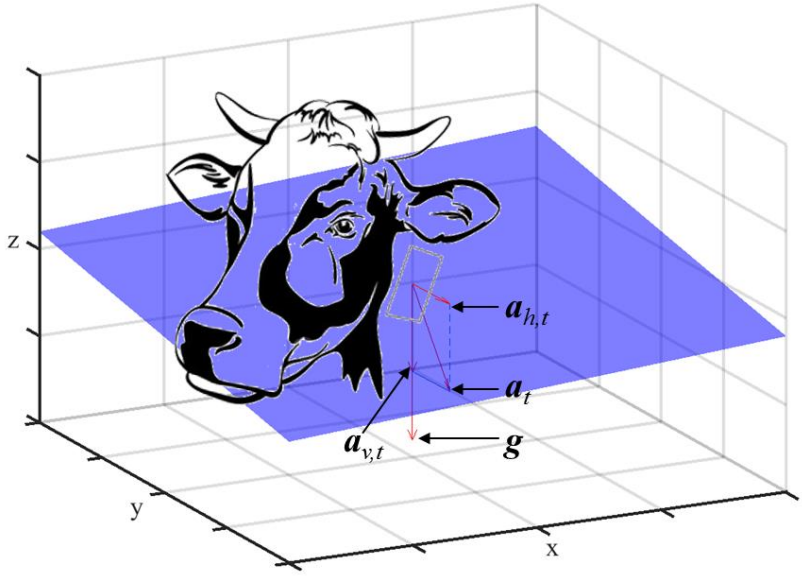


Figure 2. Projection of the acceleration vector, $\boldsymbol{a}_t$ (measurement from accelerometer) onto the vertical gravitational vector and the horizontal plane (large quadrant).

SVM setup

The SVM classifier was partitioned into two loops: one that classifies '*Lying*' and '*Upright'* including subcategories; and one that classifies '*Ruminating*'. Both loops included a preprocessing step that handled the 3D to 2D projection of the accelerometer data, divides the data into samples and extracts features from these. The sample length varies for the two classification loops, where classification of '*Lying*' and '*Upright'* uses sample length corresponding to 10 seconds (200 data points per channel) and classification of '*Ruminating*' uses sample length corresponding to 60 seconds (1200 data points per channel).

Features are extracted from each sample. The extracted features include: the mean value; the RMS value; the height and position of the main and secondary peak of the auto correlation; the height and position of the first six peaks in signal's PSD; and the accumulated signal power in five adjacent predefined frequency bands (Bunkheila 2015). The RMS value, autocorrelation and spectral features are extracted after high-pass filtering the data to remove the dc offset. The features are extracted for both channels resulting in a total of 44 features per sample.

Figure 3 shows the classification setup for '*Lying*' and '*Upright*' including subcate-gories. The setup was configured as a two-stage classification. Each sample was classified in the two main categories '*Lying*' and '*Upright*' and afterwards in the subcategories for '*Upright*', if belonging to this main category. Similarly,

Figure 4. show the classification setup for '*Ruminating*'.

The SVM classifiers in this study are implemented using LIBSVM (Chang & Lin 2011) and are configured as one-against-one classifiers. This configuration can handle both binary and multi-class classification problems. The SVMs are all configured to use a radial basis function as kernel, which is optimized using grid search.

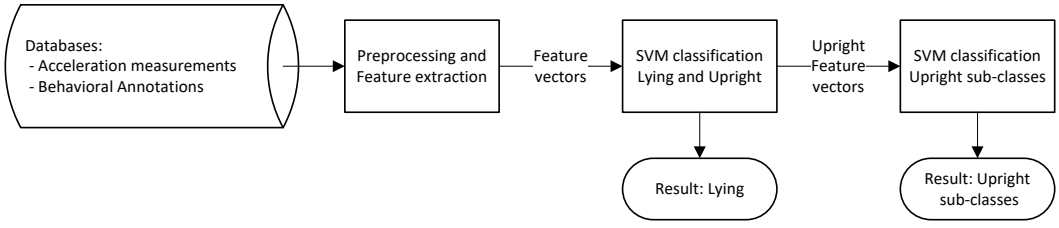


Figure 3. The *'Lying'* and *'Upright'* classification flow chart. The setup includes a preprocessing and feature extraction block followed by a 2-stage SVM configuration for classification. Both SVM setups are configured as one-vs-one, with RBF kernels and hyperparameter optimized using grid search. The loop classifies data samples with duration of 10 seconds.

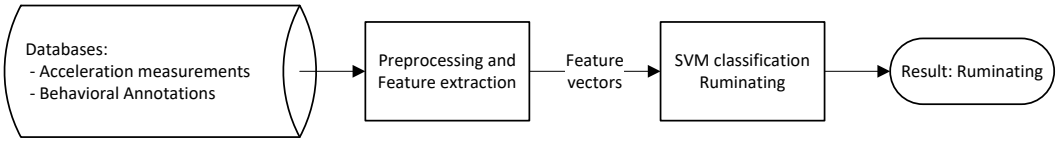


Figure 4. The *'Ruminating'* classification flow chart. The setup includes a preprocessing and feature extraction block followed by a SVM classifier. The loop classifies data samples with duration of 60 seconds.

The data was randomly split into a training and test set. In each loop, 80% of the feature vectors for each class were selected as training data and the remaining 20% was selected as test data. This ensured that all classes were represented equally in both training and test data. It leaded to 92659 feature vectors for training and 23169 feature vectors for test in the '*Lying*' and '*Upright*' loop and 8880 feature vectors for training and 2222 feature vectors for test in the '*Ruminating*' loop

Results and Discussion

The results in Table 2. show that the SVM was capable of distinguish between the two main categories ('*Lying'* and '*Upright'*) for the majority of the samples. However, the results in Table 3. show that the SVM had difficulties in classifying the subcategories of '*Upright'*. While the method performed well in classifying the subcategories '*Standing'* and '*Feeding'*, the performance on '*Walking'* and '*Drinking'* was lower. The performance drop is probably an effect of the relatively low amount of samples for these two categories.

Table 2. Classification results of the two main behavioral categories in the *'Lying'* and *'Upright'* classification. Numbers in bold and normal font indicates level of correctly and incorrect classified samples respectively. Sensitivity and precision for each class and the overall accuracy are stated in percent.

		Predicted class *Lying*	*Upright*	Sensitivity [%]
Actual class	*Lying*	**11709**	1491	88.6
	Upright	1837	**8071**	81.4
Precision [%]		86.3	84.3	Accuracy: 85.4 %

Table 3. Classification results of the *'Upright'* subcategories in the *'Lying'* and *'Upright'* classification. Numbers in bold and normal font indicates level of correctly and incorrect classified samples respectively. Sensitivity and precision for each class and the overall accuracy are stated in percent.

		Predicted class				Sensitivity [%]
		Standing	*Walking*	*Feeding*	*Drinking*	
Actual class	*Standing*	**3007**	21	488	3	85.5
	Walking	123	**52**	198	0	13.9
	Feeding	325	24	**3729**	6	91.3
	Drinking	54	0	24	**16**	17.0
Precision [%]		85.7	53.1	84.0	64.0	Accuracy: 84.3 %

Table 3 indicates some systematical patterns in the misclassifications that probably is a result of similarities between the categories or non modelled modalities in the data. E.g. The *'Feeding'* annotation only registered when the cow entered the feeding trough, not if the cow was actually feeding or just standing there, which might explain why '*Standing'* tend to be misclassified as '*Feeding'* and vice versa. The same was probably the case for the '*Drinking'* category.

The annotated '*Walking'* sessions was usually of very short duration, since the cows only moved small distances at the time. This resulted in very few samples of the required 10 sec sample length, which might have made the category underrepresented relatively to the others. The short duration of the '*Walking'* sessions was also problematic with respect to the synchronization between the behavioral annotations and the accelerometer data, since small misalignments results in the wrong behavioral pattern being captured. This might have been the case since the '*Walking'* category was misclassified as '*Standing*', an action that usually occurs before or after each '*Walking'* session; and '*Feeding'*, which was always preceded and succeeded by a '*Walking'* session. The results presented in Table 4 shows that the SVM was capable of classifying whether the cow is rumination or not with only few misclassifications.

Table 4. Classification results from the *'Ruminating'* classification. Numbers in bold and normal font indicates level of correctly and incorrect classified samples respectively. Sensitivity and precision for each class and the overall accuracy are stated in percent.

		Predicted class		Sensitivity [%]
		Not Ruminating	*Ruminating*	
Actual class	*Not Ruminating*	**1530**	30	98.1
	Ruminating	48	**614**	92.8
Precision [%]		97.0	95.3	Accuracy: 96.5 %

Conclusion

The performance of the developed method for estimating multiple activity patterns of dairy cows was high. However, the method fail to recognize some important behavioral categories, e.g. walking that is crucial for recognizing potential lameness. The underperformance on classifying walking as well as drinking is probably a result of missing details in the behavioral annotations and of the inaccuracy in the manual synchronization between the annotations and the accelerometer data.

Even though the SVM classifier performed well on the available data, the method might not generalize well, since it was only trained on data from three different cows. Data from a larger population will increase the robustness of the method.

Acknowledgements

The research was funded by the ICT-AGRI project 'HappyCow' established by the Danish Agency for Science, Technology and Innovation. Ester Bjerregaard and Merete Jensen from the Danish Cattle Research Centre are acknowledged for their efforts during the period of running the experiments.

References

Behmann, J. et al., 2016. Support Vector machine and duration-aware conditional random field for identification of spatio-temporal activity patterns by combined indoor positioning and heart rate sensors. *GeoInformatica*, 20(4), 693–714.

Bunkheila, G., 2015. Signal Processing and Machine Learning Techniques for Sensor Data Analytics. *MathWorks Inc.* Available at: https://se.mathworks.com/videos/signal-processing-and-machine-learning-

techniques-for-sensor-data-analytics-107549.html [Accessed February 10, 2017].

Chang, C.-C. & Lin, C.-J., 2011. {LIBSVM}: A library for support vector machines. *ACM Transactions on Intelligent Systems and Technology*, 2(3), 1-27.

Clark, C.E.F. et al., 2015. Rumination and activity levels as predictors of calving for dairy cows. *Animal*, 9(4), 691–695.

Gao, L. et al., 2013. A Web-based semantic tagging and activity recognition system for species' accelerometry data. *Ecological Informatics*, 13, 47-56.

Gerencsér, L. et al., 2013. Identification of Behaviour in Freely Moving Dogs (Canis familiaris) Using Inertial Sensors. *PLOS ONE*, 8(10).

GEA Group, 2017. GEA | CowScout Heat Detection & Health Management. Available at: http://www.gea.com/en/products/activity-detection-cowscout.jsp [Accessed February 10, 2017].

Hokkanen, A.-H. et al., 2011. Predicting sleep and lying time of calves with a support vector machine classifier using accelerometer data. *Applied Animal Behaviour Science*, 134(1–2), 10-15.

Lee, J. et al., 2016. Automatic Recognition of Aggressive Behavior in Pigs Using a Kinect Depth Sensor. *Sensors*, 16(5),

Martiskainen, P. et al., 2009. Cow behaviour pattern recognition using a three-dimensional accelerometer and support vector machines. *Applied Animal Behaviour Science*, 119, 32-38.

Nedap livestock management, 2017. Nedap Smarttag Neck with Heat Detection and Eating Monitoring. Available at: http://en.nedap-livestockmanagement.com/solutions/cows-and-cow-management/smarttag-neck-with-eating-monitoring/ [Accessed February 10, 2017].

Nørgaard, P. (2003) Optagelse af foder og drøvtygning. Chap. 6 in: Hvelpelund, T. and Nørgaard, P. Kvægets enæring og fysiologi. Bind 1 Næringsstoomsætning og fodervurdering. DJF Rapport, Husdyrbrug nr. 53, 120-145.

SCR, 2017. Heatime® HR LD System. Available at: http://www.scrdairy.com/cow-intelligence/heatime-hr-system.html [Accessed February 10, 2017].

Silper, B.F. et al., 2015. Short communication: Comparison of estrus characteristics in Holstein heifers by 2 activity monitoring systems. *Journal of dairy science*, 98(5), 3158–3165.

Stockman, M. & Awad, M., 2010. Multistage {SVM} as a Clinical Decision Making Tool for Predicting Post Operative Patient Status. In H. R. Arabnia et al., eds. International Conference on Bioinformatics {&} Computational Biology, {BIOCOMP} 2010, July 12-15, 2010, Las Vegas Nevada, USA, 2 Volumes. {CSREA} Press, 549–552.

Thorup, V.M. et al., 2015. Lameness detection via leg-mounted accelerometers on dairy cows on four commercial farms. *Animal*, 9(10), 1704-1712.

Session 3

Rumination and ruminal disorders

Continuous monitoring of cow activity to detect sub-acute ruminal acidosis (SARA)

M. Silberberg, B. Meunier, I. Veissier, M-M. Mialon
[1]*Université Clermont Auvergne, INRA,VetAgro Sup, UMR Herbivores, F-63122 Saint-Genes-Champanelle, France*
mathieu.silberberg@gmail.com

Abstract

Subacute ruminal acidosis (**SARA**) is a digestive disorder induced by an overload of rapidly fermentable carbohydrates and is characterised by intermittent drops in rumen pH. SARA is related to poor animal welfare and causes behavioural changes: animals are less active, eat less and spend more time lying. Real-time locating systems and activity measurements could be of great interest in detecting cows which exhibit behavioural modifications related to SARA. We investigated whether an activity monitoring system (CowView, GEA, Germany) based on cow location in the barn can detect an experimentally induced SARA episode. Cow activity was inferred from the cow's location (eating if near the feeding table, resting if in cubicles, etc.). After an adaptation period on a production diet containing 10% starch, 14 cows (SARA group) were challenged for 15 days with an acidogenic production diet containing 30% starch, before resuming their initial diet. Another 14 cows were maintained on the initial diet throughout the experiment (control group). All 28 cows were monitored with a rumen bolus which measured pH continuously. During the SARA challenge, rumen pH changed and the cows' activity levels changed drastically. Compared to the controls, SARA cows were significantly less active after morning feeding, and spent more time resting and licking salt blocks during the day. Monitoring systems based on cow activity or their location may thus be useful for detecting cows undergoing SARA episodes. Specific algorithms based on cow behaviour modification have yet to be developed and implemented in precision livestock farming systems which can adequately detect SARA and help farmers to maintain good welfare in dairy cows.

Key words: SARA, rumen pH bolus, CowView, monitoring, RTLS, welfare

Introduction

Intensive ruminant husbandry methods often use high-energy diets based on high starch and low fibre contents to stimulate meat or milk production. This practice, however, can cause frequent digestive disorders if it is not well managed. In

particular, ruminants may develop rumen acidosis if the transition from high fibre to high energy diets takes place over too short a period. The subclinical form, known as subacute ruminal acidosis (**SARA**) is frequently observed on dairy farms and its prevalence may reach up to 20% in Germany, for instance (Kleen *et al.*, 2013). SARA is associated with an erratic and/or reduced feed intake (Dohme *et al.*, 2008) and suboptimal fibre digestion with subsequent knock-on effects on production. SARA leads to many health disorders which impact animal welfare and the farmer's economic health. In a case study conducted on 500 dairy cows in the USA, Stone (1999) calculated a lost income of $400 to $475 per cow per year due to SARA.

The pathogenesis of SARA is well described. However, in-field diagnosis remains difficult due to the absence of specific clinical symptoms. Historically, rumen pH is the most frequently monitored parameter when making a SARA diagnosis. Recent development of wireless rumen *boli* which measure pH may help to objectivise SARA detection in the field. However, rumen pH measurements may not be sufficiently accurate due to high inter-animal variability (Gasteiner *et al.*, 2009). In addition, rumen *boli* are expensive and perishable devices.

The diagnostic process may also involve behavioural observations since activity changes can be observed when an animal is sick. It has already been shown that ruminants suffering from SARA modify their behaviour, particularly their daily feeding pattern. Indeed, bulls fed a 92% concentrate diet, without feed availability between feeds, were more likely to spread their meals over the entire day (Mialon *et al*., 2008). In addition, when wethers were exposed to 5-d acidosis challenges, they appeared more agitated (standing awake) during the challenges than during the recovery periods (Commun *et al*., 2012).

Many precision livestock farming systems are now available on farms and most of them are based on animal behaviour measurements which can now be recorded continuously. Promising results obtained recently with a Real Time Locating System (**RTLS**) show that anomalies in the circadian rhythm may precede the mastitis or lameness symptoms detected by farmers (Veissier *et al.*, 2017). The objective of the present study was therefore to determine whether a commercial RTLS system can be used to detect significant behavioural modifications when cows are suffering from SARA and can thus contribute to early detection of this production disease.

Materials and methods

The study was conducted at the INRA experimental facility Herbipole (UE1296, Marcenat, France), in a free-stall barn, in accordance with the animal research

guidelines of the French Ministry of Agriculture and applicable European guidelines and regulations (approval: APAFIS366). The study took place from February to May 2015 when cows were indoors.

Animals, treatments and experimental design

In total, 28 Holstein dairy cows were studied over 9 weeks (two months after the lactation peak) and were allocated to 2 groups: SARA (n=14 cows), control (n=14 cows). All cows were housed in the same pen which had 28 cubicles and individual feeding gates. After a four-week adaptation period on a production control diet containing 10.5% starch (Table 1), the starch content in the diet of the SARA cows was gradually increased to 31.5% during the 10-day transition period. SARA cows were then kept on this SARA challenge diet for 15 days before resuming their initial diet for three weeks. The control cows were maintained on the initial diet all through the experiment. The ration was distributed twice during the day: 60% of the ration was distributed in the morning after milking (07:00 a.m.) and 40% in the afternoon (02:00 p.m.). Cows had free access to water and salt blocks of pure NaCl (without buffering substances and vitamins).

Individual milk production was recorded daily throughout the experiment. During the SARA challenge, one gastro-oesophagus rumen sampling was performed on each cow to quantify rumen fermentable volatile fatty acids (VFA).

Table 1: Experimental diets, ingredients and chemical composition

Item	Control period diet	SARA challenge diet
Forage / concentrate ratio (%)	75 / 25	54 / 46
Ingredients (% DM)		
Hay	19	14
Wrapped hay	56	40
Concentrate for production	25	0
Barley / corn / wheat cereal mix	0	46
Chemical composition of diet (g/100g DM)		
Organic matter	93.3	94.7
Cellulose	25.5	18.2
NDF	52.1	39.4
ADF	30.4	21.6
Starch	10.5	31.5
Crude protein	17.4	14.2

Rumen pH kinetics

Each cow was monitored continuously with a rumen bolus which measured pH (Farm bolus; eCow, Exeter, UK). Rumen pH was recorded every 15 minutes and data were retrieved every 15 days. As in the experiment by Villot et al. described in these conference proceedings (ECPLF 2017, #565), the collected data were summarised with Excel software and a Visual Basic for Applications program was used to obtain absolute and relative daily rumen pH indicators. The absolute indicator was time spent at pH<5.8. In order to cope with inter-animal pH variability, the pH signal was normalised on 0 and relative indicators (NpH) were calculated as described in Villot *et al.* 2017: NpH range, NpH standard deviation, and time spent at NpH<-0.3 NpH unit.

Behaviour-related parameters

For continuous recording of cow activity, each cow was fitted with a RTLS CowView tag emitting a signal detected by 16 antennae in the barn (GEA Farm Technologies, Bönen, Germany). Cow position was determined every second by triangulation with an accuracy of less than 50 cm deviation. Four zones in the barn were mapped (alley, cubicles, feeding table and salt blocks) and records of the individual cows' positions were used to infer cow behaviour: standing in the alley, resting, eating, licking minerals (i.e. detected next to a salt block).

For circadian rhythm activity, a factorial correspondence analysis was run on the three main cow activities as proposed by Veissier *et al*. (2017). The observations were the hours of the day and the variables were the number of scans (across all animals and days) when each activity was detected. On the first axis of the factorial correspondence analysis, which summarised 92% of the variability, the three activities were given the following weightings: resting = −0.34; in alleys = +0.29; feeding = +0.52. For greater robustness, these weightings were calculated for the whole herd of dairy cows present in the barn (n=159). For each cow in the present study (n=28) and each day, we calculated the level of activity per hour by multiplying the percentage of time spent on each activity by the weighting attributed to the activity. Afterwards, the average level of activity and the standard deviation of the circadian variations during the day were calculated.

Statistical analyses

Statistical analyses were performed using the SAS PROC MIXED procedure for repeated measures. The fixed effects in the model were: treatment (SARA vs. control), period (control period before challenge, Transition, SARA challenge and control period after challenge), date and the treatment*period interaction. The animal was considered as a random effect. Differences were analysed using the least squares means method with a Tukey adjustment for the circadian variations. For each dependent variable, values obtained during the two first

weeks of the control period were averaged and used as covariates. Effects were considered significant for *P*-value < 0.05.

Results and discussion

Validation of the SARA challenge

Absolute and relative indicators of SARA were significantly increased in SARA cows when fed the high starch diet (Figure 1). For instance, cows under SARA challenge spent more than 65 min/d with pH<5.8, more than 230 min/d with NpH<-0.3 and their daily NpH range was 0.74 pH whereas control cows spent 15 min/d with pH<5.8, less than 80 min/d with NpH<-0.3 and their daily NpH range was 0.51.

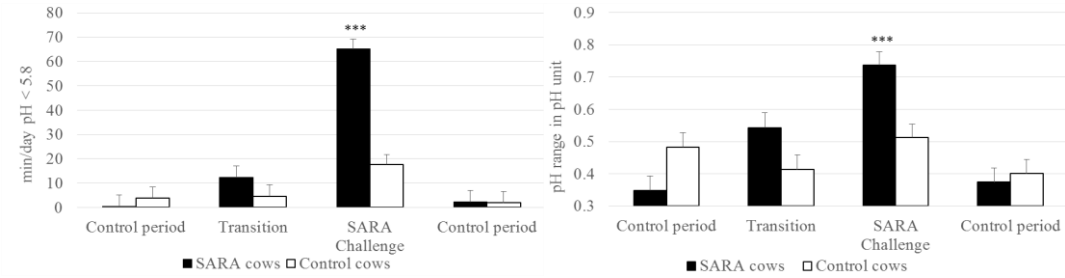


Figure 1: Time spent at pH<5.8 (left) and relative NpH range (right) as pH indicators of subacute acidosis in control (n=14) and in SARA (n=14) cows. See communication from Villot (ECPLF 2017, #565) for more details on relative NpH indicators of SARA. *, *P*<0.05. **, *P*<0.01, ***, *P*<0.001.

Moreover, SARA cows experienced a drastic modification of their VFA pattern with a significantly decreased acetate/propionate ratio (3.13 mM *vs* 4.24 mM in controls). According to Sauvant and Peyraud (2010), our cows were at risk of SARA since these authors propose a threshold of 3.0 below which ruminants may be at risk of SARA.

Milk yield is also known to be reduced when cows are suffering from SARA (Alzahal *et al.*, 2010). In our study, milk yield was slightly although significantly lowered in SARA cows compared to controls from the transition period to the end of the experiment (19.3 *vs* 20.5 L/d during transition, 18.2 *vs* 20.0 L/d during SARA challenge and 17. 9 *vs* 20.2 L/d during the last control period).

Consequently, all these results show that the cows suffered from SARA.

Circadian activity rhythm

The values obtained from the RTLS CowView system made it possible to calculate a circadian activity rhythm based on three major activities (eating, standing in alleys and resting). The mean activity level of the control cows increased throughout the experiment, possibly due to seasonal effects since the experiment ended in the spring (Dahl *et al.*, 2000).The mean activity levels of SARA cows were significantly lower than in the control cows from the transition period until the end of the experiment (Figure 2).

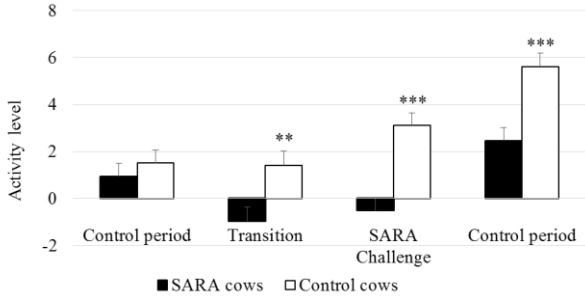


Figure 2: Mean daily activity of SARA (n=14) and control cows (n=14) during the four periods of the experiment. *, $P<0.05$. **, $P<0.01$, ***, $P<0.001$.

Moreover, at the end of the experiment SARA cows did not recover the same activity level as the control cows, although their activity level was higher than at the beginning of the experiment.

In order to explain the lower level of activity in SARA cows from the transition to the end of the experiment, we focused on the circadian rhythm during the SARA challenge (Figure 3). Two activity peaks were observed in both groups in the morning and in the afternoon, linked to the herd management system (two milkings and feeds per day). Despite these imposed components of the rhythm, SARA cows were less active during the morning after the main feed distribution. This observation can be explained by a high-energy diet which is more rapidly ingested by the animals due to a high proportion of concentrate. In addition, and as previously shown by Mialon et al. (2008) in bulls fed an acidogenic diet, we noticed that SARA cows also spread their meals over the day significantly more than control cows (data not shown).

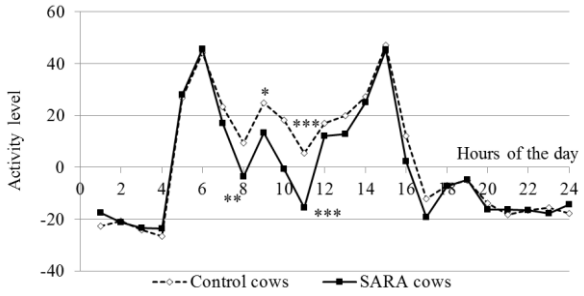


Figure 3: Circadian variations in activity level in SARA (n=14) and control cows (n=14) during the SARA challenge period. Activity level is a weighted sum of the percentage time spent on the different activities, based on the following weightings: resting = -0.34; standing in alleys = 0.29; eating = 0.52. *, *P*<0.05. **, *P* <0.01, ***, *P* <0.001.

Time spent licking salt blocks

Within the barn where the study was conducted, two salt blocks were installed at each end of the pen and cows had *ad libitum* access. The CowView system made it possible to quantify the time spent near the salt blocks for each cow in both groups. SARA cows spent more time near the salt blocks, particularly during the SARA challenge, than control cows. This observation has already been described in a previous study (Commun *et al.*, 2012). Such behaviour may enhance SARA detection.

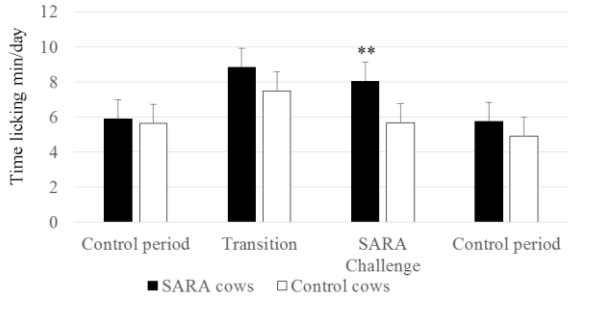


Figure 4: Licking salt blocks by SARA cows (n=14) and control (n=14) cows during the four periods of the experiment. *, *P*<0.05. **, *P* <0.01, ***, *P* <0.001.

Conclusions

These preliminary results obtained from an experimentally induced SARA situation reveal that some specific behavioural indicators could be used to detect animals suffering from SARA. An RTLS such as the CowView system appears to be a promising method of detecting such anomalies and then helping the farmer to correct the diet promptly. Such a system could therefore limit economic losses and increase animal welfare.

These first results need to be confirmed:

- First, the CowView system was installed in the barn shortly before the experiment. We plan to collect more data from the animals in the barn so as to refine the weightings attributed to the three activities in order to calculate the activity level. These weightings depend on herd management, e.g. milking and feeding time and frequency are key factors that impact on animal activity. It will therefore be necessary to estimate the weightings of the three activities over a sufficient period of time in another barn where SARA detection is needed.
- Second, a detailed analysis of each cow's activity throughout the experiment is required to ensure that no control cows behave like SARA cows and to identify the onset of changes related to SARA (so that a warning can be sent to farmers);
- Third, further studies are needed to compare modifications in behaviour when SARA is present and when other diseases or welfare problems are present so that we can identify what is specific to SARA.

Acknowledgements

The authors thank the staff of the INRA experimental facility Herbipole (UE1296, Marcenat, France) for animal care and data collection and Yoan Gaudron (UMR1213 Herbivores) for his help in data computation.

This study was part of the European project #311825 EU-PLF (Animal and farm-centric approach to precision livestock farming in Europe) co-financed by the European Commission.

References

Alzahal, O., M. M. Or-Rashid, et al. (2010). Effect of subacute ruminal acidosis on milk fat concentration, yield and fatty acid profile of dairy cows receiving soybean oil. *J Dairy Res* 77(3): 376-384.

Commun L., Silberberg M., Mialon M.M., Martin C., Veissier I., 2012. Behavioural adaptations of sheep to repeated acidosis challenges and effect of yeast supplementation. *Animal*, 6(12); 2011-2022.

Dahl, G. E., B. A. Buchanan, et al. (2000). Photoperiodic effects on dairy cattle: a review. *J Dairy Sci* 83(4): 885-893.

Dohme, F., T. J. DeVries, et al. (2008). Repeated ruminal acidosis challenges in lactating dairy cows at high and low risk for developing acidosis: ruminal pH. *J Dairy Sci* 91(9): 3554-3567.

Gasteiner, J., Fallast, M., Rosenkranz, S., Häusler, J., Schneider, K., and Guggenberger, T. 2009. in. *Proceedings Fourth European Conference Precision Livestock Farming 09*, Wageningen, the Netherlands.

Kleen, J. L., L. Upgang, et al. (2013). Prevalence and consequences of subacute ruminal acidosis in German dairy herds. *Acta Vet Scand* 55: 48.

Mialon M.M., Martin C., Garcia F., Menassol J.B., Dubroeucq H., Veissier I., Micol D, 2008. Effects of the forage to concentrate ratio of the diet on feeding behaviour in young Blond d'Aquitaine bulls. *Animal* 2. 11. 1682-1691

Sauvant, D. and J. Peyraud (2010). Calculs de ration et évaluation du risque d'acidose. *INRA Productions animales* 23(4): 333.

Stone, W. C. (1999). The effect of subclinical rumen acidosis onmilk components. *Proc. Cornell Nutr. Conf. Feed Manuf. Cornell Univ.*, Ithaca NY.

Veissier I., Mialon M. M., Sloth K. H., 2017. Early modification of the circadian organization of cows' activity in relation to disease or estrus. *J dairy Sci* 100(5):3969–3974.

Villot C., Meunier B., Bodin J., Martin C., Silberberg M., 2017. Relative reticulo-rumen pH indicators for subacute ruminal acidosis detection 1 in dairy cows. Animal, accepted 14 june 2017.

Relative rumen pH thresholds to predict subacute ruminal acidosis (SARA) in dairy cows

C. Villot[1,2,3,4], C. Martin[1], B. Meunier[1], MM. Mialon[1], M. Silberberg[1]
[1]*UMR1213 Herbivores, INRA, VetAgro Sup, Clermont université, université de Lyon, 63122 Saint-Genès-Champanelle, France*
[2]*Lallemand Animal Nutrition, F-31702 Blagnac, France*
[3]*Valorex, La Messayais, F-35210 Combourtillé, France*
[4]*Terrena, La Noëlle, F-44150 Ancenis, France*
mathieu.silberberg@inra.fr

Abstract

In ruminants, subacute ruminal acidosis (SARA) is a digestive disorder which is usually induced by an overload of rapidly fermentable carbohydrates ingested by animals and characterised by abnormal and intermittent drops in rumen pH. To date, no pH threshold has successfully described SARA in dairy cows due to the inaccuracy of measurement techniques and the high rumen pH variability between animals. In this context, two studies were carried out to propose relative pH indicators of SARA based on normalised pH kinetics. Twenty-four dairy cows were followed during two different longitudinal studies (experiment #1; n=10 and #2; n=14) which induced a long-term SARA challenge with high starch diets (30% rumen digestible starch) in both cases. Individual raw rumen pH kinetics were recorded continuously by reticulo-rumen sensors. Relative daily pH parameters were calculated on filtered and normalised pH kinetics (NpH): drift was eliminated and the pH signal was cleaned of noise and normalised on 0. NpH parameter thresholds for SARA diagnosis were described with a receiver operating characteristics (ROC) test using the daily individual dataset for experiment #1. The optimum thresholds were 0.80 and 0.20 pH units for daily NpH range and standard deviation respectively, 50 min when NpH was < -0.3 and 5 min when NpH was < -0.5 pH units. A daily NpH range above 0.80 provided the best combination of sensitivity (94%) and specificity (83%) for the prediction of SARA challenge based on the independent dataset (#2). This study demonstrated the importance of relative rumen pH indicators in overcoming various measurement issues and the high variability between animals in SARA conditions. The proposed method can be implemented in precision livestock farming devices to detect digestive disorders in cows.

Keywords: reticulo-rumen pH sensor, subacute ruminal acidosis (SARA), dairy cows, relative rumen pH indicators

Introduction

With a dairy cow prevalence of 15% in European countries (Stefańska *et al.*, 2016), the main ruminal disorder is known to be subacute ruminal acidosis (SARA) which hitherto has been characterised by intermittent and moderate periods of depressed rumen pH (Enemark *et al.*, 2002). Rumen pH is the most frequently monitored parameter when making a SARA diagnosis. Historically, depending on the severity of SARA, daily average pH thresholds of 5.50 to 6.25 have been proposed (Sauvant *et al.*, 1999). However, the measurement technique has a significant impact on pH value (Duffield *et al.*, 2004) which depends upon sampling location (Gasteiner *et al.*, 2009) and the frequency of pH measurement. The large variability of rumen conditions between animals also alters the robustness of absolute rumen pH indicators of SARA (Schwartzkopf-Genswein *et al.*, 2003). Consequently there is still no scientific consensus regarding pH thresholds for detection of SARA. The use of rumen sensors to monitor reticulo-rumen pH is growing fast. Such devices are considered to be relevant, non-invasive and affordable tools that can help prevent SARA in the field (Kleen *et al.*, 2003, Castro-Costa *et al.*, 2015). In this context, two studies were carried out to propose relative pH indicators of SARA based on filtered and normalised pH kinetics (NpH). Relative pH indicators for SARA detection were highlighted in a first study where 10 cows underwent a SARA challenge (#1) and specific thresholds were calculated for SARA diagnosis. In a second experiment these thresholds were assessed for validation on 14 other animals undergoing experimentally induced acidosis (#2).

Materials and methods

Experimental design

All cows (113 ± 11 days in milk) from experiment #1 (n=10) and #2 (n=14) were submitted to the same design for SARA induction. All the cows initially received a low-starch diet (LSD) (Table 1) as the control for 4 weeks. The amount of starch was then increased gradually every 2 days, rising to 35% and 36.5% in experiment #1 and #2, respectively, to induce SARA. In order to maintain a long-term SARA challenge, the high starch diet (HSD) was distributed for 4 weeks in #1 and for 2 weeks in #2. Finally, cows resumed their initial control diet (LSD) for 3 weeks without transition. During both experiments, diets were distributed as follow: ¾ of the diet at 9:00 am and ¼ at 4:00 pm for experiment #1 and 2:00 pm for #2, respectively. Both experiments were submitted to local ethical guidance and received ethical approval (CE#C2E2A-02 and APAFIS#366).

Table 1: Ingredients and composition of experimental diets

	Low starch diet		High starch diet	
Experiments	#1	#2	#1	#2
Concentrate : forage ratio	32 : 68	25 : 75	54 : 46	46 : 54
Ingredients (% of DM)				
Hay	7.0	19.0	1.8	14.0
Wrapped hay	0	56.0	0	40.0
Corn silage	20.0	0	29.7	0
Grass silage	41.0	0	14.7	0
Wheat and barley mix	10.6	25	41.5	46
Concentrate for production	21.4	25.0	12.3	0
Chemical composition (% of				
OM[1]	91.0	93.3	95.0	94.7
NDF[2]	39.9	52.1	30.0	39.4
ADF[3]	21.0	30.4	17.0	21.6
Starch	13.0	10.5	35.0	36.5
Rumen digestible starch	10.3	7.5	30.0	31.5
Crude protein	16.0	17.4	15.5	14.2

[1]OM = Organic matter, [2]NDF = Neutral detergent fibre, [3]ADF = Acid detergent fibre

All cows from both experiments were fitted with a reticulo-rumen Farm Bolus sensor which continuously monitored rumen pH (eCow, Exeter, UK). The sensor was calibrated according to the manufacturer's recommendations before use. Each sensor was set up to record mean pH over 15 minutes (96 data points per day) with an accuracy of ± 0.1. Data were downloaded every 15 days using the eCow handset (smartphone + antenna) with a dedicated Android application.

Experiment #1: determination of the relative pH indicators for SARA detection

Rumen pH processing and relative pH indicator calculations

All pH data from the 10 dairy cows in experiment #1 were summarised with Excel Software and a Visual Basic for Application program was developed to synchronise and process the raw reticulo-rumen pH kinetics. Each raw sequence of pH measurements was a time series (Xt) which could be modelled by adding a trend and cyclical components of different time constants: Xt = Dt + Ct + Nt; where Dt = offset and long-term drift due respectively to initial calibration (±0.05 pH unit), measurement accuracy over time (± 0.1 pH unit/30 days) and cow initial pH value, Ct = daily variation impacted by meal delivery frequency and diet composition, and Nt = high-frequency noise due to a matrix effect (rumen) and environmental conditions (temperature, pressure, electrical devices) (Figure 1). A signal processing algorithm was developed in order to isolate the potentially more interesting components (t) from abnormal or random variation (Dt and Nt). To this end a decomposition of the signal was performed using

different combinations of weighted moving averages (WMAs), which were (1) centred to avoid phase shifting, (2) weighted with a Gaussian function to give more importance to the neighbouring points and (3) windowed with a period of time adapted to the time constant of the component of interest. Thus, the noise (Nt) was removed with a WMA of 180 min, producing smoothed kinetics, and the offset and drift were modelled with a WMA of 8 weeks and subtracted from the smoothed kinetics to produce filtered-normalised kinetics. After signal processing, it was possible to calculate relative daily indicators using the filtered and normalised kinetics (NpH). The calculated relative indicators were:

- NpH range = pHmax – pHmin
- NpH standard deviation
- Time NpH< -0.3 pH units (min/d): cumulative time when NpH was below the relative pH threshold of -0.3
- Time NpH< -0.5 pH units (min/d): cumulative time when NpH was below the relative pH threshold of -0.5.

Determination of relative rumen pH thresholds

From experiment #1, a total of 560 daily data was used from the raw kinetics for rumen pH. Data from the individual 28 days of LSD were averaged by week (4 weeks) and classified as non-SARA conditions, and data from the other 28 days when the cows were fed with HSD were also averaged by week (4 weeks) and classified as SARA conditions. Relative pH thresholds of SARA indicators were determined using a receiver-operator characteristics (ROC) curve as calculated by the pROC test with the R version 3.2.3 software. ROC curves are often summarised by the area under the curve (AUC). The AUC can be interpreted as the probability that a diagnostic test or a classifier will rank a randomly chosen positive instance higher than a randomly chosen negative one. If all positive samples are ranked before negative ones, the AUC is 1.0. An AUC of 0.5 is equivalent to randomly classifying subjects as either positive or negative and is no better than tossing a coin.

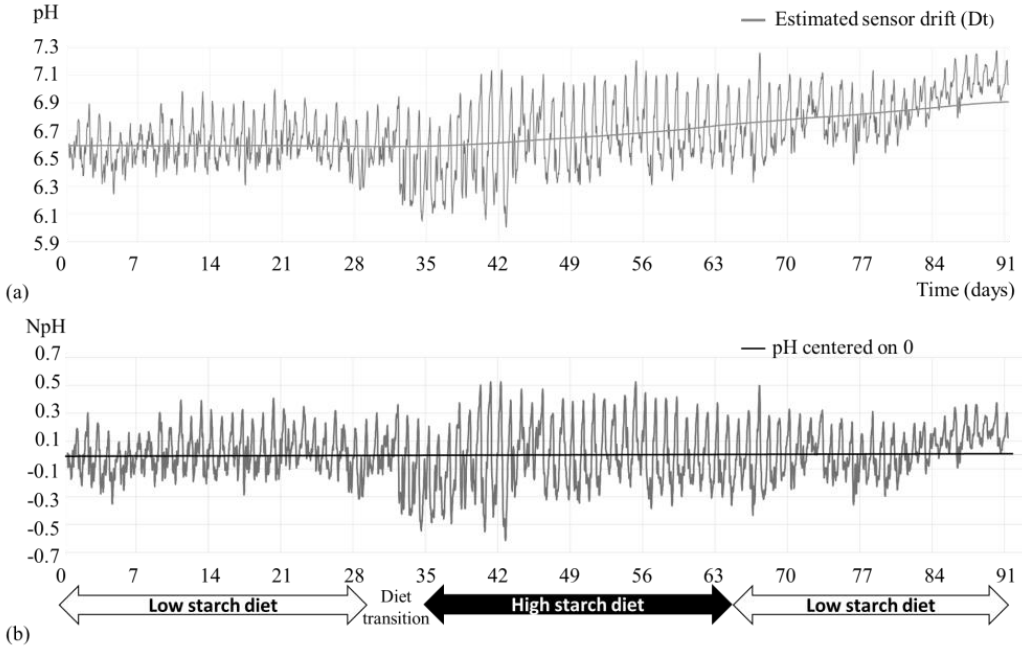


Figure 1: Comparison between (a) raw pH kinetics (Xt) with (b) filtered and normalised NpH kinetics after signal processing.

<u>Experiment #2: validation of the relative pH indicators for SARA detection</u>
This dataset was dedicated to an external validation of the previously calculated relative pH indicators. Collected data from experiment #2 were then processed as for #1 and relative indicators were also calculated based on a total of 658 daily data retrieved from 14 cows. All daily values were used for external validation. A validation matrix was subsequently built using the following items: (i) true positives (correctly predicted SARA with daily indicator values higher than thresholds during SARA challenge), (ii) false positives (incorrectly predicted SARA with daily indicators values higher than thresholds during control periods), (iii) true negatives (correctly predicted no-SARA with daily indicator values lower than thresholds during control periods), and (iv) false negatives (incorrectly predicted no-SARA with daily indicator values lower than thresholds during SARA challenge). In addition, the sensitivity, specificity, positive predictive value and negative predictive value were calculated to evaluate indicators of robustness.

Results and discussion

In a harsh environment like the reticulum where rumen fluid could slowly diffuse into the sensor and poison the reference electrode, drift (Dt) and noise

(Nt) are frequently observed (Kaur *et al.*, 2010). In our experiment #1, both Dt and Nt were detected from all 10 sensors. This long-term drift started at day 30 and lasted until the end of the study. In addition, we observed a large initial between-animal variability in daily average rumen pH (pH ranged from 6.1 to 6.7), with a standard deviation of 0.25 pH units in the first LSD period. Such observations have already been reported (Gasteiner *et al.*, 2009). In addition, absolute rumen pH changes with the SARA syndrome also appear to vary greatly, as reported in several studies (Schwartzkopf-Genswein *et al.*, 2003, Penner *et al.*, 2007). Nevertheless, SARA has historically been characterised by rumen pH depression and measurement of this indicator is still considered as the "gold" standard in diagnosing this nutritional disease (AlZahal *et al.*, 2007). Single-point measurements of rumen pH were most commonly used until the rumen sensor was commercialised, and it has been clearly demonstrated that rumen pH kinetics carry more relevant information on rumen conditions because of the large daily pH variability (Krause *et al.*, 2006). Therefore, monitoring rumen pH in real time is by far the most reliable technique to evaluate the risk of SARA (Penner *et al.*, 2007). Reticulo-rumen sensors provide high-resolution pH kinetics which need to be analysed in a standardised manner in order to obtain accurate and comparable SARA thresholds. We then chose to apply a mathematical correction of the raw pH kinetics taking into account pH drift and noise associated with inter-animal variability in order to establish more consensual SARA NpH indicators. Then, in this article we sort more information from rumen pH kinetics than the commonly used absolute indicators (e.g. mean pH, min and max pH, time spent below pH 6.0) and we focus on how relative pH indicators can help to improve the diagnosis of SARA in dairy cows.

Determination of relative rumen pH thresholds for SARA detection

In experiment #1, when cows were fed HSD, the daily mean values for NpH range and standard deviation were 0.78 ± 0.18 and 0.26 ± 0.06, respectively, whereas during the first control period (LSD) the daily NpH range was 0.46 ± 0.14 and standard deviation 0.14 ± 0.02. Time NpH< -0.3 was significantly greater in HSD than in LSD (218 ± 114 and 23 ± 44 min/day, respectively). The ROC test highlighted that the relative values of 0.80 for daily NpH range (AUC = 0.88), 0.20 for standard deviation (AUC = 0.90), 50 min/day for time NpH< -0.3 (AUC = 0.90) and 5 min/day for time NpH< -0.5 (AUC = 0.78) were the optimum thresholds for SARA detection (Figure 2). According to the ROC AUC classification established by Gardner and Altman (1989), NpH range, NpH standard deviation and time NpH< -0.3 were classed as excellent (0.81 to 0.90) for diagnosing SARA syndrome in our experiment whereas time NpH< -0.5 was classed as good. The increase in range and standard deviation of ruminal daily NpH when a high fermentable carbohydrate diet is distributed indicates that the

animals have difficulty in buffering their ruminal contents (Gasteiner *et al.*, 2009). Moreover, the ruminal microbiota is more sensitive to strong daily pH changes than to a low but stable pH (Moya *et al.*, 2014). This instability of the ecosystem can then alter the digestive health of animals, leading to an increase in other subsequent pathologies and decreasing production (Martin *et al.*, 2006). Thus, in our view, NpH range and standard deviation, and time NpH< -0.3 may be good indicators of rumen instability during chronic SARA.

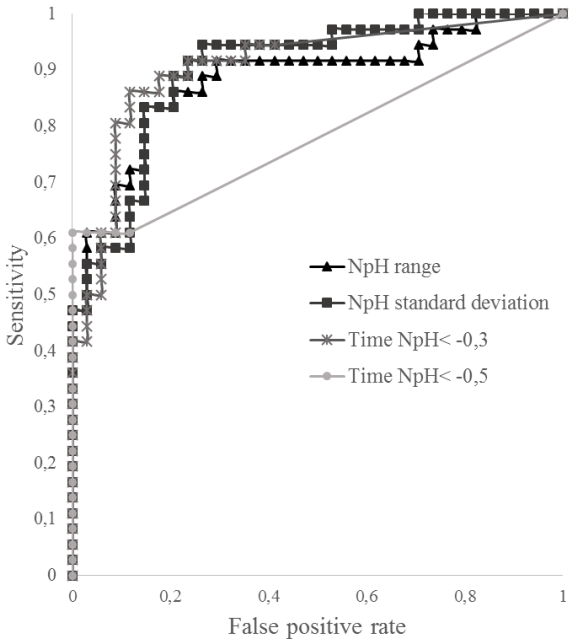


Figure 2: Receiver-operator characteristics (ROC) curves of NpH range, NpH standard deviation, time NpH< -0.3 and time NpH< -0.5 indicators predicting SARA or non-SARA situation in experiment #1 (n=10). The curves show the sensitivity (y-axis) and false positive rate at different thresholds values (x-axis) of NpH indicators for SARA detection.

Assessment of rumen relative pH SARA thresholds

Experiment #2 produced a dataset that we dedicated to external validation of the previously calculated relative indicators and their respective thresholds (Table 2). A total of 208 data during LSD (no-SARA) and 145 data during HSD (SARA) were used. According to the relative indicator values, good classification was observed when cows fed with HSD had individual daily indicators greater than or equal to the established thresholds and when cows fed with LSD had values below the thresholds. Previously calculated thresholds of 5 and 50 min/d for time NpH< -0.5 and -0.3 had a sensitivity of 41 and 72%, respectively, in the

prediction of SARA challenge in experiment #2. It appears that those indicators do not provide good SARA prediction since more than 50% (time NpH< -0.5) and 30% (time NpH< -0.3) of daily values measured during HSD were below 5 and 50 min/day, respectively. The predictive capacity of the time NpH< -0.5 indicator is consistent with the fact that the diagnostic result (ROC test in experiment #1) was only classified as good. The decrease in rumen pH during SARA is generally intermittent and can explain the low sensitivity of those indicators (Enemark *et al.*, 2002). Consequently, those indicators may not be appropriate for SARA detection when calculated and evaluated daily. Thus the evaluation should be carried out at the week scale to make it possible to conclude whether or not those indicators could detect a SARA condition. The NpH standard deviation threshold of 0.20 achieved a specificity of 95% and a sensitivity of 77%. This indicator gives good confidence for the classification of cows with no-SARA (daily values below 0.20 during LSD) whereas some values were lower than the threshold during HSD, indicating that several days in SARA conditions (20%) were missed. The threshold of 0.80 for NpH range achieved a specificity of 94% and sensitivity of 83%; this indicator was able to predict SARA and no-SARA conditions well, with only 10% false negatives. The benefits of using the AUC of ROC tests to classify SARA indicators was explained well by Colman *et al.* (2015). Nevertheless no study has highlighted the diagnostic capacity of absolute rumen pH thresholds used to characterise SARA. Therefore, we cannot discuss the diagnostic capacities of relative rumen NpH indicators on the basis of the existing literature.

Table 2: Results of rumen NpH threshold validation for SARA detection, based on 353 (208 during no-SARA and 145 during SARA conditions) daily data recorded continuously on 24 cows.

pH indicators	Time NpH < -0.3	Time NpH < -0.5	NpH range	NpH standard deviation
Selected thresholds	55 min/d	5 min/d	0.80 pH	0.20 pH unit
True negative (TN)	159	206	206	172
True positive (TP)	105	60	91	132
False negative (FN)	40	85	54	13
False positive (FP)	49	2	2	36
Sensitivity (%)	72	41	63	91
Specificity (%)	76	99	98	83
Positive predictive value (%)	68	97	97	79
Negative predictive value (%)	80	71	79	93

NpH = filtered and normalised pH, sensitivity = TP/(TP+FN) x 100, specificity = TN/(TN+FP) x 100, positive predictive value = TP/(TP+FP) x100, negative predictive value = TN/(TN+FN) x 100.

Conclusion

This validation study showed that new relative pH indicators can improve SARA diagnosis since some of them present both high sensitivity and high specificity. A threshold of 0.80 for the daily NpH range seems to be the most effective since it is able to distinguish a randomly chosen positive instance from a randomly chosen negative instance (ROC test results). The accuracy of time spent at NpH< -0.3 and NpH< -0.5, when evaluated daily, is not good enough to predict SARA. Those indicators need to be evaluated at the week scale since SARA usually occurs as repeated bouts over a long period of time.
The large daily variability of rumen pH and the instability of rumen conditions during SARA suggest that this parameter should be monitored continuously in order to produce high-resolution kinetics. Good interpretation of pH kinetics requires specific signal processing to highlight interesting indicators. In the near future, the proposed method could be implemented in some precision livestock farming devices (rumen boluses) to improve the detection of digestive disorders in cows at herd level.

References

AlZahal O, Kebreab E, France J and McBride BW 2007. A mathematical approach to predicting biological values from ruminal pH measurements. *Journal of Dairy Science* **90**, 3777-3785.

Castro-Costa A, Salama AAK, Moll X, Aguiló J and Caja G 2015. Using wireless rumen sensors for evaluating the effects of diet and ambient temperature in nonlactating dairy goats. *Journal of Dairy Science* **98**, 4646-4658.

Colman E, Waegeman W, De Baets B and Fievez V 2015. Prediction of subacute ruminal acidosis based on milk fatty acids: A comparison of linear discriminant and support vector machine approaches for model development. *Computers and Electronics in Agriculture* **111**, 179-185.

Duffield T, Plaizier JC, Fairfield A, Bagg R, Vessie G, Dick P, Wilson J, Aramini J and McBride B 2004. Comparison of techniques for measurement of rumen pH in lactating dairy cows. *Journal of Dairy Science* **87**, 59-66.

Enemark JMD, Jorgensen R and Enemark PS 2002. Rumen acidosis with special emphasis on diagnostic aspects of subclinical rumen acidosis: a review. *Veterinarija ir zootechnika* **20**, 16-29.

Gardner M and Altman D 1989. Calculating confidence intervals for proportions and their differences. Statistics with confidence. London: *British Medical Journal Publishing Group*, 28-33.

Gasteiner J, Fallast M, Rosenkranz S, Häusler J, Schneider K and Guggenberger T 2009. Measuring rumen pH and temperature by an indwelling and wireless data transmitting unit and application under different feeding conditions. In *Proceedings Fourth European Conference Precision Livestock Farming* 09, Wageningen, the Netherlands, pp. 127-133.

Kaur R, Garcia S, Horadagoda A and Fulkerson W 2010. Evaluation of rumen probe for continuous monitoring of rumen pH, temperature and pressure. *Animal Production Science* **50**, 98-104.

Kleen JL, Hooijer GA, Rehage J and Noordhuizen JPTM 2003. Subacute ruminal acidosis (SARA): a review. Journal of Veterinary Medicine Series A 50, 406-414.

Krause KM, Garrett R and Oetzel GR 2006. Understanding and preventing subacute ruminal acidosis in dairy herds: A review. *Animal Feed Science and Technology* **126**, 215-236.

Martin C, Brossard L and Doreau M 2006. Mécanismes d'apparition de l'acidose latente et conséquences physiopathologiques et zootechniques. *INRA Productions Animales* **19**, 93-108.

Moya D, Holtshausen L, Marti S, Gibb D, McAllister T, Beauchemin K and Schwartzkopf-Genswein K 2014. Feeding behavior and ruminal pH of corn silage, barley grain, and corn dried distillers' grain offered in a total mixed ration or in a free-choice diet to beef cattle. *Journal of Animal Science* **92**, 3526-3536.

Penner G, Beauchemin K and Mutsvangwa T 2007. Severity of ruminal acidosis in primiparous Holstein cows during the periparturient period. *Journal of Dairy Science* **90**, 365-375.

Sauvant D, Meschy F and Mertens D 1999. Les composantes de l'acidose ruminale et les effets acidogènes des rations. *INRA Productions Animales* **12,** 49-60.

Schwartzkopf-Genswein K, Beauchemin K, Gibb D, Crews Jr D, Hickman D, Streeter M and McAllister T 2003. Effect of bunk management on feeding behavior, ruminal acidosis and performance of feedlot cattle: A review. *Journal of Animal Science* **81**, 149-158.

Stefańska B, Nowak W, Komisarek J, Taciak M, Barszcz M and Skomiał J 2016. Prevalence and consequence of subacute ruminal acidosis in Polish dairy herds. *Journal of Animal Physiology and Animal Nutrition*.

Optimising calf rearing and weaning by monitoring the real-time development of rumination

S. Butler, P. Thomson, S. Lomax, C. Clark
Dairy Science Group, School of Life and Environmental Sciences, Faculty of Science, The University of Sydney
cameron.clark@sydney.edu.au

Abstract

Optimising calf rearing and weaning by monitoring real-time sensor-derived rumination development presents an opportunity to substantially improve animal health and productivity whilst reducing on-farm costs. Here we show the potential to monitor calf rumination using existing algorithms and for the first time, the detailed development of rumination and its variability between individuals. Observed and sensor derived rumination levels were associated ($P < 0.001$) with rumination commencing at approximately 14 days of age. However, a high level of variation was found between individual calves in both observed and sensor derived rumination levels and the development of rumination. Whilst differences in rumination development between calves may, in part, be associated with sensor performance, our work shows the potential to use remotely monitored rumination levels to customise feeding and health at an individual level to optimise the weaning process.

Keywords: validation, rumination, sensor, dairy, calf, weaning

Introduction

The Australian Dairy Industry is evolving from smaller family owned and managed farms into large scale more intensified systems (Torsein et al., 2014). The move to larger farms means that optimising the performance of the individual animal, while maintaining animal welfare is becoming increasingly difficult. In order to maintain or improve levels of productivity from these systems, our focus needs to shift rapidly from the herd to optimising individual animal processes through technology assisted management.

Calves form the basis of any successful cattle production system, with calf health and development vital for ongoing animal performance and farm profit (Gulliksen, et al., 2009). However, it is this rearing stage of a dairy animal's life, and in particular the initial month which requires the most significant investment, including veterinary and feeding expenses and higher mortality risk (Ortiz-Pelaez et al., 2008). With efficiency a key driving factor in the success of

any dairy enterprise, finding the equilibrium compromise point between financial outlay while maintaining optimum calf growth and development is crucial.
With ruminants, it is widely accepted that rumination impacts feed utilisation and intake, which are associated with weight gain, health and all round welfare of the animal (Burfeind et al., 2011; Ambriz-Vilchis et al., 2015). Furthermore, the development of the rumen in calves is directly associated with weight gain and overall physical development; therefore developing an accurate and easily measured system for monitoring rumen development provides the potential for optimising rearing and weaning times (Roth et al., 2009). A substantial decrease in feed costs and animal health inputs to the weaning stage is possible with closer monitoring of rumination on an individual basis, however, using visual observations to monitor rumination is both impractical, difficult and costly. Multiple studies have described the potential of sensor-based rumination and activity monitoring to be used as an indicator of animal welfare and health including the early detection of subclinical disease (Clark et al., 2015, Talukder et al., 2015). However, there is a gap in knowledge regarding the use of sensors to remotely monitor the progress of calf rumination development and its variability between animals.
The objectives of this study were to (1) validate a collar-based sensor system for monitoring calf rumination (2) determine the variability in rumination development between calves.

Material and methods

The use of animals was approved by the Animal Ethics Committee of the University of Sydney (N00/5-2013/3/5998). Two experiments were conducted at the University of Sydney's Corstorphine dairy research farm, Camden from 12th May to 9th July 2016. All calves were fitted with SCR heat and rumination (HR) long distance (LD) Tags on collars (Hi Tag, SCR Engineers Ltd., Netanya, Israel). These collars consisted of a tri-axial accelerometer. Collars were placed on calves with a sensor and counterweight (total weight of 707g) to ensure that the sensor maintained its position at 5 to10 cm behind the left ear. Rumination duration data were stored in 20 minute intervals, which were downloaded to a farm computer and collated.
In Experiment 1, 6 calves (aged 3 months ± 7 days) were grouped housed in open pens 42m x17m with a small shelter, fresh water and feed offered ad libitum (see Table 1). Individual animal rumination duration was recorded by continuous visual observation and with the sensor system between 0800h and 1100h for 10 days. The same observer performed all observations, with the observer positioned outside the pen. The onset of rumination was defined as the

time when regurgitation took place, specifically when a bolus came up the esophagus and reached the mouth and ending when the bolus was swallowed.
In Experiment 2, another 6 calves were fitted with the same sensors to determine rumination development in calves from 12th May 2016 to 9th July 2016 ensuring 40 days of data collection for each calf. Calves were situated in pens as per Experiment 1 and offered the same feed.

Table 1. Lucerne hay and grain-based concentrate nutritive value

	CP (g/kg)	NDF (g/kg)	ADF (g/kg)	DMOD (g/kg)	ME (MJ/kg DM)
Lucerne hay	154	207	90	733	11.0
Grain-based pellets	222	329	260	687	10.3

The association between rumination duration (minutes) summed for the 3 hour periods collected via direct observation (independent variable) and sensor derived rumination was determined using a linear mixed model fitted using a restricted maximum likelihood (REML) procedure in Genstat for Windows version 14 (VSN International Ltd, Hemel Hempstead, Hertfordshire,UK) with the individual calf as a random effect. Rumination development data was collated using Microsoft Excel into daily totals for each calf and presented using a rolling 7-day average.

Results and Discussion

In experiment 1, there was a highly significant ($P < 0.001$) association between observed and predicted (sensor derived) calf rumination duration. However, this association was variable for individual animals (Figures 1a-f) with poor associations typically due to an under prediction of observed rumination levels. Previous work (Burfield et al., 2011) has shown similar inconsistencies and they hypothesise that the frequency of rumination sounds and movements may be different in calves compared to cows, reducing the accuracy of sensor systems. Thus, further work is required to determine the differences in the rumination process between calves as a first step towards increasing the accuracy of sensor derived rumination for all calves.
In experiment 2, rumination had commenced for all calves by 14 days after birth (Figure 2). In line with these findings, the previously accepted consensus across published literature is that rumination starts at 2 weeks of age if animals are not on sole milk diet, with rumination times increasing until leveling out to 5 hours per day at between 5 to 6 weeks of age (Roth et al., 2009, Fericean et al., 2010). However, in our study there was variability between animals in this timing with some calves ruminating 7 days after birth. Further, by 40 days after birth

rumination levels between calves ranged between 39 to 300 minutes per day (Figure 2). Our findings highlight the need for further research to elucidate the differences in rumination between calves and the potential to customise feeding management to align with calf need.

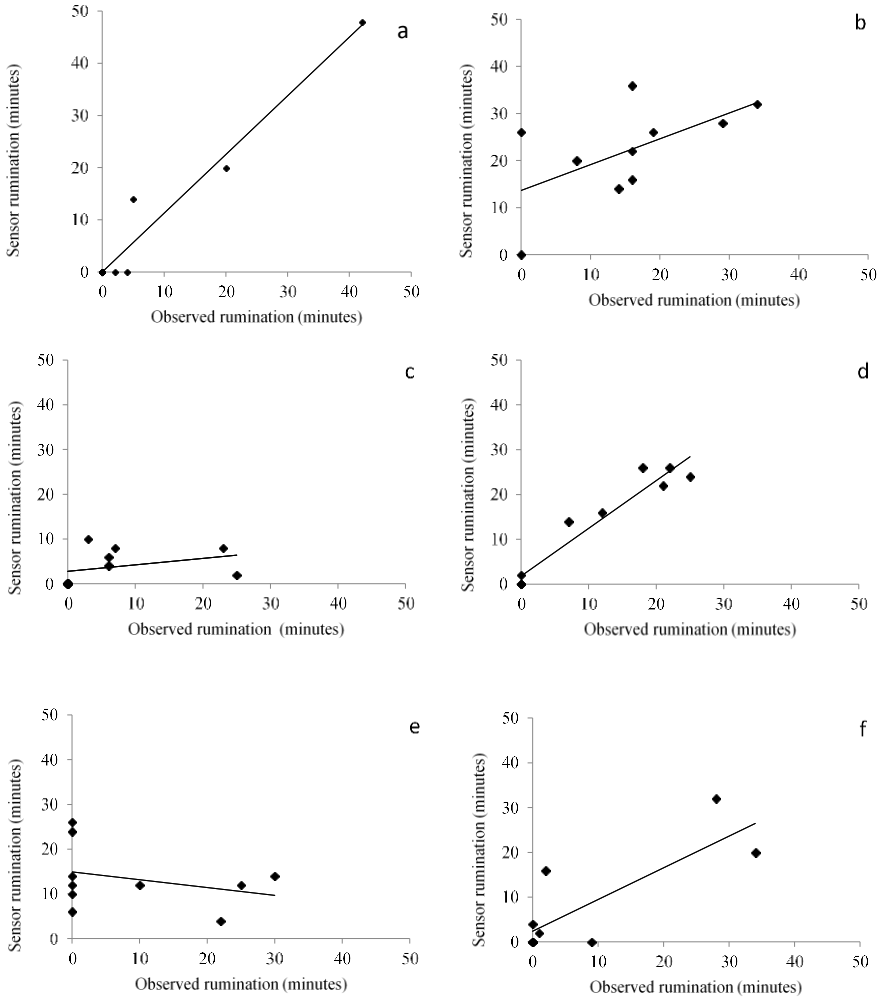


Figure 1a-f: The association between observed and predicted (sensor derived) rumination duration (minutes) for (a) calf 1; $y = 1.13x - 0.02$; $R^2 = 0.95$ (b) calf 2; $y = 0.55x + 13.7$; $R^2 = 0.34$ (c) calf 3; $y = 0.14x + 2.8$; $R^2 = 0.12$ (d) calf 4. ($y = 1.06x + 1.8$, $R^2 = 0.93$ (e) calf 5; $y = -0.18x + 14.9$, $R^2 = 0.10$ and (f) calf 6. $y = 0.70x + 2.4$ $R^2 = 0.65$

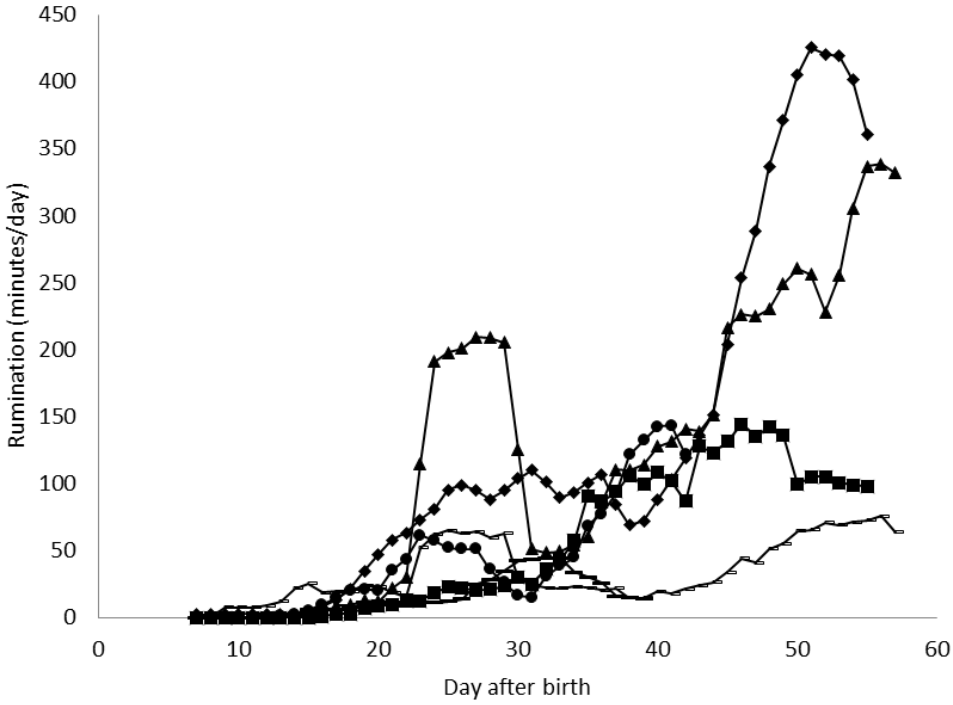


Figure 2. Rumination duration (minutes/day) profiles for the 6 calves after birth

Conclusions

New technology is providing key insights into the development of rumination in dairy calves. Further work is required to determine the differences in the rumination process between calves as a first step towards increasing the accuracy of sensor derived rumination for all calves. Our findings also highlight the need for further research to elucidate the differences in rumination development between calves and the associated opportunity to customise feeding management at an individual calf level to align with calf need.

Acknowledgements

The authors gratefully acknowledge the help of the University of Sydney Corstorphine farm staff for helping conduct this research, in particular Kim McKean.

References

Ambriz-Vilchis, V., Jessop, N., Fawcett, R., Shaw, D. and Macrae, A. 2015. Comparison of rumination activity measured using rumination collars against direct visual observations and analysis of video recordings of dairy cows in commercial farm environments. *Journal of Dairy Science*, **98**(3) 1750-1758.

Burfeind, O., Schirmann, K., Von Keyserlingk, M., Veira, D., Weary, D. and Heuwieser, W. 2011. Technical Note: Evaluation of a system for monitoring rumination in heifers And Calves. *Journal of Dairy Science* **94**(1) 426-430.

Clark, C., Lyons, N., Millapan, L., Talukder, S., Cronin, G., Kerrisk, K. and Garcia S. 2015. Rumination and activity levels as predictors of calving for dairy cows. *Animal* **9**(4) 1-5.

Fericean, M., Palicica, R. and Rada, O. 2010. The Behaviour of Calves. *Journal of Agricultural Science* **42**(2) 248-254.

Gulliksen, S., Lie, K. and Østerås, O. 2009. Calf health monitoring in Norwegian dairy herds. *Journal of Dairy Science* **92**(4) 1660-1669.

Ortiz-Pelaez, A., Pritchard, D., Pfieiffer, D. and Mawdsley, J. 2008. Calf mortality as a welfare indicator on British cattle farms. *The Veterinary Journal* **176**(2) 177-181.

Roth, B., Keil, N., Gygax, L. and Hillmann, E. 2009. Influence of weaning method on health status and rumen development in dairy calves. *Journal of Dairy Science*, **92**(2) 645-656.

Talukder S., Thomson P., Kerrisk K., Clark C. and Celi P. 2015. Evaluation of infrared thermography (IRT) body temperature and collar mounted accelerometer and acoustic technology for predicting time of ovulation of cows in a pasture-based system. *Theriogenology* **83** 739-748.

Torsein, M., Jansson-Mörk, M., Lindberg, A., Hallén-Sandgren, C. and Berg, C. 2014. Associations between calf mortality during days 1 to 90 and herd-level cow and production variables in large Swedish dairy herds. *Journal of Dairy Science* **97**(10) 6613-6621.

Session 4

Sound and Image for chickens/pigs

Online detection of piglet crushing using vocalisation analysis and context information

C.Manteuffel[1], E. Hartung[2], M. Schmidt[3], G. Hoffmann[3], P. C. Schön[1]
[1]Leibniz Institute for Farm Animal Biology, Institute of Behavioural Physiology, Wilhelm-Stahl-Allee 2, 18196 Dummerstorf, Germany
[2]Christian-Albrechts-University Kiel, Institute of Agricultural Engineering, Max-Eyth-Str. 6, 24118 Kiel, Germany
[3]Institute for Agricultural Engineering and Bioeconomy, Department of Engineering for Livestock Management, Max-Eyth-Allee 100, 14469 Potsdam, Germany
christian.manteuffel@fbn-dummerstorf.de

Abstract

Fatal piglet crushing is a pervasive ethical and economic issue. Changing the own body posture to free trapped piglets is part of the natural behaviour repertoire of sows. However, up to 40% of the sows did not show this behaviour in replay studies using piglet dummies and pre-recorded screams. Actively stimulating posture changes in non-reacting sows using aversive stimulations might decrease the risk of lethal crushing. The present study investigated whether the detection of stress articulation through vocalisation analysis would be sufficient to identify trapped piglets. It also investigated the effectiveness of different context filters to improve the detection performance. For this purpose 20 sows were monitored with directional microphones, light barriers for posture detection and event controlled video recordings. The results show, that trapping related stress articulations were outnumbered by other stress articulations of piglets by a factor of 1:140 in a farrowing compartment with 4 sows per trial run. Most stress articulation was detected in the context of nursing in the monitored and neighbouring pens. By filtering the articulation with respect to the current posture of the sow, the age of its piglets and the duration since the last posture change, the ratio between trapping and other stress events could be reduced to 1:3. Hence, vocalisation analysis alone would be insufficient to safely trigger posture changes, but could be feasible in combination with context filters. Compared to pens with farrowing cage, timed aversive stimulations would limit the impairment of welfare to only those individuals that crush piglets and to the time of crushing events.

Keywords: online vocalisation analysis, piglet crushing detection, active crushing prevention, context filters

Introduction

Fatal piglet crushing is a pervasive issue concerning animal welfare and economy (Weber et al., 2006). One commonly used counter measure is equipping farrowing pens with farrowing cages. However, this installation compromises the welfare of the sow for the benefit of her piglets and the farmer (Broom et al., 1995). Under natural conditions, the mother sow would free trapped piglets by changing her body posture. Such timely posture changes are suited to save the piglet despite the huge weight difference between piglet and sow. Weary et al. (1996) observed a survival rate of about 95% for piglets which were trapped for less than 60 seconds. However, these posture changes are not demonstrated by all individuals in domesticated sows (Hutson et al., 1991). To induce posture changes in these sows using aversive stimulations could constitute an alternative to the farrowing cage.

In practice, experienced personnel is often able to identify trapped piglets acoustically from their stress articulation. Sows not reacting at these screams would then be forced up manually. Studies found that such a continuous piglet watch really reduces piglet mortality, yet also involves a high workload (Kirkden et al., 2013). Precision livestock farming methods could help to reduce this workload. The current study addresses the aspect of detecting trapped piglets automatically in real-time. Earlier studies investigated stimulations for promoting posture changes in sows (Hutson et al., 1993; Manteuffel et al., 2014). This article is a shortened version of Manteuffel et al. (2017) which also addresses the localisation issue.

Material and methods

Animals and husbandry conditions

For a total of 20 sows (Large White × German Landrace) in their 1st to 7th parity and 271 piglets the behaviour was recorded and analysed until the 14th day post natum. Per trial run 4 sows were kept in a research compartment of a commercial breeding facility. The compartment was aired using the trickle ventilation system. The sows were housed in farrowing pens of 2.6 m x 1.84 m size. The crates had a length of up to 2.0 m and a width of about 0.75 m. One side of the crate was equipped with a liquid feeding system and a nipple drinker. The other side could be angled to ease the entering by the sows. The piglets were provided with open heated creep areas and heat lamps.

Audio and video recordings

Each pen was equipped with a directional microphone (NTG-2, RØDE, Australia) oriented at the centre of the pen. Vocalisation audio data were

analysed for stress articulation using the software STREMODO (Schön et al., 2004). At the detection of stress articulation, automated video recordings documenting the behaviour of the sow and her piglets were created for a time range 2 min prior and after the event. The precise cause of the 2098 detected stress articulations was identified retrospectively by manual labelling. For this purpose the nomenclature given in Table 1 was utilised. Time and duration of the events were registered relative to the start of the corresponding video in a database. In addition, the pens were continuously monitored by dome cameras without sound (WV-CW364S, Panasonic, Japan). These dome cameras were utilised to independently confirm crushed piglets and to identify the exact onset of parturition with the expulsion of the first piglet.

The event triggered video recording was disabled at the day of parturition because it was combined with a system using floor vibration as aversive stimulation principle to prevent piglet crushing. The deactivation was done out of respect for the commercial breeding facility, as the error rate of the system was initially unknown. Frequent aversive stimulations could have prolonged the farrowing and hindered colostrum uptake due to frequent posture changes.

Table 1. Nomenclature used for classifying detected stress events.

label	definition
pen	noise from interaction with pen interior such as the farrowing cage
p2p	vocalisation from social piglet interaction
p2s	vocalisation from social piglet / sow interaction
feeding	noise from the liquid feeding system
tread	vocalisation from a piglet that’s being trod
manage.	vocalisation during management procedures (e.g., injections and markings)
neighbour	noise from neighbouring pens
personnel	noise produced by the personnel such as conversation
sow	vocalisation by the sow
nursing	any piglet vocalisation during nursing
drinker	noise from the nipple drinker mechanic and water flow
unclear	noise of unclear origin
trapped	vocalisation by a trapped piglet that survived
crushed	vocalisation by a trapped piglet crushed to death
ref.	reference vocalisations for assumed crushing events on day 0

Context data

The body posture of the sows was detected using light barriers at the head, torso and hind region and recorded to a database. The synchronisation of video and posture data of the different pens was performed with the network time protocol (NTP). For the analysis, all data were in addition put into relation to the age of the piglets. As reference for the age served the parturition start, which was determined for each sow individually. Based on this context information, different filters were defined that eliminated certain stress events as crushing events, if predefined parameters exceeded or went below particular threshold values. One of the evaluated parameters was "duration of vocalisation" in seconds with the threshold values (1.5 s, 5 s, 10 s), which is encoded in Table 2 as *durX*. Other parameters were "sow is lying", encoded as *lying* with the logical threshold (yes), "sow moved within a time range before the event" in seconds, encoded as *mX* with the threshold values (15 s / 30 s) and "event occurred before the 4th day post natum" encoded as *3d* with the logical threshold (yes).

Analysis

The analysis focused on determining the relation between actual crushing situations and other stress articulations as well as on the evaluation of the effects of different context filter combinations on the classification performance. The classification performance of a crushing detection based on vocalisation analysis alone could not be determined exactly due to the methodical limitations imposed by the commercial breeding facility described in section *Audio and video recordings*. To at least estimate the effect of the context filters on the detection of crushing related vocalisation, the data for day 0 was amended with reference crushing data recorded at previous trials (Tab. 1 – ref). This data was recorded at a different facility with a similar compartment configuration, using 22 sows and 265 piglets and the same technical setup. No fatal crushing event was missed by the vocalisation analysis for the reference data as well as for the present study. Fatal crushing events without a registered vocalisation of the piglet were not observed.

To estimate the classification performance, confirmed events involving trapped or fatally crushed piglets were counted as true positive classifications. If context filters excluded such events, they were counted as false negative classification. Events not related to potential crushing situations that were not excluded by the filters were counted as false positive classification. The remaining non-crushing events were taken as true negative. The analysis was performed using R 3.0.2 (R Core Team, 2013).

Results and Discussion

The number of other stress detections exceeded the estimated number of crushing related events by far. Relying on the stress detection system STREMODO alone would have led to a detection precision of 0.7% (Tab. 2 – unfiltered). Considering only sows that recently changed their posture to lying slightly improves the precision up to 18% (Tab. 2 – lying/m15). Ignoring short vocalisation events improves the precision up to 20% but also reduces sensitivity to 33% (Tab. 2 – lying/m30/dur10) . Combinations of filters rejecting events from piglets older than 3 days and filters for movement context achieved a precision of about 30% while reducing the sensitivity to 60-70% (Tab. 2 – lying/m30/3d). This precision corresponds to roughly one erroneous crushing detection per lactation period and sow. However, the detected events were not evenly distributed among the sows. For the actually affected sows, on average 2 erroneous detections per lactation period would have occurred. The maximal value was 7 errors for one sow. This value could be reduced, if the system would be deactivated during treatments of the piglets.

Table 2. Classification performance for a crushing detection with different context filters. Investigated filters were *lying*, *3d* (within the first 3 days after farrowing), *m X* (within X seconds after lying down) and *dur Y* (events longer than Y seconds) and combinations thereof. Correct detections were shaded in grey and subsumed as *correct*. Errorneous detections were subsumed as *errors* and stated as errors per sow (*error/sow*). The estimated classification performance was specified by precision (*prec.*), sensitivity (*sens.*) and specificity (*spec.*) (n=20 sows, 271 piglets), *estimated values

video content	un-filtered	lying	lying /3d	lying /m30	lying/ m15	lying /m30 /dur1.5	lying /m30 /dur5	lying /m30 /dur10	lying /m30 /3d	lying /m15 /3d
pen	26	11	9	1	1	1			1	1
p2p	205	123	43	14	5	13	9	3	2	2
p2s	16	7	2							
feeding	25	2								
tread	9	7	3							
manage.	61	28	15	8	7	8	7	4	5	4
neighbour	521	416	105	19	9	17	11	5	6	5
personnel	4	3	1							
sow	7	7	3							
nursing	1038	893	314	26	12	26	15	6	13	7
drinker	2	2	1							
unclear	179	125	38	7	6	4	3	2		
trapped	4	3	2							

crushed	1	1	1	1		1	1	1	1	
ref*	10	10	10	10	9	10	8	4	10	9
errors	2093	1624	534	75	40	69	45	20	27	19
correct*	15	14	13	11	9	11	9	5	11	9
error/sow	104	81	26.7	3.75	2.0	3.45	2.25	1.0	1.35	0.95
prec. (%)*	0.7	0.9	2.4	12.8	18.4	13.8	16.7	20.0	28.9	32.1
sens. (%)*	n. a.	93.3	86.7	73.3	60.0	73.3	60.0	33.3	73.3	60.0
spec. (%)*	n. a.	22.4	74.5	96.4	98.1	96.7	97.9	99.0	98.7	99.1

The validity of the presented results is limited because the frequency of stress events was not validated with a second independent method and because the day of parturition was not observed. None the less, the results show that STREMODO is in its current state not suited to differentiate between crushing related and other stress articulation of piglets. However, in combination with context filters, the classification performance could be improved to a precision of about 30% (Tab. 2). Given this precision, a system for active crushing prevention would produce on average one erroneous detection per lactation. This makes a fast habituation to aversive stimulation mechanisms for posture change induction improbable. In its simplest configuration, such a system requires only one microphone and individual movement sensors. The movement sensor could not only monitor the body posture of the sows. It could also allow the automatic detection of the parturition start and thereby automatically determine the piglet age and autonomously activate the crushing prevention system (Manteuffel et al., 2015).

Conclusions

The presented approach could allow to replace farrowing in a cage with a timed stimulation system, limiting the impairment of welfare to only those individuals that crush piglets and to the time of crushing events. The detection precision could be improved by a analysis tool that is more specific to crushing related vocalisation. To what extend trapped piglets are able to free themselves after induced posture changes and afterwards survive until weaning needs to be investigated in further studies.

Acknowledgements

This study was supported by funds of the Federal Ministry of Food and Agriculture (BMEL) based on a decision of the Parliament of the Federal Republic of Germany via the Federal Office for Agriculture and Food (BLE) under the innovation support programme. The Authors would like to thank the staff of the Schweineanlage Wiechmann, Big Dutchman and especially Anne Elkmann for cooperating in this project.

References

Broom, D. M., Mendl, M. T., Zanella, A. J. (1995). A comparison of the welfare of sows in different housing conditions. Animal science, 61(02), 369-385.

Hutson, G.D., Dickenson, L.G., Wilkinson, J.L., Luxford, B.G. (1993). The response of sows to novel visual, olfactory, auditory and tactile stimuli. Applied Animal Behaviour Science, 35 (3), 255–266.

Hutson, G. D., Wilkinson, J. L., Luxford, B. G. (1991). The response of lactating sows to tactile, visual and auditory stimuli associated with a model piglet. Applied Animal Behaviour Science, 32(2), 129-137.

Kirkden, R. D., Broom, D. M., Andersen, I. L. (2013). Invited review: piglet mortality: management solutions. Journal of Animal Science, 91(7), 3361-3389.

Manteuffel, C., Tuchscherer, A., Schmidt, M., Hoffmann, G., Schön, P. C. (2014). Using air-blow and floor vibration to trigger posture changes in gestating and lactating sows. Computers and Electronics in Agriculture, 104, 105-110.

Manteuffel, C., Hartung, E., Schmidt, M., Hoffmann, G., Schön, P. C. (2015). Towards qualitative and quantitative prediction and detection of parturition onset in sows using light barriers. Computers and Electronics in Agriculture, 116, 201-210.

Manteuffel, C., Hartung, E., Schmidt, M., Hoffmann, G., Schön, P. C. (2017). Online detection and localisation of piglet crushing using vocalisation analysis and context data. Computers and Electronics in Agriculture, *135*, 108-114.

R Core Team. (2013). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. http://www.R-project.org/

Schön, P. C., Puppe, B., Manteuffel, G. (2004). Automated recording of stress vocalisations as a tool to document impaired welfare in pigs. Animal Welfare, 13(2), 105-110.

Weary, D. M., Pajor, E. A., Fraser, D., Honkanen, A. M. (1996). Sow body movements that crush piglets: a comparison between two types of farrowing accommodation. Applied Animal Behaviour Science, 49(2), 149-158.

Weber, R., Keil, N. M., Fehr, M., Horat, R. (2006). Ferkelverluste in Abferkelbuchten: ein Vergleich zwischen Abferkelbuchten mit und ohne Kastenstand. (Piglet mortality in farrowing pens: a comparison between farrowing pens with and without farrowing crate.), FAT-Berichte, 656, 1-8.

Frequency Analysis of Vocalisations to Monitor Broiler Chicken Production Performance in Real-Life Farm Conditions

L. Carpentier[1] , T. Norton[1], D. Berckmans[2], I. Fontana[3], M. Guarino[3] , E.Vranken[1,4], and D. Berckmans[1]
[1]*M3-BIORES: Measure, Model & Manage Bio-responses, KU Leuven, Kasteelpark Arenberg 30, 3001 Heverlee, Belgium*
[2]*SoundTalks NV, Kapeldreef 60, 3001 Heverlee, Belgium*
[3]*Department of Health, Animal Science and Food Safety (VESPA), University of Milan, Via Celoria 10, 20133 Milan, Italy*
[4]*Fancom BV, Wilhelminastraat 17, 5981 XW Panningen, The Netherlands*
Daniel.Berckmans@kuleuven.be

Abstract

In today's broiler houses, birds are reared in large groups, with up to 50,000 often together in one house. Supervising all these animals is difficult or even impossible for the farmer. Sensors like microphones can help the farmer by continuously monitoring the productivity of the animals and raising early alarms in the case abnormalities in the house. As regards linking sound to production performance, recent studies indicate that there is an inverse relation between the peak frequency of animal sounds and their weight. This study aims to monitor the frequencies of the vocalisations in a broiler house and compare these to the weight evolution of the chickens. The resulting curves compare different production cycles with the aim to provide the farmer with a tool to compare the performance of the current and previous production cycles. Pre-processing was performed by filtering the data in order to remove the machinery noise. After this the median frequency was extracted from the data. It was found that between day 3 and 25, there was a clear difference in frequency values between a production cycle with heavier birds (lower frequency values) and a production cycle with lighter birds (higher frequency values). Based on these results, there is an indication that the method developed has potential to differentiate between light and heavy flocks in a commercial broiler house. Comparing the different batches using the developed approach can help the farmer to distinguish a good and a bad production cycle early and assist the farmer in adapting his management practice.

Keywords: bioacoustics, spectral analysis, signal processing, precision livestock farming

Introduction

By 2050 the world's population is expected grow 34% to reach 9.1 billion (FAO, 2009). In addition, the income levels will rise resulting in a larger and richer population. An increase in food production is needed to feed this population. Therefore, the annual meat production will need to rise 74% by 2050, 200 million tonnes higher than 2009 (FAO, 2009).

In 2014, a total of 62 billion chickens were slaughtered for consumption in the world (FAOSTAT, 2016). Most of which are broiler chickens which are reared for meat production. Broiler farmers are affected with increasing production costs and lower profit margins due to legislation on the environment, animal health, and animal welfare (Marquer et al. 2015). Resulting in larger farms where broilers are housed with thousands together.

Monitoring all the animals individual and accurate is difficult and time consuming for the farmer. Therefore, monitoring the flock automatic and continues using weighing scales, cameras, and microphones can help the farmer to make management decisions (Cangar et al., 2006; Fontana et al., 2015a, 2015b; Kashiha et al., 2013). As broilers are reared in a short period, slaughter age 5~7 weeks, problems affecting the production performance, health, and welfare should be detected and solved quickly.

The weight evolution of broilers is an important parameter in modern broiler rearing (Aerts et al., 2003; Rizzi et al., 2013). Therefore farmers assess the weight of their broilers either manual or automatic. Manual weighing samples in the flock is labour intensive and time consuming. Broiler weighing scales, "step-on scales", could help to assess the weight continues and automatic.

Recent studies of Fontana et al. (2015a, 2015b) show that the weight of the broilers is inversely related to the frequency of the vocalisations. Sound analysis to monitor bio-responses of animals is not new, examples consist out of cough analysis (Van Hirtum et al., 1999; Exadaktylos et al., 2008; Vandermeulen et al., 2016), and feed intake monitoring of chickens (Aydin et al., 2015, 2016). This study works further on the relation between the weight and the vocalisations in a commercial production environment.

The objective in this study is to analyse the frequencies of broiler vocalisations recorded in a commercial broiler farm. The frequency is compared against the weight evolution in order to identify if deviations in weight between production cycles could be noticed using the sound, hence the sound algorithm has the potential to be used as early warning system.

Materials and Methods

Experimental data

This study was conducted in a commercial broiler rearing farm located in the Netherlands. Sound data was recorded continuous during the entire time span the birds were in the house and this for three different production cycles. Details about the three production cycles can be observed in Table 1. The dimensions of the house measured 96 m by 19 m and the total floor area available was 1235m². The house was equipped with an automatic broiler weighing system which was a commercial available 'step-on-scale' (Fancom®).

Table 1. Details about animals in the house during the production cycles observed in this study

Production cycle	Time period	Animals placed in shed on start date	Genotype	Days in house
1	31/10/2014 – 11/12/2014	*	Ross 308	41
2	30/12/2014 - 12/02/2015	27,800	Ross 308	45
3	19/02/2015 - 02/04/2015	27,635	Ross 308	43

*Information not available

Recordings were made with a commercial available sound recording device (SoundTalks®) especially designed to measure sound continuous in farms. The device was also used in previous studies on sound analysis (Berckmans et al., 2015; Fontana et al., 2015a; Vandermeulen et al., 2016). Sounds were recorded using a condenser microphone (Behringer C4) and a sound card (ESI MAYA 44). The sampling frequency was set at 22.05 kHz and a 16- bit resolution was used. Recordings were stored in chunks of five minutes in Waveform Audio File (WAV) format on external hard drives so the data could be analysed offline. The microphone was mounted 1 m above the ground level.

Signal analysis

The recorded data were processed using a commercial available software package (MATLAB 2014b, The MathWorks Inc., Natick, MA, 2000). The median frequencies for each five minute file recording were determined (Cortopassi, 2006). Median frequency was chosen over peak frequency, which is used in the work of Fontana et al. (2015a, 2015b), because the median frequency

tend to be more robust to noise (Cortopassi, 2006). Robustness to noise is important for the algorithm so it can work in a commercial broiler house.
To calculate the median frequency, the raw sound recording was filtered using a high pass filter (1000 Hz) to remove to lower frequency noise of the ventilation, heaters, and feeder lines. Next the spectrogram was calculated using a window of 256 samples and 50 percent overlap. This spectrogram was used to compute the aggregated spectrum envelope by summing all values over time, resulting in a frequency axis of 129 bins. The median frequency was extracted from the distribution (Cortopassi, 2006).
In addition to the filtering, moments when it was dark in the house were removed from the data set as broilers tend to vocalise little when it is dark. Due to this, the moments would not be representing the median frequency of the vocalisations emitted by the broilers but by the noise (e.g. ventilation, feeding line, heater) in the house.

Results and Discussion

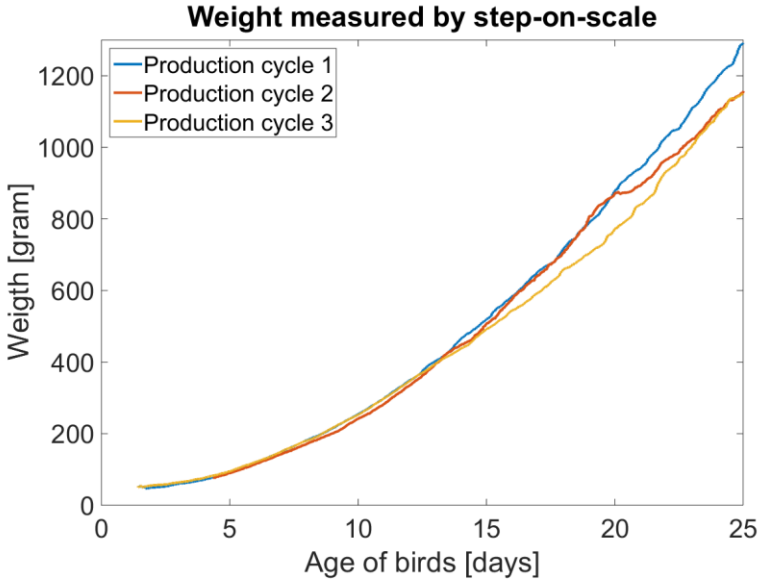


Figure 1: Average weight broiler chickens measured by the ‘step-on-scale’

The weights measured in the broiler house, by the ‘step-on-scale’, for the first 25 days in the production cycle are represented in Figure 1. Looking at the graph it can be noticed that production cycle 3 starts to deviate from production cycle 1 and 2 around day 15. The measured average weight of production cycle 3 is lower than for the other production cycles. A similar deviation between production cycle 1 and 2 can be noticed after 20 days.

Around that date the birds in production cycle 2 tend to grow slower than the birds in production cycle 1.
Figure 2 shows the average median frequency of each day from day 3 till day 25 in the production cycle. The first three days were removed as they tend to contain much environmental noise, hence the signal is depending on the machine noise and not on the animal vocalisations. After day 25 the signal was removed as the frequency of the vocalisations decreases and comes closer to the frequency of the background noise making it difficult to differentiate between the vocalisations and the background. The frequencies observed are in the same order of magnitude as the peak frequencies in the work of Fontana et al. (2015a, 2015b).
In Figure 2 an increase of the median frequency of production cycle 3 can be observed around day 12, 3 days before there was an visual decrease in the weight measured by the automatic weighing scales. A similar reaction can be observed around day 20 for production cycle 2. However, this deviation was also noticeable in Figure 1 around the same day. Hence, the deviation was not detected earlier with the median frequency. This corresponds with the findings in the work of Fontana et al. (2015a, 2015b) that peak frequency and weight or inversely correlated.
In Table 2 the average median frequency and the standard deviation can be observed for day 3 till day 25.

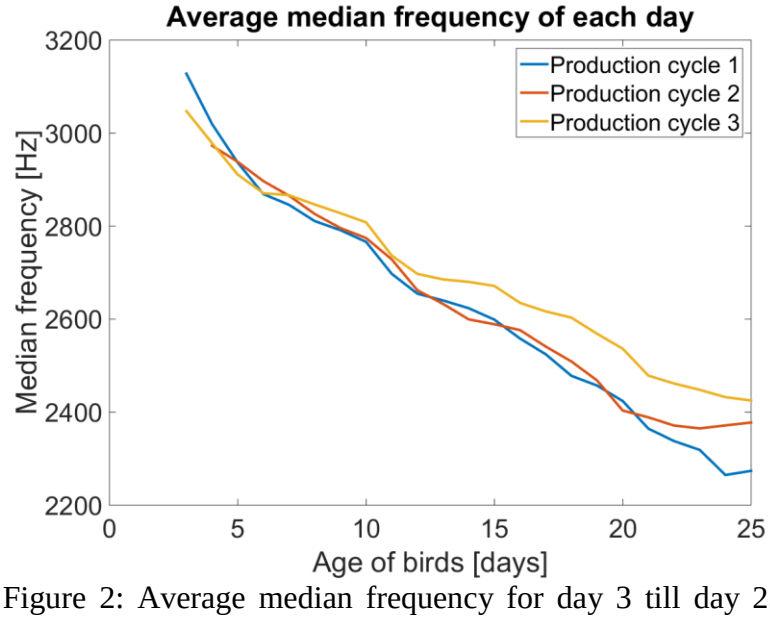


Figure 2: Average median frequency for day 3 till day 25 in each production cycle

Table 2. Average median frequency for day 3 till day 25 in the production cycle

Day	**Production cycle 1** Mean (±standard deviation) Hz	**Production cycle 2** Mean (±standard deviation) Hz	**Production cycle 3** Mean (±standard deviation) Hz
3	3125.9 (± 80.4)	-	3038.0 (± 58.1)
4	3017.1 (± 78.8)	2978.4 (± 65.6)	2978.6 (± 63.3)
5	2938.0 (± 61.0)	2935.8 (± 51.4)	2910.0 (± 47.5)
6	2865.4 (± 53.6)	2896.0 (± 45.1)	2866.7 (± 43.7)
7	2847.8 (± 33.9)	2865.2 (± 41.1)	2866.5 (± 43.7)
8	2806.2 (± 38.1)	2826.1 (± 39.6)	2848.1 (± 29.9)
9	2793.1 (± 37.3)	2796.8 (± 34.0)	2827.2 (± 30.9)
10	2765.8 (± 36.2)	2773.9 (± 28.6)	2807.1 (± 23.8)
11	2692.9 (± 65.3)	2732.3 (± 40.6)	2736.6 (± 47.2)
12	2660.2 (± 38.5)	2657.6 (± 33.5)	2694.3 (± 36.6)
13	2640.3 (± 34.4)	2633.4 (± 36.9)	2688.0 (± 38.6)
14	2621.3 (± 48.2)	2598.0 (± 32.9)	2680.0 (± 30.3)
15	2601.3 (± 60.0)	2590.1 (± 35.8)	2670.5 (± 42.5)
16	2557.2 (± 57.6)	2577.6 (± 40.7)	2636.2 (± 55.7)
17	2528.6 (± 61.8)	2541.9 (± 57.7)	2616.4 (± 44.5)
18	2470.4 (± 76.8)	2506.6 (± 56.2)	2605.3 (± 54.7)
19	2462.5 (± 86.1)	2465.3 (± 56.9)	2566.5 (± 64.8)
20	2422.3 (± 80.2)	2405.7 (± 61.6)	2535.7 (± 45.6)
21	2362.7 (± 94.9)	2388.2 (± 52.4)	2478.1 (± 65.0)
22	2336.7 (± 96.9)	2372.3 (± 61.5)	2461.5 (± 63.1)
23	2324.7 (± 95.7)	2364.3 (± 65.1)	2449.2 (± 72.6)
24	2259.4 (± 96.0)	2372.9 (± 70.1)	2429.2 (± 53.3)
25	2276.7 (± 114.7)	2377.5 (± 66.2)	2426.6 (± 60.6)

In figure 3 the median frequency was plotted against the weight to observe how both variables are related to each other over the different production cycles. Production cycle 3 shows an average median frequency which is slightly higher than that of production cycle 1 and 2. This can be explained as the median frequency can differ due to different conditions in the house e.g. higher ventilation rate, constant heater noise. Further research is needed to evaluate the influence of the seasons on the median frequency.

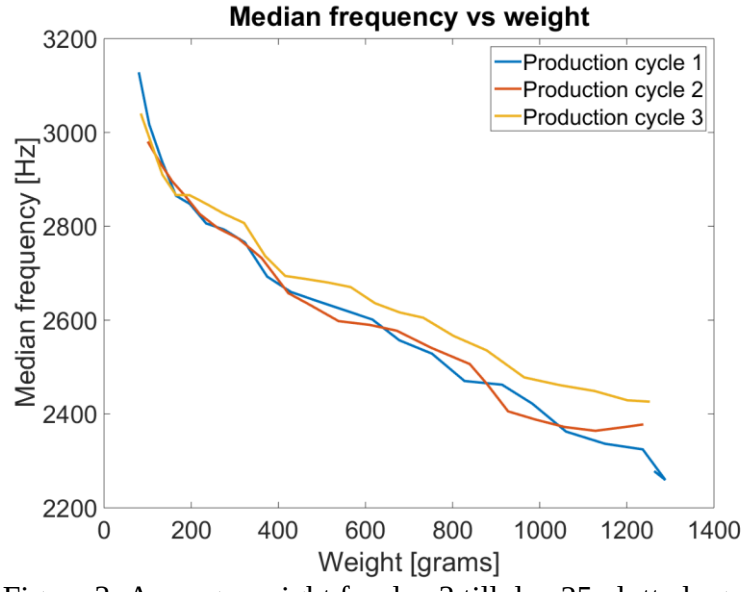


Figure 3: Average weight for day 3 till day 25 plotted against the average median frequency for the corresponding days

Conclusions

The results indicate that the median frequency can be used to differentiate between flocks with a better (heavier birds) or worse (lighter birds) production performance in a commercial broiler house. Visual inspecting the median frequency indicates that a deviation could be noticed 0 to 3 days before it was clearly visual in the weighing scale information. Hence, the systems has the potential to be used as early warning tool. Further analysis is needed to observe the robustness of the median frequency. Additionally, improving the algorithm performance over the total production cycle (day 0 till day …) should be investigated.

Acknowledgements

The authors gratefully acknowledge the European Community for financial support in Collaborative Project EU-PLF KBBE.2012.1.1-02-311825 under the 7th Framework Programme.

References

Aerts, J.-M., Van Buggenhout, S., Vranken, E., Lippens, M., Buyse, J., Decuypere, E. and Berckmans, D. 2003. Active control of the growth trajectory of broiler chickens based on online animal responses. *Poultry Science* **82**(12): 1853-1862.

Aydin, A., Bahr, C., Viazzi, S., Exadaktylos, V., Buyse, J., Berckmans, D. 2014. A novel method to automatically measure the feed intake of broiler chickens by sound technology. Computers and Electronics in Agriculture, 101, 17 – 23

Aydin, A., Bahr, C., Berckmans, D. 2015. A real-time monitoring tool to automatically measure the feed intakes of multiple broiler chickens by sound analysis. Computers and Electronics in Agriculture, 114, 1 - 6

Berckmans, D., Hemeryck, M., Berckmans, D., Vranken, E., van Waterschoot, T., 2015. Animal Sound…Talks! Real-time Sound Analysis for Health Monitoring in Livestock. Proceedings of the International Symposium on Animal Environment and Welfare. Chongqing (China), October 23-26, 215-222

Chedad, Ö., Aerts, J.-M., Vranken, E., Berckmans, D., 2006. End-weight prediction in broiler growth. British Poultry Science. 47(3), 330-335

Cortopassi, K.A. (2006). Automated and Robust Measurement of Signal Features. The Cornell Lab of Ornithology Bioacoustics Research Program. http://www.birds.cornell.edu/brp/research/algorithm/autoated-and-robust-measurement-of-signal-features. Accessed 20 November 2015

FAO, 2009. How to feed the world in 2050. Available from: http://www.fao.org/fileadmin/templates/wsfs/docs/expert_paper/How_to_Feed_the_World_in_2050.pdf

FAO. Database Livestock Primary. Dataset Producing Animals/Slaughtered: Meat, chickens. Latest update: 2014. Accessed 01/05/2017. http://www.fao.org/faostat/en/#data/QL

Exadaktylos, V., Silva, M., Aerts, J.-M., Taylor, C., Berckmans, D. 2008. Real time recognition of sick pig cough sounds. Computers and Electronics in Agriculture, 63(2), 207 – 214

Fontana, I., Tullo, E., Peña Fernández, A., Berckmans, D., Koenders, E., Vranken, E., McKinstry, J., Butterworth, A., Bercmans, D., Guarino, M., 2015a. Frequency analysis of vocalisations in relation to the growth in broiler chicken. Proceedings of Precision Livestock Farming '15. Joint Eropean Conference on Precision Livestock Farming. Milan (Italy), 15-18 September 2015, 174-182

Fontana, I., Tullo, E., Butterworth, A., Guarino, M. 2015b. An innovative approach to predict the growth in intensive poultry farming. Computers and electronics in agriculture. 119, 178-183

Kashiha, M., Pluk, A., Bahr, C., Vranken, E., Berckmans, D. 2013. Development of an early warning system for a broiler house using computer vision. Biosystems engineering. 116(1), 36-45

Marquer, P., Rabade, T., Forti, Roberta, 2015. Meat production statistics. Accessed from http://ec.europa.eu/eurostat/statistics-explained/index.php/Meat_production_statistics#Poultry_meat (on 01/05/2017)

Rizzi, C., Contiero, B. and Cassandro, M. 2013. Growth patterns of Italian local chicken populations. *Poultry Science* **92**(8): 2226-2235.

Van Hirtum, A., Aerts, J.−M., Berckmans, D., Moreaux, B., Gustin, P. 1999. On−line cough recognizer system. Journal of the Acoustical Society of America, 106, 2191−2191

Vandermeulen, J., Bahr, C., Johnston, D., Earley, B., Tullo, E., Fontana, I., Guarino, M., Exadaktylos, V., Berckmans, D., 2016. Early recognition of bovine respiratory disease in calves using automated continuous monitoring of cough sounds. Computers and Electronics in Agriculture, 129, 15-26

The use of imaging to learn on piglet level of development

A. Antoine[1], Y. Billon[2], L. Liaubet[1], L. Canario[1]
[1]*INRA, UMR 1388 INRA-INPT GenPhySE: Génétique, Physiologie et Systèmes d'Elevage, F-31326 Castanet-Tolosan, France*
[2]*INRA, UE 1372 GENESI: Génétique, Expérimentation et Systèmes Innovants, F-17700 Surgères, France*
Laurianne.Canario@inra.fr

Abstract

Piglet maturity at birth is defined as the level of full development, which is a major determinant of postnatal survival. Our objective was to identify biometric indicators of the level of piglet maturity using external body length measurements. Dead piglets were fixed on a board to be photographed in a standardised way. Images were subsequently analysed using ImageJ software (Abramoff et al., 2004). Measurements included body length, body width, body surface, head surface, skull length, head length and head width. In addition, it was possible to measure humerus, femur, tibia and foot lengths because these bones were clearly visible through the skin. Body measurements enabled us to compare allometric development of 312 progeny from contrasting breeds for maturity at birth: the Meishan (MS) and the Large White (LW). A crossbreeding design with use of mixed semen from the two breeds enabled us to study differences in development between purebreds (PB) and crossbreds (CB) developing in a LW or a MS uterine environment. Similar allometric slopes (>0.70) for body width and femoral length relative to body length were found at 90d dvp in LW PB and MS PB, but null slopes observed at 110d dvp in MS PB indicated a slowing of development. Head development did not differ between genetic types. In conclusion, body development was slower in MS PB than in other genetic types in late gestation, indicating that full body development was reached in MS PB only.

Key-words: Image analysis, biometrics, allometry, piglet development, crossbreeding effects

Introduction

Pig breeders constantly express concern about the high level of piglet losses that occur in the neonatal period. The heritability of piglet survival traits is too low to expect a direct genetic improvement. Selection for lean growth rate and litter size has had a negative impact on the physiological status of piglets at birth (Canario

et al., 2007). Genetics have a strong impact on the so-called level of maturity at birth, as shown by Herpin et al. (1993) in a comparison of Meishan (MS) piglets with White breeds of piglet. Prenatal development is a predisposing factor to perinatal losses, which have increased in recent decades in parallel with selective breeding. Due to heterosis effects, crossbred (CB) piglets have higher vigour than purebred (PB) piglets (Sellier 1970). In order to decipher the genetic roots underlying piglet maturity, the use of imaging was proposed to facilitate biometric analysis of 312 piglet foetuses obtained from crossbreeding of two contrasting breeds for piglet vitality at birth. The comparison was therefore based on PB and CB developing in a LW or a MS dam uterine environment.

Materials and methods

Data

The experiment was carried out in the INRA experimental herd at Le Magneraud (INRA GENESI, Charentes-Maritimes, France). Sows were in their second gestation. Caesarean sections were performed at 90 d (+1d) and 110 d (+/- 1d) of gestation. Foetuses were euthanised at birth by IV injection of 5 ml saturated potassium chloride solution, and the inert body was moved to a different location for macroscopic examination. Dead piglets were fixed on a board to be photographed in a standardised way. The body weight (BW) of each foetus was then measured.
The reason for using two types of semen mixed in equal proportions to inseminate each sow was to obtain ideally 50% purebreds and 50% crossbreds within a litter. The population, including 312 foetuses from 9 LW sows and 10 MS sows, is described in Table 1.

Table 1 – Mean characteristics (SD) for second parity Large White (LW) and Meishan (MS) sows producing both purebreds and crossbreds within the same litter

Sow breed	LW	LW	MS	MS
Gestation stage (j)	90	110	90	110
N	6	3	7	3
Litter size at caesarean	16,5	19,2	15,1	13,6
N purebred piglets	78	49	31	16
N crossbred piglets	23	10	77	28

Image analysis

Images were subsequently analysed using ImageJ software (Abramoff et al., 2004). Image capture was standardised, as a) all foetuses were placed in the same position on the work area, b) a reference measuring tape was used at a consistent position from the head, and c) the camera was fixed at a standardised distance from the work area to minimise measurement inaccuracies. Measurements included body length, body width defined as the distance between a tangent line from the top of the back to the rear of the front leg (Figure 1), body surface, head surface, skull length, head length (= skull length + snout length) and head width defined as the distance between a tangent line from the top of the head to the throat. It was also possible to measure humerus, femur, tibia and foot lengths because these bones were clearly visible through the skin. In the event of uncertainty due to a non-optimal position of the foetus on the board, the measurement was disregarded.

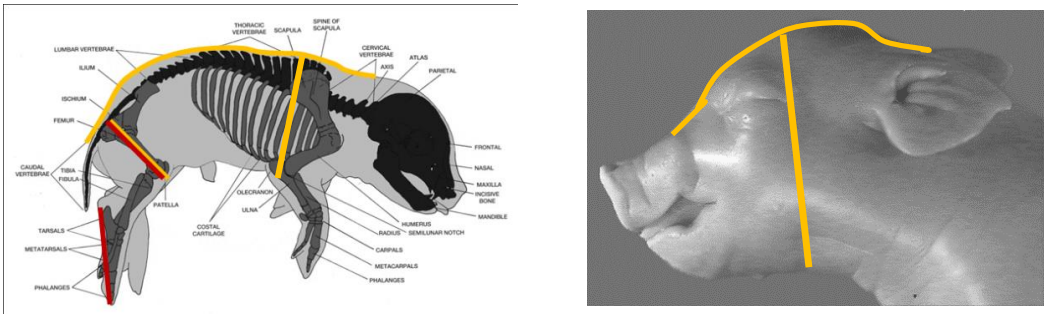


Figure 1. Left: Illustration of foetal body and bone length measurements from image analysis; Right: Measurement for head width to head length ratio.

Biometric analysis

All the measurements collected were tested as biometric indicators of maturity at birth.

Statistical analysis

The statistical methodology was inspired by Vallet and Freking (2006). To compare phenotypic differences between the four genetic types, raw data were analysed after natural log transformation. The model for analysis under the PROC MIXED procedure of SAS (SAS Institute, 2006) included the fixed effect of sex, the interaction between genetic type and age of development (dvp), the percent of PB in the litter and litter size as covariates, and the sow random effect.

Bivariate allometry relating body or skeletal length (y) to body length (x) in each line was analysed by Huxley's (1932) allometric equation transformed to natural logarithms $ln\, y = ln\, a + k\, ln\, x$ where $ln\, a$ is the intercept and k is the regression coefficient. The slope that is the coefficient of allometry defines a simple constant of proportionality, and the intercept represents a scaling coefficient (White and Gould, 1965). The model for analysis of allometric growth relative to body shape included the fixed effect of gender, the interaction between genetic type and age of dvp, the linear effect of the log of foetal BL, the genetic type x age x linear effect of foetal BL interaction, the percent of PB in the litter and litter size as covariates, and the sow random effect.

Results and discussion

Table 2 – Estimates for biometric measurements of purebred and crossbred foetuses which developed in the same maternal Large White (LW) or Meishan (MS) environment

	Age (d)	**LWxLW** lsmean	**MSxLW** lsmean	**LWxMS** lsmean	**MSxMS** lsmean	RSD	**LWxLW vs MSxLW** Prob(D=0)	**MSxMS vs LWxMS** Prob(D=0)
BW (g)	90	524.95 e	602.15 e	579.58 e	500.55 e	177		0.10
	110	1166.78	1218.04	1065.07	903.16			
Body length (cm)	90	18.53 e	18.62 e	18.58 e	16.77 e	1.66		<.0001
	110	23.91	23.08	22.91	21.36			0.11
Body width (cm)	90	3.50 e	3.94 c	4.03 b	3.90	0.49	0.001	
	110	4.78	4.93	4.66	4.53			
Body surface (cm²)	90	92.56 e	104.74 c	104.63 b	95.34 a	21.33		
	110	148.06	150.51	136.67	123.26			
Head length (cm)	90	10.86 e	11.24 e	11.19 e	10.89 e	0.63		
	110	13.33	13.56	13.14	12.96			
Head width (cm)	90	6.02 e	6.21 d	6.47 e	6.34 e	0.36		
	110	6.80	6.85	7.24	7.16			
Humerus length (cm)	90	3.96 e	4.19 e	4.27 e	3.99 d	0.44		0.04
	110	5.36	5.34	5.19	4.79			
Femur length (cm)	90	6.17 e	6.67 d	6.42 e	6.19 d	0.63	0.02	
	110	7.91	8.23	7.74	7.47			
Foot length (cm)	90	4.08 e	4.29 e	4.43 e	4.11 e	0.45		0.01
	110	5.56	5.52	5.51	5.11			

Level of significance for changes from 90d to 110d dvp: a: p<0.10; b: p<0.05; c: p<0.01; d: p<0.001; e: p<0.0001. RSD: residual standard deviation.

The comparison focused on 1) within-genetic type changes from 90d to 100d dvp and 2) differences between PB and CB genetic types developed in a given dam breed environment.
In LW sows, PB and CB did not differ in terms of BW and BL (Table 2). In MS sows, CB foetuses tended to be heavier than PB at 90d dvp and to be longer than PB at 90d and 110d dvp. In LW sows, the thorax was 11% thinner in PB than in CB and the difference between the two genetic types was not significant at 110d dvp. With regard to the ponderal index (BW/BL^3), we observed in MS PB only that BW increased at the expense of BL at 110d dvp, so that BL reached a plateau before birth in that genetic group. LW PB had a shorter femoral bone (7.5%) at 90d dvp than their CB counterparts but this contrast was offset at 110d dvp. A large increase in head dimensions from 90d to 110d dvp was found in the four piglet genetic types, with increases of 20% in head length and 12% in head width. We proceeded with the comparison of body development in proportion to BL or head length.

Table 3 - Linear slopes ± SE for the relationships between the log of body (head) size and the log of body (head) length in purebred and crossbred foetuses developed within the same maternal Large White (LW) or Meishan (MS) environment

	Age (d)	**LWxLW** lsmean	**MSxLW** lsmean	**LWxMS** lsmean	**MSxMS** lsmean	**LWxLW vs MSxLW** Prob(D=0)	**MSxMS vs LWxMS** Prob(D=0)
Head width	90	0.35 ± 0.10 b	0.09 ± 0.27 b	0.35 ± 0.11	0.05 ± 0.18		
	110	0.65 ± 0.10	1.32 ± 0.51	0.48 ± 0.19	0.38 ± 0.36		
Body Width	90	0.83 ± 0.13 a	0.76 ± 0.40	0.85 ± 0.16	0.73 ± 0.22 a		
	110	1.17 ± 0.14	1.33 ± 0.54	1.08 ± 0.23	0.08 ± 0.32		0.008
Femur length	90	1.00 ± 0.08	0.55 ± 0.25 a	0.92 ± 0.10	0.83 ± 0.14 b	0.08	
	110	1.10 ± 0.08	1.25 ± 0.33	1.09 ± 0.15	0.29 ± 0.19		0.0006

Level of significance for changes from 90d to 110d dvp: a: p<0.10; b: p<0.05; c: p<0.01; d: p<0.001; e: p<0.0001.

Allometric analyses are shown in Table 3. Proportional changes in foetal bone size with changes in foetal size (i.e. isometric changes) are reflected by a slope of 1. A slope greater than 1 is indicative of a positive allometry, i.e. foetal tissue dvp is enhanced compared to foetal whole body dvp. Conversely, a slope of less than 1 refers to a negative allometry and is indicative of a sparing effect, i.e. foetal tissue dvp is slower than foetal whole body dvp.

A negative allometry on head dvp was observed in the four foetal genotypes at 90d dvp. The acceleration of head widening relative to head lengthening was high in LW CB and moderate in LW PB. The analysis of body width relative to BL indicated that the dvp of LW PB was accelerated in late gestation ($p<0.05$). At 110d dvp, an abrupt change in the allometric slope towards zero was observed in MS PB. This slowing of dvp suggests full dvp in MS PB. The PB and CB dvp was more heterogeneous in MS sows ($p=0.008$) than in LW sows. The trend for delayed femoral bone dvp relative to BL in LW CB as compared to LW PB detected at 90d dvp ($P=0.08$) changed to isometry at 110d. In MS sows, a difference between PB and CB in femur lengthening relative to body lengthening was found at 110d dvp. Maximum femur length relative to breed standards at birth was likely to be reached in MS PB.

Conclusions

Our study validated the suitability of imaging to analyse piglet developmental level. Rapid development occurred at the end of gestation with some acceleration perceived in LW CB. Only MS PB foetuses achieved full body size development before birth. Several measurements were validated as biometric indicators of maturity at birth.

In this study, we identified new criteria that could be included in the breeding goal of maternal lines, as a means of limiting delayed maturity at birth. We are now confident about the validity of several new traits for routine recording on the farm. The genetic determinism of these new phenotypes is under study. To save time and facilitate data acquisition by farmers, the next step will be to develop a tool which can be used to take pictures or measurements automatically. Different technologies are suitable, including sensors coupled with ISO electronic devices which enable individual piglet identification. Development of algorithms to extract the relevant information will also be necessary. The outcome will be provide a reliable tool system for individual recording of maturity data in young animals which could be used on a large scale in breeding herds for the acquisition of high-throughput phenotypes.

Acknowledgements

This study received financial support from the French National Agency of Research (PORCINET project, ANR-09-GENM005). The authors are thankful to the technical staff from the experimental unit, animal surgeons who performed caesareans and euthanasia in compliance with ethical rules (European Union legislation (Directive 86/609/EEC) and French legislation of the Midi-Pyrénées region in France (Décret n∘:2001-464 29/05/01), and the many scientists and lab technicians who participated in data collection.

References

Abramoff M.D., Magelhaes P.J., and Ram S.J. 2004. "Image Processing with ImageJ". *Biophotonics International* **11**(7) 36-42.

Canario L., Père M.C., Tribout T., Thomas F., David C., Gogué J., Herpin P., Bidanel J.P., and Le Dividich J. 2007. Estimation of genetic trends from 1977 to 1998 of body composition and physiological state of large white pigs at birth. *Animal.* **1**(10) 1409-1413.

Herpin P, Le Dividich J, and Amaral N. 1993. Effect of selection for lean tissue growth on body composition and physiological state of the pig at birth. *Journal of Animal Science* **71**(10) 2645-53.

Huxley, J. S. 1932. *Problems of relative growth.* Methuen: London. Reprinted 1972, Dover Publications: New York.

Sellier P. 1970. Hétérosis et croisement chez le porc. *Annales de Génétique et Sélection Animale.* **2** 145-207.

Vallet, J.L., and Freking, B.A. 2006. Changes in fetal organ weights during gestation after selection for ovulation rate and uterine capacity in swine. *Journal of Animal Science* **84** 2338-2345.

White J.F., and Gould S.J. 1965. Interpretation of the coefficient in the allometric equation. *American Naturalist* **99** 5-18.

How much free space do pigs have in pens according to current EU legislation?
- Automatic measurement of static space of weaned piglets kept in groups of eight during six weeks -

M. Fels[1], K. Konen[1,2], E. Hessel[2], C. Bonk[3], C. Cruse[3], N. Kemper[1]
[1]*Institute for Animal Hygiene, Animal Welfare and Farm Animal Behaviour, University of Veterinary Medicine Hannover, Foundation, Bischofsholer Damm 15, 30173 Hannover, Germany*
[2]*Department of Animal Sciences, Georg-August-University of Göttingen, Gutenbergstraße 33, 37075 Göttingen, Germany*
[3]*CLK GmbH, Zur Steinkuhle 3, 48341 Altenberge, Germany*
michaela.fels@tiho-hannover.de

Abstract

Adequate space allowance is important for ensuring animal welfare in pig production. In the present study, the floor space covered by piglets kept in groups was determined by an automatic image analysis in order to evaluate current space recommendations and spatial requirements given by EU-legislation. In each of three batches, two groups of eight piglets were formed after weaning (35th day of life). Using 3D-cameras that recorded the piglets' pen from top view and a software for image analysis, the static space covered by the piglets' bodies in different positions was detected automatically during six weeks. Measurements were done weekly during one hour in the morning, every 10 seconds. The area covered by eight piglets increased almost linearly with increasing body weight until week 6 (R^2 = 0.99). The maximum space was measured in week 6 (1.72 m^2, 25.2 kg) when all piglets in the group were lying. In the same week, the mean space coverage of eight piglets was 1.5 m^2. It was found that piglets (10-20 kg) kept in groups of eight covered up to 91% of the pen size required by EU-legislation by their bodies. Piglets weighing 20-30 kg needed 63% on average for their static space. By the automatic method, realistic results on the static space requirements of piglets kept in groups were achieved. It became evident that piglets kept in groups of eight always covered more than 60% of the space required by EU-legislation by their bodies. Thus, less than 40% remain for behavioural activities.

Keywords: piglet, group, static space, space allowance, image analysis

Introduction

The amount of space that a pig is required to have during the rearing period is important for ensuring animal welfare in modern pig farming. In the European Union, farmers are bound by the EU Directive 2008/120/EC where the minimum spatial requirements for pigs are tailored to the weight of the animal being raised. However, current space recommendations are largely based on estimates, in the majority of cases resulting from the equation: Space = k * body weight$^{0.667}$ which was proposed for the first time by Petherick (1983). Since that time, the constant factor k varied between different studies and consequently different recommendations for appropriate space allowance were given (Gonyou et al., 2006). Indeed, it is not a simple manner to determine how much space an individual animal needs, and in the past different scientific approaches were developed to get a deeper knowledge on the space required by pigs for maintaining their welfare and biological performance. According to McGlone and Pond (2003) the floor space in a conventional pig pen consists of two components: used space and free space. While used space was defined as the space occupied by the pigs' bodies, free space was specified as the unoccupied remaining space which can be used for different behavioural activities. The used space which was also defined as static space (Petherick, 1983) of pigs in a pen can be measured for each individual by means of its body dimensions. Consequently the amount of free space can be quantified. This is an important approach to evaluate current spatial requirements in pig farming (Hurnik and Lewis, 1991; Anil et al., 2007). However, exact data about the body dimensions of group-housed pigs in different age and weight categories are currently lacking and for the measurement of space taken up by a group of pigs, a precise method which is easily applicable on farm was also missing so far. Therefore, the aim of the present study was to determine the static space of groups of eight weaner pigs during six weeks by means of an automatic image analysis.

Material and Methods

Animals and housing

The study was carried out on the research farm of the University of Veterinary Medicine Hannover, Foundation, Germany. There, a total of 80 sows and their piglets were kept in a conventional housing system. Before weaning, sows and piglets were kept in farrowing pens with a partially slatted floor where the sows were placed in farrowing crates. After weaning at five weeks of age, piglets were mixed into groups of eight and moved to conventional rearing pens (1.73 m x 1.60 m) with a fully slatted plastic floor providing space allowance of 0.35 m^2 per animal. Weaned piglets were fed ad libitum with dry feed and the

animal:feeding place ratio was 1:1. Water was also available ad libitum in one nipple drinker per pen. For the present study, on the day before weaning, all piglets were weighed individually. The study was carried out in a total of three batches. Per batch, 16 piglets were selected and two groups of eight piglets each were formed on the day of weaning. These newly formed groups, balanced regarding weight and sex, were moved to two adjacent pens in the same rearing compartment. The initial average body weight of all piglets was 8.55 kg ± 1.32 kg. In each group, piglets were marked individually on their backs with numbers 1 to 8, using standard colour stock markers before being moved to the rearing pens. A total of 48 piglets from the fifth to the tenth week of life were used for the study. Groups of piglets were kept in the rearing compartment for a total period of six weeks. During the experiments, temperature and relative humidity (%) in the piglets' compartment were measured every ten minutes using a data logger (DK650 "rugged-Visual", Driesen + Kern GmbH, Germany).

Experimental procedure

Above each of the two pens, at a height of 2.5 m, a camera (Kinect V2 M for Xbox One, Microsoft corporation) was installed and connected with a personal computer. Pictures of the piglets' pen were taken from top view. Subsequently, the images were analysed by a software which was developed and commercially offered by the company CLK GmbH (Altenberge, Germany). This software was able to calculate, in combination with 3D-cameras, the floor space covered by a group of piglets. The proper function of the software was examined prior to the study by measuring a plastic pig model, using a laser triangulation method under laboratory conditions. A deviation of 3% compared to the highly accurate laser triangulation method showed the high accuracy of the results obtained by the software. The algorithms used for image analysis in this study are owned by the company CLK GmbH (Altenberge, Germany) from which the software has been purchased. The camera pictures were stored by the program, and the floor space covered by the group of piglets was calculated in each image and specified in cm^2. Data collection was carried out weekly during one hour in the morning for a total period of six weeks per batch. Every week, each piglet was weighed individually. The software automatically took pictures of each group of eight piglets in their home pen from top view. All images were checked by a human observer, in each case verifying whether all piglets of a group were correctly identified by the program, and thus included in the calculation of the group area. For this user control, the recognised surface of each animal was surrounded automatically with a line by the program. If all individuals of a group were correctly identified by the program, this image was used for the study. A total of 1,645 images were analysed. When the images were checked by an observer, also the percentage of standing, sitting and lying (ventral and lateral) piglets

within the group was determined as well as the percentage of huddling. Huddling was defined as the position of at least two piglets, the body of one piglet being covered by at least 25% by another piglet. Different body positions were not automatically detected by the software and were therefore recorded manually.

Figure 1: Image of a group of piglets from top view generated by the program for image analysis (CLK GmbH, Altenberge, Germany)

Statistics

Statistical analysis was performed using the software IBM SPSS Statistics (Version 23, IBM, New York, USA). First, histograms for results of group spaces in different weeks were generated to assess data for normal distribution. Since data were normally distributed, ANOVA analysis was carried out followed by post hoc tests according to Student Newman Keuls to detect any significant differences between the floor spaces covered by groups in different weeks. In addition, R^2 was calculated in order to find any linear relationships between the average body weight of piglets within a group and the space covered by a group.

Results

Floor space covered by groups of eight piglets

From week 1 of the experiment (when piglets were five weeks old) to week 6, the average body weights of piglets within a group increased continuously from 8.6 kg to 25.2 kg (Table 1). Simultaneously, the floor space covered by a group increased almost linearly with increasing average body weight, indicated by R^2 = 0.99 (Figure 2). In each experimental week, significantly more space was covered by a group than in the previous week, respectively ($p<0.05$; Table 1).

Referring to all measurements, the highest values of space coverage were found during week 6 of the experiment. The mean space coverage by a group of eight piglets during week 6 was 1.5 m^2 (Table 1). For situations when 100% of piglets were lying and lying with 25% huddling nearly the same mean space coverage was found (1.5 m^2). When 100% of piglets in the group were standing, 1.36 m^2 were covered on average. The maximum space coverage during week six was measured when 100% of piglets in the group were lying without huddling (1.72 m^2). The minimum space coverage was 1.21 m^2 which was detected when 25% of piglets were lying with huddling, 50% were standing and 25% were sitting.

Table 1: Means ± standard deviations (m^2 ± s) of floor space covered by groups of eight piglets depending on body weight or week, and mean temperature and humidity in the barn air in different weeks. Significant differences between mean floor spaces are indicated by different letters ($p<0.05$).

Week	Mean body weight (kg)	n (images)	Mean covered floor space (m^2)	Temperature (°C)	Relative humidity (%)
1	8.55 ± 1.32	242	0.75 ± 0.05 [a]	24.6 ± 1.0	48.7 ± 4.1
2	9.9 ± 1.44	358	0.78 ± 0.06 [b]	25.7 ± 1.1	38.6 ± 1.4
3	11.93 ± 2.03	75	0.83 ± 0.05 [c]	22.1 ±4.5	34.8 ± 5.0
4	15.25 ± 2.46	91	1.04 ± 0.09 [d]	22.3 ± 2.6	46.4 ± 7.4
5	19.81 ± 2.89	302	1.27 ± 0.09 [e]	22.0 ± 2.3	41.9 ±3.6
6	25.16 ± 3.93	577	1.50 ± 0.11 [f]	20.5 ± 0.9	49.0 ± 5.9

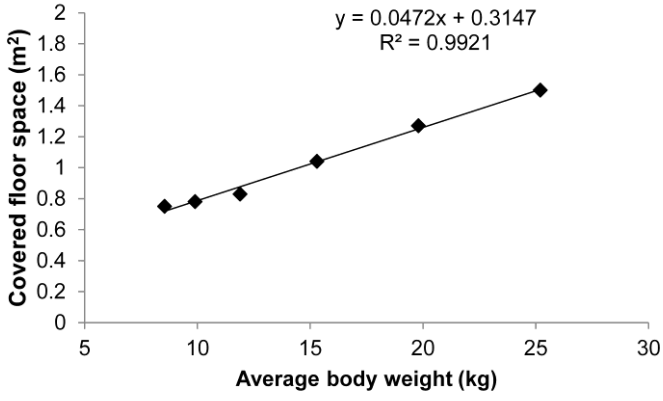


Figure 2: Mean floor space (m^2) covered by groups of eight piglets depending on the average body weight within groups measured during six weeks,
n = 1, 645 measurements

Floor space covered by groups of eight piglets in comparison to spatial requirements in the European Union

Legal spatial requirements are usually given in m^2 per pig for a range of body weights. Table 2 shows the spatial requirements given by the EU directive 2008/120/EC and the percentage of space that would be covered by the pigs' bodies within a group of eight in relation to the spatial requirements for this group size (referring to the mean and the maximum space coverage measured for a certain body weight in the present study). When considering the mean values for static space measured in this study, it becomes evident that at most 79% of the required pen size is covered by the pigs' bodies in a group of eight (EU: 10-20 kg body weight). It was also shown that sometimes, piglets cover up to 91% of the required pen size in Europe with their bodies, i. e. they needed almost the whole pen for their static space requirements. This result was found for a weight range of 10-20 kg in the EU. The lowest mean space coverage in relation to the EU directive 2008/120/EC was measured for a mean group weight of 25 kg (63%). In this weight class, a maximum space coverage of 72% was measured.

Table 2: Mean and maximum floor spaces covered by groups of eight piglets in relation to spatial requirements in the EU (2008/120/EC).

Body weight (kg)	Recommen-ded space/pig (m^2) in EU	Recommen-ded space (m^2) for 8 piglets	Mean space covered by 8 piglets (m^2)	Max. space covered by 8 piglets (m^2)	Mean covered space (%)	Max. covered space (%)
5-10	0.15	1.2	0.78 (10 kg)	0.93	65	77.5
10-20	0.2	1.6	1.27 (20 kg)	1.45	79.4	90.6
20-30	0.3	2.4	1.5 (25 kg)	1.72	62.5	71.7

Discussion

The aim of this study was to measure the floor space that a group of eight pigs covered from the day of weaning in the fifth week of life until the end of the rearing period during the tenth week of life. The detection of the static space of piglets kept in groups can serve as a basis for realistic assessment of current space recommendations in piglet rearing, not relating to estimates or theoretic calculations. In the past, different scientific approaches were developed for calculating space requirements for pigs. According to Spoolder et al. (2012) the amount of space occupied by an animal depends on its size and body weight, the body position it assumes and the level of shared space. All these four aspects were considered in the present study by measuring the total space covered by entire groups of piglets. In earlier studies, different mathematic formulas were described for calculating space requirements for pigs (Petherick and Baxter, 1981; Pastorelli et al., 2006; Petherick and Phillips, 2009). However, the recommendations derived from those formulas are based on theoretical calculations and the multiplicity of existing formulas leads to an uncertainty concerning the assessment of current stocking densities in pig farming. In contrast, the method used in our study which was developed by the company CLK GmbH (Altenberge, Germany) offers the possibility of obtaining precise results concerning the space covered by the pigs' bodies in groups based on image analysis. In the present study, for the first time, a method based on automatic image analysis was used to measure the static space requirements of pigs in their home pen without the necessity to interfering with the animals.
Our results revealed that current space requirements are often very closely dimensioned. However, it is undisputed that insufficient space allowance has negative consequences not only for the welfare but also for the performance of animals (Whittaker et al., 2012). With regard to legal space requirements in the EU, it became evident that always more than 60% of the required space allowance is needed for the piglets' static space in groups of eight. According to EU-legislation, the highest percentage of covered floor space was found for piglets from 10 kg to 20 kg body weight (79%), resulting in a mean remaining space for activity of 0.3 m^2 for a total of eight piglets. When considering that pigs usually remain in the same pen throughout the rearing period until they leave the rearing compartment for fattening, it seems useful to assess the available space at the end of the rearing period with about 25 kg body weight. At this stage, on average 63% of the required pen size would be needed by eight piglets only for their body dimensions.

For an adequate space allowance, the additional space required for activities such as feeding, exploring, carrying out social behaviour or withdrawing from visual

contact with others should also be considered (EFSA, 2005). Although it is not possible to make any statements about the required free space based on the measurements of the present study, it can be assumed that taking into account current space recommendations, in many cases the remaining free space is likely not to be sufficient to carry out space-grabbing movements, to separate functional areas or to avoid visual contact with other pigs. Pigs are motivated to divide their living areas into regions for specific activities such as eating, drinking, sleeping and dunging (Geers, 2007). If these behaviours cannot be expressed, animal welfare may be adversely affected. In relation to our results, it seems rather unlikely that piglets can separate different areas for lying and dunging with a free space of 0.3 m^2. However, to interpret the results of the present study, it is important to emphasise that these relate to a group size of eight animals. For larger groups, different values for the remaining free space are possible.

In the present study, the pigs' compartment was heated in order to minimize thermoregulatory behaviour, and temperature was measured using a data logger. When temperature is too low or too high, piglets change their body positions in order to reduce heat loss or to cool down. For weaned piglets at the age of five or six weeks, the ambient temperature should be around 26°C (Le Dividich & Herpin, 1994). In weeks 1 and 2 of our experiment (age of piglets: 5 and 6 weeks), mean temperatures between 24°C and 26°C were measured. From the third week after weaning, it is recommended to reduce the ambient temperature by 2-3°C per week (Le Dividich & Herpin, 1994). Ideally, room temperature should be 22°C for pigs weighing 15 kg (Whittemore and Green, 2001). In our study, we measured 22°C on average during the experimental period from week 3 to week 5, while in week 6, 20.5°C was measured on average. Since these temperatures were within the optimal range for this age group, no thermoregulatory behaviour such as body postural changes was expected which could have influenced the results of space coverage in the present study.

Conclusions

The new method for measuring piglets' static space based on image analysis, which was offered by the company CLK GmbH (Altenberge, Germany) was shown to be suitable to provide reliable results concerning the space that is needed by the body dimensions of pigs kept in groups. The results of the present study quantified static spatial requirements of groups of eight piglets which are directly relevant for assessing space recommendations for small groups. This study was not primarily intended to enhance legal space requirements for pig production, however to demonstrate the amount of free space which remains per

pig after deduction of the space needed by the pigs' bodies. The method for measuring static space used in this study can provide a basis for further investigations concerning adequate space allowance for pigs.

Acknowledgements

The authors wish to thank CLK GmbH (Altenberge; Germany) for software development and support on all technical issues. Furthermore, thanks go to Dr. Andreas Briese for giving some initial ideas regarding the potential of 3D-cameras for area assessment.

References

Anil, L., Anil, S.S., and Deen, J. 2007. Effects of allometric space allowance and weight group composition on grower-finisher pigs. *Canadian Journal of Animal Science* **87**(2), 139-51.

EFSA, 2005. Opinion of the scientific panel on animal health and welfare on a request from the commission related to welfare of weaners and rearing pigs: effects of different space allowances and floor types. *The EFSA Journal* **268**, 1–19.

Geers, R. 2007. 2. Lying behaviour (location, posture & duration). In: *On farm monitoring of pig welfare* (ed. Verlarde, A. & Geers, R.), Wageningen Academic Publishers, Wageningen, The Netherlands, 19-24.

Gonyou, H.W., Brumm, M.C., Bush, E., Deen, J., Edwards, S.A., Fangman, T., McGlone, J., Meunier-Salaun, M., Morrison, R.B., Spoolder, H., Sundberg, P.L., and Johnson, A.K. 2006. Application of broken-line analysis to assess floor space requirements of nursery and grower-finisher pigs expressed on an allometric basis. *Journal of Animal Science* **84**(1), 229-235.

Hurnik, J.F., and Lewis, N.J. 1991. Use of body surface area to set minimum space allowances for confined pigs and cattle. *Canadian Journal of Animal Science* **71**, 577-80.

Le Dividich, J.L., and Herpin, P. 1994. Effects of climatic conditions on the performance, metabolism and health status of weaned piglets: a review. *Livestock Production Science* **38**, 79-90.

Mc Glone, J., and Pond, W. 2003. *Pig production: biological principles and applications*. Thomson, USA.

EU Directive. Council Directive 2008/120/EC of 18 December 2008 laying down minimum standards for the protection of pigs.

Petherick, J.C., and Baxter, S.H. 1981. Modelling the static spatial requirements of livestock. In: *Modelling, design and evaluation of agricultural*

buildings, CIGR Section 2 Seminar. Scottish Farm buildings investigation unit, Aberdeen, UK, 75-82.

Petherick, J.C. 1983. A biological basis for the design of space in livestock housing. In: *Farm Animal Housing and Welfareg* (ed. Baxter, S.H., Baxter, M.R. MacCormack, J.A.D.), Martinus Nijhoff, The Hauge, 103-120.

Petherick, J.C., and Phillips, C.J.C. 2009. Space allowances for confined livestock and their determination from allometric principles. *Applied Animal Behaviour Science* **117**, 1-12.

Pastorelli, G., Musella, M., Zaninelli, M., Tangorra, F., and Corino, C. 2006. Static spatial requirements of growing-finishing and heavy pigs. *Livestock Science*, 260-264.

Spoolder, H.A.M., Aarnink, A.A.J., Vermeer, H.M., van Riel, J., Edwards, S.A. 2012. Effect of increasing temperature on space requirements of group housed finishing pigs. *Applied Animal Behaviour Science* **138**, 229-239.

Whittaker, A.L., Van Wettere, W.H., and Hughes, P.E. 2012. Space requirements to optimize welfare and performance in group housed pigs - a review. *American Journal of Animal and Veterinary Sciences* **7**(2), 48-54.

Whittemore, L.T., and Green, D.M. 2001. Growth of the young weaned pig. In: *The weaner pig: Nutrition and managemen*t (ed. Varley, M.A. and Wiseman, J.), CABI Publishing, Wallingford, UK, 1-14.

Leg disorder detection in broilers using automated Precision Livestock Farming systems

T. Van Hertem[1], T. Norton[2], D. Berckmans[2], E. Vranken[1,2]
[1]*Innovation – Research department, Fancom BV, Panningen, the Netherlands*
[2]*Division Animal and Human Health Engineering, KU Leuven, Leuven, Belgium*
tvhertem@fancom.com

Abstract

Leg deformities and lameness cause a major welfare concern in the European poultry industry. In this study, the aim was to evaluate the potential of Precision Livestock Farming systems to identify leg problems in broilers.
Data were gathered from five different commercial farms in Europe. Leg problems in broilers were assessed on a discrete scale according to the Welfare Quality Protocol by trained local human experts. Bird activity was continuously monitored with a camera-based system in the ridge of the house, mounted in top-down perspective. The camera software analysed the recorded images and calculated the distribution and the activity of the birds in the flock. Bird weight was automatically sampled with an automatic weighing scale in the house.
Data analysis showed a linear trend between activity level of the flock on the day of the assessment (ACT) and the average gait score of the flock (GS): $GS = -0.21 * ACT + 2.85$ (R^2=0.55). The negative coefficient implies that higher activity levels are associated with lower gait scores, i.e. better animal gait. Gait score and flock activity are negatively correlated (r=-0.741), whereas gait score and flock distribution are positively correlated (r=0.705). Due to differences in management and broiler breeds, the absolute values in activity level and gait score vary between farms. The linear trend is however clear in all farms (R^2=[0.53-0.74]).
This study showed the potential of a camera-based monitoring tool for flock behaviour analysis as a warning tool for the poultry farmer to detect possible leg problems in commercial farm settings.

Keywords: Precision Livestock Farming, broilers, welfare, leg problems, activity index, weight monitor

Introduction

The interest in animal welfare is growing in Europe and in the rest of the world as well (Turner et al., 2005). The EU-funded research project called “Welfare Quality” developed a manual animal welfare scoring protocol executed by

human experts, and leg problems such as impaired gait, hock burns and foot pad lesions were part of the welfare criteria (Botreau et al., 2009). Trained experts make on-farm observations of all criteria, and based on these observations and scores, the welfare level of the animals can be assessed. These traditional methods of scoring animal based information by human experts remain however difficult, subjective, time consuming and expensive when implemented in commercial farms (De Vries et al., 2013). On top of that, the visit of a human expert at the commercial farm might induce a risk for infection to the flock.

Rather than constructing lists of a variety of welfare indicators and give each of them the same weight, the UK Farm Animal Welfare Council suggested in 1979 to look for "iceberg indicators" in animal behaviour (FAWC, 1979). The work of Dawkins is an example on this that uses animal behaviour monitoring for the on-farm assessment of animal welfare (Dawkins, 2004). There are many potential welfare benefits by monitoring broiler activity level in the farm. A decrease or increase in the level of activity in the flock may indicate an emerging disease (Colles et al., 2016) or change in behaviour towards aggression due to lack of feed or water (De Montis et al., 2013; Kashiha et al., 2013).

The increasing availability of low cost sensor technology makes automated monitoring of animal welfare feasible (Rushen et al., 2012). Camera technology is one such low cost sensor technology. Camera technology has been used in other species as well for gait analysis (Viazzi et al., 2013; Stavrakakis et al., 2014; Van Hertem et al., 2014). The research in other species is mostly focused on the gait analysis of the individual animal, whereas for broilers most camera-based technologies are focused on flock behaviour. Cameras offer the possibility to monitor a big part of flock in a non-invasive manner. A previous small-scale study under laboratory conditions has shown the potential of an automatic camera monitoring system for bird activity as an automatic tool for gait scoring in broilers (Aydin et al., 2010). The chickens were grouped per gait score level. Broilers with Gait Score 4 and 5 had significantly lower activity levels. Broilers with Gait Score 3 showed significantly higher activity levels than the other gait score groups, possibly due to their higher need for feed.

In commercial farms however, lame and non-lame are mixed together in the flock. A previous study showed the potential of optical flow analysis as a monitor for footpad dermatitis and hock burn problems in commercial farms (Dawkins et al., 2017). The skew and kurtosis of the optical flow measurements had more power to predict leg problems than other measured variables. They also mentioned four benefits of automated gait scoring: continuous measurements throughout the lifecycle of the flock, fully automated technology, completely non-invasive and non-intrusive, and no biosecurity risk of human assessors visiting different farms (Dawkins et al., 2009).

The aim of this study was to evaluate the possibility to use automated PLF technologies for the assessment of leg problems during the rearing period of the flock. In this study, key variables will be identified that are strongly related with broiler flock gait score, hock burn levels and foot pad lesions.

Material and Methods

Animals and Housing

Data were collected during the EU-PLF project in five commercial broiler farms spread over Europe (Netherlands, UK, Spain, UK and Italy). The characteristics of each farm and the number of assessed flocks in each farm are presented in Table 1.

Table1: Farm Characteristics in this study. The light scheme is expressed in length of light period (L; hours) and length of dark period (D; hours).

Farm	Country	House area	Max number of birds	Light scheme	Number of flocks assessed	Number of welfare assessments
A	Netherlands	1298	28000	4x L4D2	9	31
B	United Kingdom	2530	45000	3x L6D2	9	30
C	Spain	2260	42000	natural	4	10
D	United Kingdom	2200	51750	L23D1	9	31
E	Italy	1560	30000	3x L6D2	6	18

List of variables.

In order to give the reader an overview of the abbreviations in this manuscript, all used abbreviations are listed in Table 2.

Table 2. Overview of the variables in this study

Variable name	Variable description	Unit
HBS	Hock Burn Score; average value of birds hock burn scores on an assessment day assessed by a trained Welfare Quality Expert	.
FPL	Foot Pad Lesions; average value of birds foot pad lesions scores on an assessment day assessed by a trained Welfare Quality Expert	.

Gait	Average value of birds gait score on an assessment day assessed by a trained Welfare Quality Expert [0: no gait impairment – 5:severe gait impairment]	.
actMean	Average value of bird activity levels on the day of the assessment assessed by the automatic camera system.	%
actVar	Variance of bird activity data on the day of the assessment assessed by the automatic camera system.	%
distVar	Variance of bird distribution index data on the day of the assessment assessed by the automatic camera system.	%
distMean	Average value of bird distribution index levels on the day of the assessment assessed by the automatic camera system.	%
mDM	Maximum value of daily average bird distribution index levels from the start of the flock until the day of the assessment assessed by the automatic camera system.	%
LQS	Litter Quality Score as assessed by a trained Welfare Quality Expert	.
Weight	Average body weight of the birds in the flock on the day of the assessment, assessed by the automatic bird weighing system	Kg
Age	Age of the birds in the house	Days
SD	Stocking Density; the number of animals per square meter in the house on the day of the assessment	$\frac{Animals}{m^2}$
SD_kg	Stocking density per kg; the amount of bird weight per square meter in the house on the day of the assessment.	$\frac{Kg}{m^2}$

Welfare assessments

Because the farms were spread over four different countries, four different and trained local human assessors were making the Welfare Quality assessments. All trained observers received the same training protocol in order to eliminate inter-observer variability in the assessment data. This study focussed on the results of the farm assessment of leg problems (impaired gait, hock burns and foot pad lesions) in broilers. The assessments were performed in week 3, week 4 and week 5 of the rearing period. In each farm, during each assessment, at least 100 birds (129±37 birds) were randomly caught by hand at locations randomly spread in the house. The assessors assessed gait score on a discrete 6-level scale (0: no gait impairment; 5: severe gait impairment), hock burn score on a discrete 5-level scale (0: no damaged skin at hocks; 4: severe skin burns at hock burns) and foot pad lesions on a discrete 5-level scale (0: no lesions at foot pad; 4:

severe lesions at foot pads). For each assessment day, the average for gait score, hock burn level and foot pad lesion score was calculated and used in the analysis. On the day of the assessment, litter quality in the house was evaluated, flock age was determined and stocking density was calculated from the number of birds in the house and the area of the house.

Flock behaviour data

Each farm was equipped with a commercially available camera-based automatic animal behaviour monitoring tool (eYeNamic™, Fancom BV, Netherlands). The camera system comprised four cameras that were installed in top-down perspective at the ridge of the house. Images were recorded in 1296x972 formats, and only during the light periods (Table 1). The eYeNamic software analysed every minute a set of consecutive images, on average taken at a time interval of 697±120 milliseconds. Image analysis resulted in an activity image, showing the movement of the birds in the images and the distribution index. The Activity Index is expressed as a percentage, i.e. the ratio of the number of moved pixels and the total number of pixels in the image frame. Image analysis resulted also in a Distribution Index. The Distribution Index was deduced from the occupation rate of the birds in the image, and ranged between 0 and 100% (Kashiha et al., 2013). A Distribution Index of 0 implied that the birds were clustered together in some place(s), whereas a Distribution Index of 100 implied that the birds were evenly spread over the floor space.

The eYeNamic software generated per minute an Activity Index and a Distribution Index. For the analysis in this study, these data were aggregated into daily mean values (ActMean and DistMean) and a value depicting the variation within the day (ActVar and DistVar).

Thinning out of the broiler flock has an impact on the Distribution Index values, causing a drop in these data after thinning. Therefore, another variable was introduced: the maximal daily mean Distribution Index (mDM) of the flock until the day of the assessment.

Bird Weight Monitor

In four out of the five farms (not Italy), the broiler house was equipped with at least one automatic weighing scale (F47, Fancom BV, Netherlands). The automatic weighing scale registers all body weights of the birds that hop on and off the weighing scale platform. This technique was initially introduced by (DOYLE and LEESON, 1989), and later on fine-tuned (Chedad et al., 2003). In case more than one weighing scale was present, the weight data from both scales was averaged in order to get daily body weight estimation.

Results

Data correlations.

The correlations between the assessor scores for gait, foot pad lesions, hock burns and litter quality and the sensor data were calculated and presented in Table 4. From Table 4 it can be noticed that the average value of bird activity level as measured by the camera on the day of the manual assessment (actMean) is negatively correlation (r = -0.741) with the manual gait score. The maximum value of daily average bird distribution from the start of the flock until the day of manual assessment as measured by camera (mDM) is positively correlated (r = 0.705) with the manual gait score. Animal weight as measured by the PLF scale (Weight) is positively correlated with manual gait score (r = 0.873), manual hock burn score (r = 0.539), and manual foot pad lesion score (r = 0.525).

For identifying highly correlated variables, we looked at the absolute values of the correlations. For most sensor variables, the correlation with gait score was higher than with the other human assessment scores.

Table 4: Table with the correlation coefficients of the continuous farm data and the human assessment variables for leg disorders (Gait: average Gait Score of the flock; FPL: average Footpad Lesion score in the flock; HBS: average level of Hock Burns in the flock) and litter quality (LQS: average level of Litter Quality Score in the house).

		Gait	**FPL**	**HBS**	**LQS**
Flock data					
Age	[days]	0.541	0.373	0.483	0.356
SD	[animals/m^2]	-0.215	0.012	-0.235	0.142
Biometric data					
Weight	[kg]	**0.873**	**0.525**	**0.539**	0.364
SD_kg	[kg/ m^2]	0.723	0.480	0.424	0.491
eYeNamic data					
actMean	[%]	**-0.741**	-0.329	-0.346	-0.261
distMean	[%]	0.512	0.053	0.295	0.316
mDM	[%]	**0.705**	0.297	0.547	0.490
actVar	[%]	-0.557	-0.239	-0.195	-0.273
distVar	[%]	0.053	0.229	0.175	0.067

Farm-specific eYeNamic data.

In every farm, a negative correlation between activity level and gait score was visible. The lower the activity level was in the house, the higher the gait score in the flock was. Despite the clear negative trend in the data across all farms, the difference between farms was significant as expected. The farm-specific trend line fitted through the data points, presented in Table 4, shows these differences between the farms.

The relationship between average gait score and the maximum average distribution index until day of manual assessment was showing a positive linear trend, i.e. the higher the distribution index in the house was, the higher the gait score of the flock was. This trend was clearly visible in all farms (Table 4), but differences between farms were visible.

Farm E had, for both the activity index and the distribution index, the lowest coefficient of determination, indicating that this trend is less clear in this farm.

Table 5: Linear regression coefficients ($y = a * x + b$) of the relation between Gait Score and daily average activity levels (left) and maximum daily distribution index levels until the day of the assessment. Goodness of fit is expressed by the coefficient of determination (R^2).

		Activity Index			**Distribution Index**		
	n	a	b	R^2	a	b	R^2
Farm A	24	-0.1808	2.8953	0.7367	0.0251	0.0247	0.8360
Farm B	17	-0.1884	2.8468	0.7056	0.0346	-0.2359	0.8045
Farm C	10	-0.2127	3.4345	0.7370	0.0189	0.7180	0.6522
Farm D	21	-0.3544	3.1736	0.6328	0.0361	-0.3176	0.6815
Farm E	16	-0.1939	2.1674	0.5282	0.0189	-0.2581	0.4092
All farms	88	-0.2078	2.8497	0.5488	0.0315	-0.3271	0.4970

Discussion

The results in this study show the relation between flock behaviour and gait problems in broilers. A camera-based system was used in a previous study as well to identify lameness in broilers (Silvera et al., 2017). Their experimental setup was however different. A human assessor had to perform a walk-through in the house. In their study, they found a relation between the gait score level of the flock and the amplitude difference in peak activity and the baseline level of

activity. In principal, their conclusion is similar to the one in this study: the more activity in the flock, the less chance on lameness in the flock. So both techniques can be used as an automatic assessment tool for lameness, but bear in mind that the reaction of the birds towards a walk-through was used in the analysis of Silvera et al. (2017), whereas in this study no walk-through or any other induced action is required.

The relation between flock behaviour and hock burns or foot pad lesions was less straight forward. The results showed a more clear relationship between hock burns or foot pad lesions and litter quality, as was proven in other studies as well (Haslam et al., 2007; Allain et al., 2009). This shows the potential of an online monitoring tool for litter quality in the broiler house, as it will provide the farmer a tool to control the level of hock burns and foot pad lesions in the house.

This study showed a linear trend between the activity levels of the flock and the gait score level of the flock. In a previous study, a trend was observed with an maximum activity level for animals of gait scores 2 and 3 whereas the pens with animals assessed with gait score 4 and 5 resulted in lower activity levels (Aydin et al., 2010). The difference in outcome might be due to the difference in experimental setup. In the study of Aydin et al. (2010), five birds with equal gait score were placed in a same smaller pen, resulting in a grid of six pens, one for each level of gait score (range: 0 - 5). So the animals were not able to mix between each other. In this study, we have monitored the activity level of an entire flock in commercial farms, i.e. a mixture of animals with different gait scores that walk freely around in the house. The proportion of birds with high gait score levels is very low compared to the rest of the flock.

Our study suggests maintaining the activity level of the flock in the house on a high level in order to reduce the chance for gait problems in broilers. The effect of locomotor activity on leg disorders is well described in other studies (Prayitno et al., 1997; Reiter and Bessei, 2009; van der Pol et al., 2015). The activity level can be influenced by the distance between water and feeder lines (Reiter and Bessei, 2009), the light schedule (van der Pol et al., 2015) and the light colour (Prayitno et al., 1997).

The automatic measurement of flock behaviour turned out to be farm dependent. First of all, the farms in this study were located in four different countries so differences in feed, breed and climate are expected. Second, the internal layout of the broiler house and a difference in housing systems might impact the assessment of flock behaviour. The number of feeding and water lines in the recording field of interest differs between farms, and different behaviours in the feeding, drinking and resting zones might be expected (Reiter and Bessei, 2009). Environmental factors such as food management can influence bird behaviour (Murphy and Preston, 1988). Third, all farms applied a different light scheme to the birds. The camera was only able to record during light period, and therefore a

difference in behaviour in response to the light schedules might be expected (Prayitno et al., 1997; van der Pol et al., 2015). Finally, the difference in management by the farmer can never be excluded as a main actor in the process.
Camera-based monitoring tools have great potential in monitoring animal behaviour in an automated and non-invasive manner (Pastell et al., 2006; Ahrendt et al., 2011; Van Hertem et al., 2014). Because animal behaviour is a key indicator in the assessment of animal welfare (Rushen et al., 2012), these technological developments have the ability to improve the on-farm monitoring of animal welfare indicators. It is however important that methods should be developed to measure in a wider range of behavioural patterns because welfare in multifactorial. Animal welfare assessment schemes should not place undue emphasis on behavioural indicators solely on the basis that they can be monitored automatically (Rushen et al., 2012).
Camera-based technologies cannot only be used for welfare assessments, but they might also monitor technical processes that are ongoing in the house, such as feed distribution in the feeding lines, water provision in the water lines and drinking nipples, climate controls etc. So technical problems in the house might be detected by changes in bird behaviour, as was proven by (Kashiha et al., 2013).

Conclusion

This study showed the potential of a camera-based monitoring tool for flock behaviour as a warning tool for the poultry farmer for possible gait problems in a commercial farm setting. Flock behaviour profiles were farm dependent, so farm specific reference curves need to be implemented. The experiments of this research were done on a large scale in commercial farms in order to obtain these results. The classification accuracy of gait problem detection by flock behaviour was better than the classification accuracy of hock burn or foot pad lesion detection. Hock burns and foot pad lesions were better predicted by litter quality in the house. Gait score and flock activity were negatively correlated (r=-0.741), whereas gait score and flock distribution was positively correlated (r=0.705).

Acknowledgements

This work was supported by the 7th framework program of the European Union [collaborative project EU-PLF KBBE.2012.1.1-02-311825].

References

Ahrendt, P., T. Gregersen, and H. Karstoft. 2011. Development of a real-time computer vision system for tracking loose-housed pigs. Comput. Electron. Agric. 76:169–174. doi:10.1016/j.compag.2011.01.011.

Allain, V., L. Mirabito, C. Arnould, M. Colas, S. Le Bouquin, C. Lupo, and V. Michel. 2009. Skin lesions in broiler chickens measured at the slaughterhouse: relationships between lesions and between their prevalence and rearing factors. Br. Poult. Sci. 50:407–417. doi:http://dx.doi.org/10.1080/00071660903110901.

Aydin, A., O. Cangar, S.E. Ozcan, C. Bahr, and D. Berckmans. 2010. Application of a fully automatic analysis tool to assess the activity of broiler chickens with different gait scores. Comput. Electron. Agric. 73:194–199. doi:10.1016/j.compag.2010.05.004.

Botreau, R., I. Veissier, and P. Pern. 2009. Overall assessment of animal welfare: Strategy adopted in Welfare Quality. Anim. Welf. 18:363–370.

Chedad, A., J.-M. Aerts, E. Vranken, M. Lippens, J. Zoons, and D. Berckmans. 2003. Do heavy broiler chickens visit automatic weighing systems less than lighter birds?. Br. Poult. Sci. 44:663–668. doi:http://dx.doi.org/10.1080/00071660310001643633.

Colles, F.M., R.J. Cain, T. Nickson, A.L. Smith, S.J. Roberts, M.C.J. Maiden, D. Lunn, and M.S. Dawkins. 2016. Monitoring chicken flock behaviour provides early warning of infection by human pathogen Campylobacter. Proc. R. Soc. B 283. doi:http://dx.doi.org/10.1098/rspb.2015.2323.

Dawkins, M.S. 2004. Using behaviour to assess animal welfare. Anim. Welf. 13:3–7. doi:10.1177/1091581812471490.

Dawkins, M.S., H. Lee, C.D. Waitt, and S.J. Roberts. 2009. Optical flow patterns in broiler chicken flocks as automated measures of behaviour and gait. Appl. Anim. Behav. Sci. 119:203–209. doi:http://dx.doi.org/10.1016/j.applanim.2009.04.009.

Dawkins, M.S., S.J. Roberts, R.J. Cain, T. Nickson, and C.A. Donnelly. 2017. Early warning of footpad dermatitis and hockburn in broiler chicken flocks using optical flow, bodyweight and water consumption. Vet. Rec. 5. doi:10.1136/vr.104066.

DOYLE, I., and S. LEESON. 1989. Automatic Weighing of Poultry Reared on a Litter Floor. Can. J. Anim. Sci. 69:1075–1081. doi:10.4141/cjas89-122.

FAWC. 1979. Five Freedoms. Accessed April 27, 2017. https://www.gov.uk/government/groups/farm-animal-welfare-committee-fawc.

Haslam, S.M., T.G. Knowles, S.N. Brown, L.J. Wilkins, S.C. Kestin, P.D. Warriss, and C.J. Nicol. 2007. Factors affecting the prevalence of foot pad dermatitis, hock burn and breast burn in broiler chicken. Br. Poult. Sci. 48:264–275. doi:http://dx.doi.org/10.1080/00071660701371341.

Van Hertem, T., S. Viazzi, M. Steensels, E. Maltz, A. Antler, V. Alchanatis, A.A. Schlageter-Tello, K. Lokhorst, E.C.B. Romanini, C. Bahr, D. Berckmans, and I. Halachmi. 2014. Automatic lameness detection based on consecutive 3D-video recordings. Biosyst. Eng. 119:108–116. doi:10.1016/j.biosystemseng.2014.01.009.

Kashiha, M.A., A. Pluk, C. Bahr, E. Vranken, and D. Berckmans. 2013. Development of an Early Warning System for a broiler house using computer vision. Biosyst. Eng. 116:36–45.

De Montis, A., A. Pinna, M. Barra, and E. Vranken. 2013. Analysis of poultry eating and drinking behavior by software eYeNamic. J. Agric. Eng. 44:166–172. doi:10.4081/jae.2013.s2.e33.

Murphy, L.B., and A.P. Preston. 1988. Food availability and the feeding and drinking behaviour of broiler chickens grown commercially.No Title. Br. Poult. Sci. 29:273–283.

Pastell, M., a M. Aisla, M. Hautala, V. Poikalainen, J. Praks, I. Veermäe, and J. Ahokas. 2006. Contactless measurement of cow behavior in a milking robot.. Behav. Res. Methods 38:479–486. doi:10.3758/BF03192802.

van der Pol, C.W., R. Molenaar, C.J. Buitink, I.A. van Roovert-Reijrink, C.M. Maatjens, H. van den Brand, and B. Kemp. 2015. Lighting schedule and dimming period in early life: consequences for broiler chicken leg bone development.. Poult. Sci. 94:2980–2988. doi:10.3382/ps/pev276.

Prayitno, D.S., C.J. Phillips, and D.K. Stokes. 1997. The effects of color and intensity of light on behavior and leg disorders in broiler chickens.. Poult. Sci. 76:1674–1681.

Reiter, K., and W. Bessei. 2009. Effect of locomotor activity on leg disorder in fattening chicken. Berliner Munchener Tierarztl Wochenschrift 122:264–270.

Rushen, J., N. Chapinal, and A.M. De Passillé. 2012. Automated monitoring of behavioural-based animal welfare indicators. Anim. Welf. 21:339–350. doi:10.7120/09627286.21.3.339.

Silvera, A.M., T.G. Knowles, A. Butterworth, D. Berckmans, E. Vranken, and H.J. Blokhuis. 2017. Lameness assessment with automatic monitoring of activity in commercial broiler flocks. Poult. Sci.. doi:https://doi.org/10.3382/ps/pex023.

Stavrakakis, S., J.H. Guy, O.M.E. Warlow, G.R. Johnson, and S.A. Edwards. 2014. Walking kinematics of growing pigs associated with differences in musculoskeletal conformation, subjective gait score and osteochondrosis. Livest. Sci. 165:104–113. doi:http://dx.doi.org/10.1016/j.livsci.2014.04.008.

Turner, J., L. Garcés, and W. Smith. 2005. The welfare of broiler chickens in the European Union. Hampshire, United Kingdom.

Viazzi, S., C. Bahr, a Schlageter-Tello, T. Van Hertem, C.E.B. Romanini, a Pluk, I. Halachmi, C. Lokhorst, and D. Berckmans. 2013. Analysis of individual classification of lameness using automatic measurement of back posture in dairy cattle.. J. Dairy Sci. 96:257–66. doi:10.3168/jds.2012-5806.

De Vries, M., B. Engel, I. Den Uijl, G. Van Schaik, T. Dijkstra, I.J.M. De Boer, and E.A.M. Bokkers. 2013. Assessment time of the Welfare Quality protocol for dairy cattle. Anim. Welf. 22:85–93. doi:10.7120/09627286.22.1.085.

Session 5

Production diseases

Infrared thermography as a tool for mastitis diagnosis

E. S. J. Rezende[1], D. J. Moura[1] and J. L. A. R. Pereira[2]
[1]*Agricultural Engineering College, Campinas State University, Campinas, Brazil*
[2]*FederalInstitute of Education, Science and Technology from Minas Gerais, Campus, Inconfidentes, Brazil*
Daniella.moura@feagri.unicamp.br

Abstract

We assessed the correlation of the temperatures of the udder, eye and vulva measured with a thermographic camera (IRTU, IRTE and IRTV) with somatic cell count (SCC), California mastitis test (CMT), rectal temperature, milk yield, and teat cup testing in dairy cows. This study, conducted at IFSULDEMINAS, Inconfidentes campus, in the state of Minas Gerais, Brazil, tested 12 black-and-white Holstein cows confined in a free stall system. For data collection, cows were lined up at random during milking, and three thermographic pictures, from which surface temperatures were measured, were taken from each animal per collection period. The CMT was performed immediately after the teats were cleaned. Milk was collected and taken to the Milk Clinic Laboratory (Laboratório da Clínica do Leite, ESALQ-USP) for SCC analysis. Descriptive analyses of the IRTU, IRTE, IRTV, SCC and CMT were conducted with the SAS System® Version 9.2. software. Somatic cell count correlated best with the IRTU, which also showed a high and positive correlation with IRTV and morning and evening CMT. Thus, IRTU can be used as a tool for mastitis diagnosis in dairy cows.

Keywords: cattle, mastitis diagnosis, infrared, surface temperature

Introduction

Recent decades have seen a great deal of progress in terms of improvements in milk quality. Nonetheless, mastitis is still one the main causes of reduction in quality and quantity, both in milk yield and in commercialisation of the product. Diagnostic tests for mastitis can be performed either at the farm (field tests) or in a laboratory. The field tests are simpler and can be carried out daily, during milking, but the most precise diagnostic methods cannot be applied as often, due to difficulties inherent in the field routine and to their high cost (Ribeiro Júnior et al., 2008).

Determination of somatic cell count (SCC) requires the milk sample to be sent to a laboratory, resulting in a lead-time that is too long to support daily management decisions. To deal with this problem, indirect methods of mastitis identifi-

cation have been developed for application in the field. The California mastitis test (CMT) is one of the earliest indirect methods for determination of SCC, and is still used on dairy farms (Rodrigues, 2008). More recently, infrared thermography has emerged as a useful tool, with good applicability in the fields of animal production and environment (Stewart et al., 2005). Advantages of this method include requiring no direct physical contact with the monitored surface and measuring the temperature of the animal in its natural environment, without the need for stressful procedures such as capture and restraint (Stewart et al., 2005; Silva et al., 2010).

The purpose of this work was to determine the correlation between infrared thermography of the udder, eye and vulva (IRTE, IRTU and IRTV), measured with a thermographic camera, and SCC, CMT, rectal temperature (RT), milk yield (MY), and the teat cup test (CT), as well as the relationship between these variables. Eye and vulva surface temperature were included in this research in an attempt to identify the easiest place to measure the infrared temperature.

Materials and methods

This study was approved by the Committee on Ethical Use of Animals at the Federal Institute of Education, Science and Technology of the South of Minas Gerais (Instituto Federal de Educação, Ciência e Tecnologia do Sul de Minas Gerais – IFSULDEMINAS). We conducted the study at the Production Training Unit – Dairy Cattle (Unidade Educativa de Produção - bovinocultura leite) at Inconfidentes campus, in the state of Minas Gerais, Brazil, avoiding unnecessary animal discomfort.

In this experiment, we randomly chose12 cows of the black-and-white Holstein breed, confined in a free stall system, at different lactation stages, and weighing 550 kg on average. Each animal was evaluated in the morning (7:00 h) and in the evening (18:00 h) of 23 August 2014 and 20 September 2014. Temperature points on the udder and teats, vulva and eye were measured during milking and the average temperature was then calculated. The ambient temperature during data collection varied between 23.3ºC and 26.5ºC on the first day, and between 24.1ºC and 28.5ºC on the second day.

To diagnose clinical mastitis, the first three gushes of milk prior to milking were collected in a teat cup (Figure 1) to determine the presence of alterations in the milk, such as lumps, clots, pus, bloody secretions or watery milk (Costa, 2008). A positive result in the teat cup test (CT) was scored 1 and a negative result was scored 0, for analysis purposes. After the CT, the CMT was performed. Each quarter was milked into the corresponding well of a CMT paddle until the milk reached the first mark in the well (2 ml), then anionic reagent was added up to the second mark (2 ml). The milk and reagent were mixed with gentle circular

motions, then the viscosity of the mixture was scored on a five-point scale (adapted from Santos and Fonseca, 2007), where score 1 means a completely negative reaction; score 2, traces of a reaction; score 3, a weakly positive reaction (+); score 4, a positive reaction (++); and score 5, a strongly positive reaction (+++).

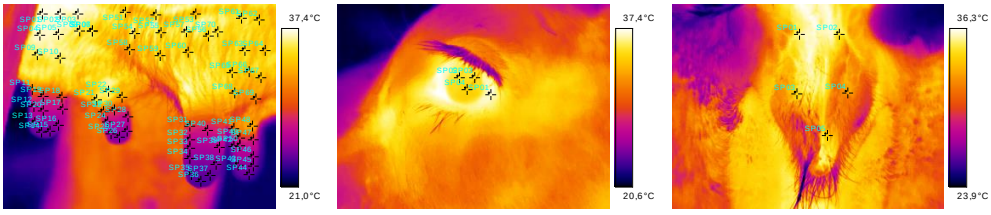
Figure 1: Teat cup test (CT)

For analysis of SCC, 50 mL samples of milk were collected in sterile plastic tubes containing one tablet of the preservative Broad Spectrum Microtabs II (D&F Control Systems, Norwood, MA, USA), gently inverting the flask multiple times to ensure complete mixing of sample and preservative. Each sample was labelled with the collection site, animal identification number, date and time of collection. Samples were stored in an icebox and shipped to the Milk Clinics Laboratory at the Animal Production Department, Escola Superior de Agricultura "Luiz de Queiroz" (ESALQ-USP), Piracicaba, SP, Brazil, where SCC analysis was performed within 4 hours of sample collection with an automated somatic cell count instrument (Somacount 300®, Bentley Instruments, Chaska, MN, USA).

Cows were milked in a conventional parlour (Alfa Laval® Alpro System, Alfa Laval Ltda., São Paulo, SP, Brazil), for milk yield measurement (litres/animal/day). Rectal temperature was measured with a digital clinical thermometer (ANIMED, Incoterm®, Porto Alegre, Rio Grande do Sul, Brazil) introduced into the rectum of the animal so that the bulb stayed in contact with the mucosa until the temperature stabilised.

Surface temperature was measured with a thermographic camera (FLIR B400 Infrared Camera, FLIR Systems Co., Ltd, Shatin, New Territories, Hong Kong). Cows were randomly lined up during morning and evening milking, and three pictures were taken for each collection period, giving a total of 6 pictures per site

of each animal. Images were collected from a distance of 20 cm, at an emissivity of 0.95. All thermal images were obtained from the right side of the animals, to allow measurement of the actual body temperature fluctuation without contamination of the surface temperature by the digestive processes taking place in the rumen (Montanholi et al., 2008). Image analysis was performed with the QuickReport®/FLIR-Systems software (FLIR Systems Co., Ltd, Shatin, New Territories, Hong Kong). Captured images displayed different temperatures along the udder temperature; the software's "point" tool was used to obtain the mean temperature, which was calculated from 70 randomly chosen points on the udder and both right teats (IRTU). Four points were measured for the eye (IRTE), and five points for the vulva (IRTV) (Figure 2).



(a) (b) (c)

Figure 2: Images obtained with the infrared camera, measuring points on the udder and teats (A), eye (B) and vulva (C)

Descriptive analyses of the IRTU, IRTE, IRTV, SCC, and morning and evening CMT (CMTM and CMTT, respectively) were carried out using the PROC MEANS procedure. Pearson's correlation was obtained by the PROC CORR command and the regression using PROC REG in the statistical software SAS System® Version 9.2.

Results and discussion

Table 1 shows the values of the descriptive statistics for the variables IRTU, IRTE, IRTV, SCC and CMT. The number of samples (n) was 3360 for IRTU (70 points from each udder, multiplied by 12 cows in 4 measurement sessions), 192 for IRTE and 240 for IRTV. For SCC and CMT, n=24 (Table 1). The standard errors of the mean for IRTU, IRTE and IRTV were low, and the lowest was for IRTU, 0.03 (Table 1). The standard deviations for IRTU, IRTE and IRTV ranged from 1.7 to 2.2ºC (Table 1). This demonstrates the low variability of the data in relation to the mean. The lowest temperature measured by the infrared camera was on the udder (23.9ºC) and the highest was on the vulva (40.5ºC) (Table 1), as was highest mean temperature (35.1ºC) (Table 1). The mean SCC was 706,000 cells/mL, ranging from 37,000 to 5,942,000 cells/mL (Table1). The var-

iability of SCC values, confirmed by the standard deviation and by the standard error of the mean, indicates that the sample included animals without mastitis, with subclinical mastitis and with clinical mastitis. This result is extremely important to the work, and for definition of the correlations and regressions between the temperatures measured by the infrared camera and somatic cell count (Table 1). The CMT, both in the morning and in the evening, presented a mean score of 3. In both periods analysed, the results ranged from 1 to 5 (Table 1).

The correlations obtained allow us to infer the degree of interaction between the variables studied (Table 2). The temperature in the eye of the animal, measured with the infrared camera, showed a high and positive correlation with IRTU and IRTV (0.718, $p< 0.0001$; and 0.686, $p= 0.0002$, respectively). The other traits, however, presented a low and positive correlation with eye temperature (Table 2). Stewart et al. (2007) validated the eye temperature, measured through infrared thermography, for measurement of stress in dairy cattle challenged with adrenocorticotropic hormone (ACTH) and subjected to psychological stress conditions (social isolation). Increases in concentrations of both cortisol and ACTH and in eye temperature confirmed that the hypothalamic-hypophyseal-adrenal axis was stimulated in those conditions. Eye temperature measurements, therefore, may suffer direct interference from stimuli such as pain and stress, including heat stress.

Table 1: Average surface temperatures of the udder, eye and vulva, SCC and CMT.

Parameters	IRTU (ºC)	IRTE (ºC)	IRTV (ºC)	SCC (x1000cells/mL)	CMT (score 1-5)
Mean	34.2	34.8	35.1	706	3
Standard error	0.03	0.12	0.13	250.76	0.35
Median	34.8	34.5	35.3	245	3
Standard deviation	2.2	1.7	2.1	1228.5	1.7
Minimum	23.9	28.4	27.1	37	1
Maximum	38.3	38.3	40.5	5942	5
Number of samples	3360	192	239	24	24

Caption: Average surface temperatures of the udder, eye and vulva (IRTU, IRTE and IRTV, respectively), Somatic Cell Count (SCC) and California Mastitis Test in the morning and evening (CMTM and CMTT, respectively).

The IRTU had high and positive correlations with IRTV, SCC, CMTM and CMTT. According to Hovinen et al. (2008), somatic cell count, in addition to

determining a qualitative aspect of milk, is inherently related to the health of the udder of the cow, since a high somatic cell count is indicative of inflammatory reaction of the mammary tissue. Increased local temperature is a characteristic of inflammation, due to the greater amount of blood flowing through the local vessels. Thus, observation of the surface temperature of the affected area can be used to diagnose an infection or lesion. Kennedy (2004), Willits (2005) and Pezeshki et al. (2011) reported an increase of 2 to 3ºC in the surface temperature of the udder in a study inoculating Escherichia coli into different parts of the udder of dairy cows. Polat et al. (2010) found that infrared thermography could be used for subclinical mastitis screening, through measurement of the surface temperature of the udder, with a diagnostic capacity similar to the CMT.

The correlation of IRTU with RT (rectal temperature) in the morning and in the evening and with the CT in both periods was low but positive (RT $p<0.0$; CT $p< 0.05$). Perissonotto et al. (2007) reported that the normal RT of dairy cows, at thermoneutrality and at rest, ranges from 38.0°C to 39.0°C. According to Martello et al. (2002), RT changes with time of day, being higher in the evening than in the morning.

Milk yield had a low and negative correlation with IRTU (Table 2). Subclinical mastitis is among the leading diseases on dairy farms, causing great losses to farmers, mainly due to the reduction in milk yield (Ruegg, 2003; Zafalon et al., 2007). The loss estimates range from 10% to 30% of the milk yield per lactation, but also in the next lactation, endangering the total yield of the animal (Auldist and Hubble, 1998).

Vulva temperature had a high and positive correlation with SCC, CMTM and CMTT, and a low, but positive, correlation with both CT and RT. The regressions SCC vs. IRTU, SCC vs. IRTV, IRTU vs. CMTM and IRTU vs. CMTT, and the coefficient of determination are shown in Figures 3 to 6. The regression equation for SCC and IRTU was $Y= 138.99x2- 9649.2x+167437$ (with a coefficient of determination, R2, of 0.95, indicating an excellent fit of the regression) meaning that each increase of 1ºC on the udder surface corresponded to an additional 157,926 cells/mL of milk (Figure 3).

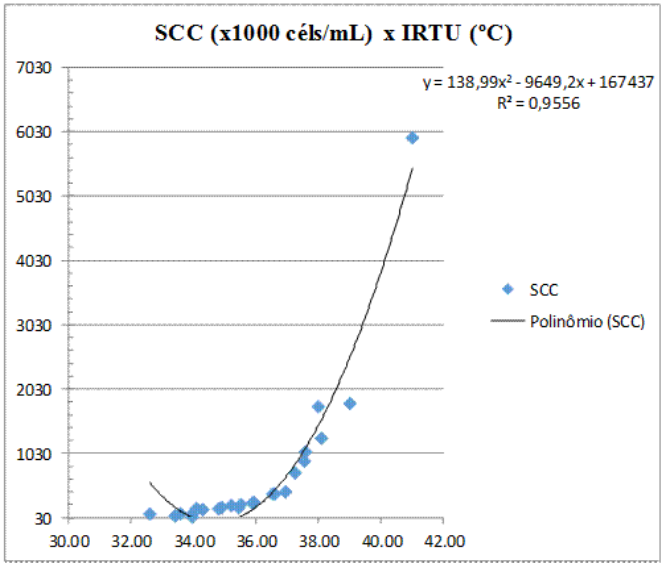


Figure 3: Quadratic regression between somatic cell count (SCC) and images of the udder taken with an infrared camera.

Figure 4 shows that the regression equation for SCC vs. IRTV (Y= 230.48 x2 – 16317x +288634) had an R2 of 0.85, still indicating an excellent fit. According to this correlation, for each 1ºC rise in vulva temperature, there was an increase of 272,547 cells/mL of milk (Figure 4).

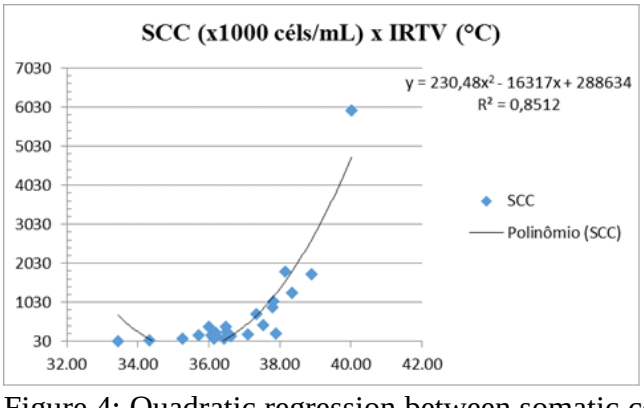


Figure 4: Quadratic regression between somatic cell count (SCC) and the images of the vulva taken with an infrared camera

Table 2: Coefficients of correlation between surface temperatures of the eye, udder and vulva measured with the infrared camera (IRTU, IRTE and IRTV, respectively), somatic cell count (SCC), California mastitis test in the morning and evening (CMTM and CMTT, respectively), rectal temperature in the morning and evening (RTM and RTT, respectively), milk yield in the morning and evening (MYM and MYT, respectively) and teat cup test in the morning and evening (CTM and CTT, respectively).

	IRTE	IRTU	IRTV	SCC	CMTM	CMTT	RTM	RTT	MYM	MYT	MY	CTM	CTT
IRTE	1												
IRTU	0.718^{**}	1											
IRTV	$0{,}686^{**}$	0.836^{**}	1										
SCC	0.474^{**}	0.792^{**}	0.717^{**}	1									
CMTM	0.549^{**}	0.731^{**}	0.715^{**}	0.485^{*}	1								
CMTT	0.495^{**}	0.687^{**}	0.646^{*}	0.467^{*}	0.955^{**}	1							
RTM	0.237^{ns}	0.350^{*}	0.424^{*}	0.349^{ns}	0.372^{ns}	0.443^{ns}	1						
RTT	0.197^{ns}	0.266^{ns}	0.188^{ns}	0.366^{ns}	0.098^{ns}	0.087^{ns}	0.371^{ns}	1					
MYM	0.212^{ns}	0.022^{ns}	-0.083^{ns}	0.021^{ns}	0.194^{ns}	0.210^{ns}	-0.132^{ns}	0.013^{ns}	1				
MYT	0.133^{ns}	-0.128^{ns}	-0.131^{ns}	-0.171^{ns}	-0.030^{ns}	-0.089^{ns}	0.035^{ns}	-0.058^{ns}	0.568^{*}	1			
MY	0.203^{ns}	-0.042^{ns}	-0.115^{ns}	-0.061^{ns}	0.117^{ns}	0.102^{ns}	-0.073^{ns}	-0.017^{ns}	0.929^{**}	0.831^{**}	1		
CTM	0.001^{ns}	0.219^{ns}	0.316^{ns}	0.182^{ns}	0.251^{ns}	0.239^{ns}	0.126^{ns}	0.045^{ns}	0.086^{ns}	0.181^{ns}	0.139^{ns}	1	
CTT	0.251^{ns}	0.547*	0.579^{*}	0.788^{*}	0.363^{ns}	0.345^{ns}	0.327^{ns}	0.305^{ns}	0.124^{ns}	0.079^{ns}	0.119^{ns}	0.691^{*}	1

*P<0.05; **P<0.01

For the other two parameters, IRTU vs. CMTM and IRTU vs. CMTT, shown in Figures 5 and 6, no regression was found with R2 above 0.6, leading us to the conclusion that IRTU was not a good parameter for predicting the results of the CMT test.

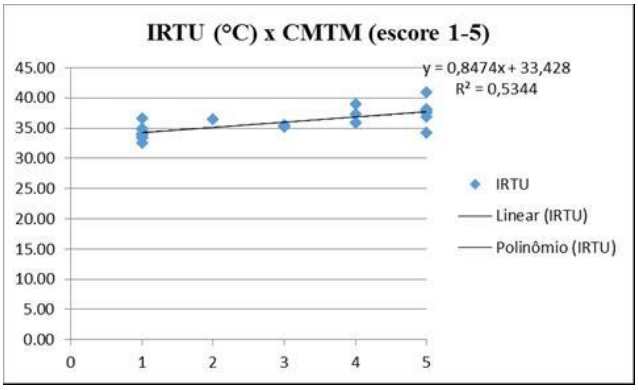


Figure 5: Quadratic regression between the images of the udder (IRTU) taken with an infrared camera and California Mastitis Test – morning period (CMTM).

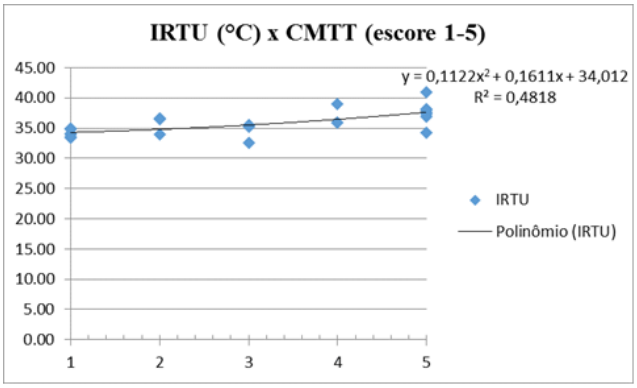


Figure 6: Quadratic regression between images of the udder (IRTU) taken with an infrared camera and California Mastitis Test – morning period (CMTT).

Conclusions

This study shows that somatic cell count was best correlated with the infrared temperature of the udder (r = 0.79, R2 = 0.95). The IRTU also had a high and positive correlation with the IRTV, and with CMTM and CMTT. Therefore, IRTU is a useful tool for the diagnosis of mastitis in dairy cows. A novel paper is being developed with modelling including IRTU and SCC to show the potential of the IRTU as a mastitis predictor,

Acknowledgements

This project was funded by CNPq, a Brazilian Federal Agency which supported a PhD student with a scholarship, and Fapesp, State of Sao Paulo Agency, which gave us the funding to purchase the thermal camera.

References

Auldist, M. J., and I. B. Hublle, 1998. Effects of mastitis on raw milk and dairy products. Aust. *Journal of Dairy Technology*. 53:28−36.

Costa, G. M. 2008. *Bovine mastitis in dairy herds of the south region of Minas Gerais State.* DSc Thesis. Federal University of Minas Gerais - Veterinary School. Belo Horizonte, Brazil.

Hovinen, M., J. Siivonen, and S. Taponen, 2008. Detection of clinical mastitis with the help of a thermal camera. *Journal of Dairy Science.* 91:4592−4598.

Kennedy, A. 2004. Mastitis detection using infrared thermography. *Western Dairy Digest*, v.5, n.4, p.15.

Martello, L. S., S. Jr. Holmer, da L. e S. Saulo, and A. T. T. Evaldo. 2004. Physiologic and performance responses of Holstein cows in milking under different environments. *Revista Brasileira de Zootecnia*. 33:181−191.

Perissinotto, M., D. J. de Moura, I J. O. da Silva, and S. V. Matarazzo. 2005. Influence of the ambient conditions on water intake by dairy cows. Rev. Bras. *Engenharia Agricola e Ambiental*. 9:289−294.

Montanholi, Y. R., N. E. Odongo, K. C. Swanson, F. S. Schenkel, B. W. Mcbride, and S. P. Miller, 2008. Application of infrared thermography as an indicator heat and methane production and its use in the study of skin temperature in response to physiological events in dairy cattle (Bos taurus). *Journal of Thermal Biology* 33:468–475.

Pezeshki, A., P. Stordeur, H. Wallemacq, F. Schynts, M. Stevens, P. Boutet, L. J. Peelman, B. de Spiegeleer, L. Duchateau, F. Bureau, and C. Burvenich. 2011. Variation of inflammatory dynamics and mediators in primiparous cows after intramammary challenge with Escherichia coli. *Veterinary Research*. 42:15.

Polat, B., B. Colak, M. Cengiz, L. E. Yanmaz, A., Bastan, S. Kaya, and A. Hayirl, 2010. Sensitivity and specificity of infrared thermography in detection of subclinical mastitis in dairy cows. *Journal of Dairy Science.* 93:3525−3532.

Ribeiro Júnior, E., M. H. Silva, S. A. A. Viegas, E. J. Ramalho, M. D. Ribeiro, and F. C. S. Oliveira, 2008. California Mastitis Test (CMT) and whiteside evaluation as indirect diagnosis methods for subclinical mastitis. *Revista Brasileira de Saúde na Produção Animal*. 9(4):680−686.

Rodrigues, A. C. de O. 2008. *On-farm bacterial identification of bovine mastitis to guide treatment protocols.* DSc Dissertation. University of São Paulo - Luiz de Queiroz College of Agriculture, Piracicaba, Brazil.

Ruegg, P. L. 2003. Investigation of mastitis problems on farms – Review. *Veterinary Clinics of North America: Food Animal Practice*. 19:47−63.

Santos, M. V., and L. F. L Fonseca. 2007. *Estratégias para controle de mastite e melhoria na qualidade do leite: conceitos sobre mastite bovina e métodos diagnósticos.* Barueri: São Paulo: Manole, 314 p.

Silva N. S., J. A. S. da Silveira, C. P. Pinheiro, M. G. S. de Sousa, C. M. C. Oliveira, C. L. de Mendonça, M. D. Duarte, and J. D. Barbosa. 2010. Etiology and antimicrobial susceptibilities of bacteria isolated from sheep with mastitis in northeastern Pará, Brazil. *Pesquisa. Veterinaria Brasileira*. 12:1043−1048.

Stewart, M., J. R. Webster, A. L. Schaefer, N. J. Cook, and S. L. Scoot. 2005. Infrared thermography as a non-invasive tool to study animal welfare. *Animal Welfare*. 14:319−325.

Monitoring ruminal temperature as an early sign of pneumonia to implement precision antimicrobial therapy: interests and limits approached in a field study with young bulls

G.Lhermie[1,2], A. Bousquet-Melou[3], H. Seegers[2], S. Assié[2]
[1,2]*Department of Population Medicine and Diagnostic Sciences, Schurmann Hall*
College of Veterinary Medicine, Cornell University, Ithaca, NY, 15853, USA
[2]*BioEpar, Oniris, INRA*
Oniris, site de la chantrerie, La chantrerie, 44307 Nantes, France
[3]*Toxalim, ENVT, Ecole nationale vétérinaire de Toulouse*
23 chemin des capelles 31076, Toulouse, France.
gl467@cornell.edu

Abstract

We evaluated the therapeutic efficacy of an early treatment protocol with a decreased fluoroquinolone regimen in a field study on young bulls (YBs) presenting spontaneous signs of Bovine Respiratory Disease (BRD). A total of 195 YBs were assigned to one of two experiment groups, based on time of detection of BRD and on first line marbofloxacin regimen. Each YB was administered orally a reticulo-rumen bolus, which allowed continuous monitoring of ruminal temperature. In each farm, in the groups E2 (early, 2 mg/kg of marbofloxacin), YBs presenting early signs of BRD, *i.e.*, an increase in ruminal temperature over a threshold of 40.2°C and persisting more than 12h, confirmed by a clinical examination, were given 2 mg/kg of marbofloxacin. In the groups L10 (late, 10 mg/kg of marbofloxacin), YBs presenting clinical signs of BRD at visual inspection, confirmed by a clinical examination were given 10 mg/kg of marbofloxacin. If needed in the following days, YBs were given a relapse treatment. The treatments incidences [amount (mg)/ Used Daily Dose (mg/kg)] for a standard YB of 300 kg at risk were calculated, showing a lower amount of marbofloxacin but higher amount of relapse treatments in the E2 groups compared to the L10 groups. In the groups E2, the proportion of 1st line treatments was significantly higher (P<0.05), while the proportion of relapse treatments tended to be higher (P=0.08) than in the groups L10. In both groups, clinical score (CS) as well as rectal temperature decreased within 24h after treatment. Our results suggest that the combination of an early detection of diseased animals with a lower fluoroquinolone regimen might reduce drug consumption at the herd level without significantly affecting treatment

efficacy, under condition of accurate identification of animals in an early stage of illness.

Key words: antimicrobial use, veterinary precision medicine, cattle, bovine respiratory disease, early treatment.

Introduction

Antimicrobial use (AMU) in veterinary medicine may lead to the selection of resistant bacteria, potentially transferred to humans, representing a public health hazard (Aarestrup, 2012; Mcewen and Fedorka, 2002). In this context, decreasing the number of animals unnecessarily treated, and optimization of antimicrobial regimen, remains a major topic to maintain their effectiveness.
Marbofloxacin is a fluoroquinolone used to treat Bovine Respiratory Disease (BRD) (Vallé et al., 2012). In the field, the delay between clinical detection of BRD and treatment onset may impact therapeutic efficacy, as clinical signs possibly reflect extensive pulmonary damages which had time to develop prior to treatment (Fulton, 2009). Furthermore, late intervention leads to treat high bacteria inocula, constituting a risk of therapeutic failure and increasing the risk of emergence of resistant bacteria (Ferran et al., 2011; Kesteman et al., 2009).
As demonstrated in mice infection models (Ferran et al., 2011; Lhermie et al., 2015), it has been shown in an experimental model of bovine lung infection that efficacious marbofloxacin dosage regimen could be decreased if it is given at an early stage of disease, when the infectious bacterial load is low (Lhermie et al., 2016). However in field conditions, the lack of diagnostics tools allowing identification of pathogens and bacterial load constitutes a major barrier to implement such a treatment strategy. An alternative could be to monitor early signs of BRD, such as increase in core body temperature, which has been demonstrated to appear before clinical signs (Timsit et al., 2011a, 2011b). Combining appropriate doses of antimicrobials and early detection of BRD could thus allow a reduction in AMU.
The objective of our study was to assess in a field experiment the therapeutic efficacy of a decreased fluoroquinolone therapy given at an early stage of BRD, based on ruminal's temperature monitoring, compared to a standard therapy administered after clinical disease appraisal.

Material and Methods

Study design

In 6 commercial French fattening units, 195 ruminant Young Bulls (YBs) of the Charolais, Limousin and Rouge des Prés breeds, aged between 7 and 10 months with an average body weight of 299 kg were recruited. In each fattening unit, YBs were administered orally a reticulo-rumen temperature bolus (San'phone, Medria SAS, Chateaugiron, France), and were separated in pens containing 7 to 12 animals. Each pen was randomly assigned to one of the two experiment groups Early 2 (E2) and Late 10 (L10) groups, characterized by the different methods of detection of BRD and 1st line treatment regimen. Follow-up of the YBs started on the first day on feed and lasted 30 days.

BRD detection and inclusion criteria

In the L10 group, detection of BRD in YBs was only based on visual inspection of undisturbed animals followed by clinical examination in case of discomfort signs. A validated grid developed to perform visual inspection was used. Briefly, a YB presenting clinical signs of BRD after a veterinary physical examination, such as moderate or severe signs of depression, nasal discharge, cough, and increased respiratory efforts at visual inspection, was considered as late detected if also presenting a rectal temperature ≥ 39.7°C, and included in the study.

In the E2 group, BRD detection was based on the combination of ruminal temperature continuous monitoring and veterinary clinical examination. Ruminal temperatures of YBs were recorded during 30 days after the arrival at the farm, as described by Timsit et al. (2011a). Briefly, the rumen temperature was recorded every 5 minutes by the temperature bolus. Data extracted were analyzed by the program provided by the manufacturer, and finally represented graphically by a curve showing ruminal temperature as a function of time. The curves were observed three times daily by a veterinarian. If an increase of ruminal temperature over a threshold of 40.2°C and persisting more than 12h was observed, a clinical examination of the suspected animal was performed within 12h. Upon examination, YBs with a rectal temperature ≥ 39.7°C and no or mild clinical signs of BRD (normal demeanor; respiratory rate <60; heart rate <100, no or mild nasal discharge; normal respiration; normal or slightly decreased appetite) were considered as early detected and included. A YB with a rectal temperature < 39.7°C at the time of examination was considered as not detected.

Young bulls presenting clinical signs differing from respiratory disease signs (e.g. lameness, diarrhea) were excluded from the study.

Clinical follow up

In case of detection of disease, rectal temperature of the YB was recorded and a complete clinical examination was performed at the time of 1st line treatment (day 0) and at d1, 2, 3, 7, 10, and 21 after treatment. Young bulls were monitored using a scoring system adapted from (Dowling et al., 2002). The Clinical Score (CS) was calculated daily for each YB.

At d1, 2, and 3, YBs presenting an increase of their CS compared to d0 or an increase >0.5°C of their rectal temperature measured at d0 were given a relapse treatment. From d4 to the end of the study, a YB already treated and presenting moderate to severe clinical signs of BRD was also given a relapse treatment. If no clinical improvement was observed 2 days after the administration of the relapse treatment, a 3rd treatment was given to the YB.

Antimicrobial treatments

Prophylactic antimicrobial treatments

In herds A, B, and C, a prophylactic intramuscular treatment of 4 mg/kg body weight tildipirosin was administered at the auction market place before entering the farm. In herds D, E, and F, no prophylactic treatment was implemented.

1st line treatments

In the L10 group, animals identified after clinical examination as late detected were immediately given a single intramuscular dose of 10 mg/kg marbofloxacin (Forcyl, Vetoquinol, Lure, France), and a single intramuscular dose of 2 mg/kg tolfenamic acid, a non-steroidal anti-inflammatory drug (NSAID) (Tolfine, Vetoquinol, Lure, France).

In the E2 group, animals identified after clinical examination as early detected were immediately given a single intramuscular dose of 2 mg/kg marbofloxacin (Marbocyl, Vetoquinol, Lure, France), and a single intramuscular dose of 2 mg/kg tolfenamic acid.

Relapse treatments

During the study period, YBs received when needed a relapse treatment. According to the farmers' habits, the relapse treatment was a single subcutaneous injection of 40 mg/kg of florfenicol in herds A, B, and C, and a single subcutaneous injection of 2.5 mg/kg of tulathromycin in herds D, E, and F.

Outcomes

In each fattening unit and each group, the proportions of curative 1st line and relapse treatments were calculated as the number of YBs treated with a 1st line or relapse treatment divided by the number of YBs in the group, and expressed in percentages.

Antimicrobial consumption was calculated using treatment incidences (TI_{UDD}) based on Used Daily Dose per YB (UDD_{YB}) of prophylactic treatment ($UDD_{tildipirosin}$), 1st line treatment ($UDD_{marbofloxacin}$) and relapse treatment ($UDD_{relapse}$ = $UDD_{tulathromycin}$ or $UDD_{florfenicol}$) using the following formula.

$$TI\ UDD = 1000 \frac{amount\ of\ antimicrobial\ x\ used\ (mg)}{\frac{UDDx\ \left(\frac{mg}{kg}\right)}{corrective\ factor\ x} * YBs\ at\ risk * observation\ period\ (d)}$$

UDD was defined as the administered dose per day per kilogram. For marbofloxacin, the retained value of UDDmarbo/YB was 2 mg/kg; for tulathromycin, the value of UDD tula/YB was 2.5 mg/kg; for florfenicol, the value of UDD flor/YB was 40 mg/kg; and for tildipirosin, the value of UDD til/YB was 4 mg/kg. To encounter the long acting formulation of some drugs, a corrective factor, corresponding to the estimated duration of effects (in days), was attributed to each drug, according to references already used by authorities (EMA, 2013).

Results and discussion

Among the 195 young bulls included in the study, one YB presenting severe signs of lameness 3 days after the start of the study, and one YB with abnormal behavior, were excluded. 38 YB were given the early treatment, and 23 were given the late treatment. Figure 1 represents the distribution of the YBs in function of the type of treatment performed and the initial allocation group. Treatments were administered between 2 and 14 days after entering the fattening unit. In E2 groups, the proportion of 1st line treatments and relapse treatments were respectively 45 (± 9) and 37 (± 14) %. In L10 groups, the proportion of 1st line treatments and relapse treatments were respectively 25 (± 25) and 7 (± 8) %. Only 3 YBs from the E2 groups received a 3rd curative treatment. The proportion of 1st line treatments was significantly higher ($P < 0.05$) in E2 groups compared to L10 groups, regardless of the implementation of prophylactic treatment. The proportion of relapse treatments tended to be higher ($P = 0.08$) in E2 groups compared to L10 groups. We observed a strong variability between herds. Overall, herds that did not implement prophylactic antimicrobial treatment had a slightly higher proportion of 1st and relapse treatments compared to those with. One YB of the E2 group from herd A which received a relapse treatment died after the end of the study. Necropsy results reported severe lesions of suppurative cranial bronchopneumonia, caudal emphysema and fibrino-haemorragic pleuritis.

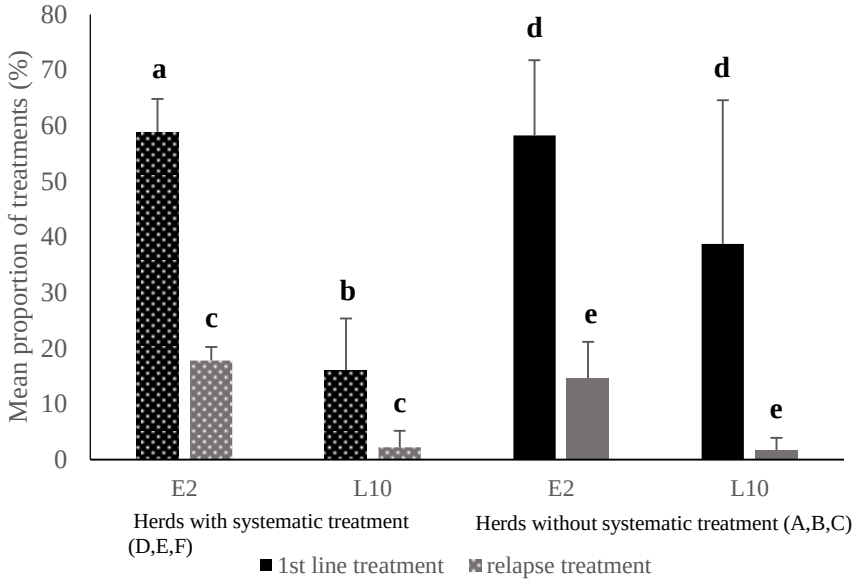


Figure 1: Mean proportion of 1st and relapse treatments in E2 and L10 groups. The proportion (expressed in percentage) of 1st line treatments is calculated as the number of YBs treated with a 1st line treatment in the group / number of YBs in the group. The proportion of relapse treatments is calculated as the number of YBs treated with a relapse treatment in the group / number of YBs in the group. Different letters in superscripts indicate if values are statistically different (P <0.05).

The adjusted marbofloxacin dosage was based upon pharmacokinetic/pharmacodynamic evaluation of antimicrobial efficacy *in vitro* (Valle et al., 2012; Potter et al., 2013) and in a mice model (Lhermie et al., 2015) previously published. This dosage was also successfully tested for the treatment of an experimental lung infection with *Mannheimia haemolytica* in calves (Lhermie et al., 2016). In the present study, at the time of inclusion, mean CS and rectal temperature values were 5.9 and 40.2 °C in the E2 group, and 9.9 and 40.6 °C in the L10 group. In both groups, CS as well as rectal temperature decreased rapidly over time after treatment. 24h after treatment, a significant decrease ($P < 0.05$) in the CS was observed in all groups. (see Figure 2).

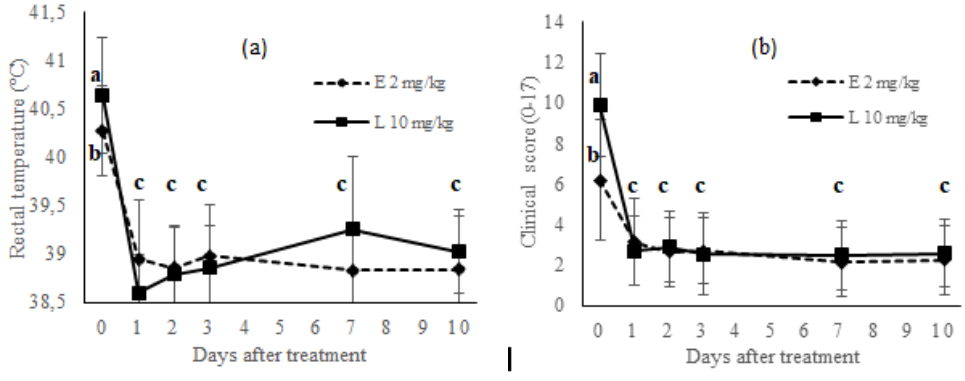


Figure 2: Evolution of rectal temperature (a) and clinical score (b) of YBs treated for BRD with a treatment of 2 or 10 mg/kg of marbofloxacin and with tolfenamic acid. Different letters in superscripts indicate if values are statistically different (P<0.05).

Mean TI_{UDD} marbo per 1000 YB at risk/d was higher in the L10 groups compared to the E2 groups (43 vs 16), In the E2 groups, there were less difference between the TI_{UDD} marbo values between herds than in the L10 groups. Mean TI_{UDD} tula-flor were significantly higher in the E2 group compared to the L10 group (25 vs. 3), (P<0.05). Figure 3 depicts the impact of prophylactic antimicrobial treatment on global antimicrobial consumption. TI_{UDD} of prophylactic treatment represented 90% of the total TI_{UDD} in herds where a prophylactic antimicrobial treatment was implemented. TI_{UDD} marbo and TI_{UDD} tula-flor were higher in herds not implementing prophylactic antimicrobial treatment. We observed that regardless of the initial prophylactic strategy implemented, curative antimicrobial consumption was decreased in E2 groups. Despite a slightly lower number of 1st and relapse treatments, the amount of antimicrobial used for prophylactic treatment represented more than 90% of the total amount of antimicrobials, in herds with prophylactic antimicrobial treatment. This observation suggests that rationalization of prophylactic antimicrobial treatment might significantly reduce global antimicrobial consumption.

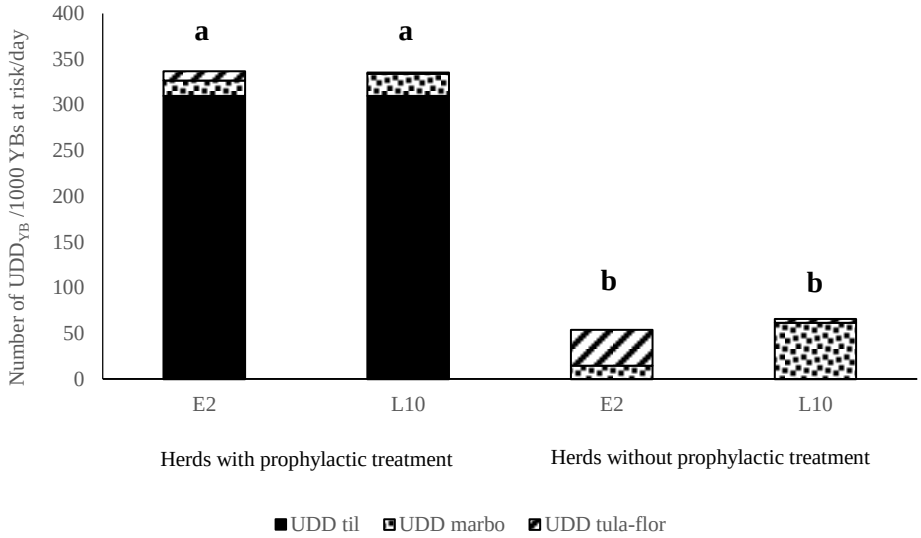


Figure 3: Mean antimicrobial usage (tildipirosin for prophylactic treatment, marbofloxacin as 1st line, tulathromycin or florfenicol as relapse), expressed in TI_{UDD}, according to the prophylactic strategy implemented in the herds (absence or presence), and the therapeutic strategy (E2 or L10). Different letters in superscripts indicate if values are statistically different, (P<0.05).

Various assumptions can be stated to explain the higher proportion of 1st line treatments observed in the E2 groups. In the E2 groups, YB were considered as early detected in our study upon the basis of a first persistent increase in their ruminal temperature above 40.2 °C for more than 12 h, and confirmed by a rectal temperature > 39.7 °C at the time of clinical examination. These thresholds were based on previous field studies in YBs. Timsit et al. (2011b) showed that YBs with a ruminal hyperthermia for more than 6 h and a rectal temperature > 39.7 °C, demonstrated first clinical signs of BRD 19 h after the onset of hyperthermia. The positive predictive value of this method of detection of BRD was 85 %. Two other field studies assessing early detection of BRD on 24 and 133 weaned calves reported predictive positive values of 80 and 75 % of ruminal hyperthermia for detection of BRD (Schaefer et al., 2007; Timsit et al., 2011a). The reticulo-ruminal temperature of 40.2 °C was fixed as a threshold alert value since reticulo-ruminal temperature was found to be well correlated with rectal temperature, with a mean difference of 0.5 °C. The rectal temperature value of 39.7 °C is commonly retained as the threshold value for diagnosis of abnormal temperature in YB (Galyean et al., 1995; Schaefer et al., 2007; Timsit et al., 2011a). It has been shown that clinical signs of BRD were not systematically observed in YBs presenting ruminal hyperthermia (Timsit et al., 2011b). Hence, it is possible that we

included YBs in E2 groups that would not have presented clinical signs, explaining the higher proportion of 1st line treatments in the E2 groups.

Regarding the tendency of increased proportion of relapse treatments in the E2 groups, several hypotheses can be stated. Indeed, in our field conditions study, it was impossible to determine the presence of the pathogen at the infectious site. Therefore, the decreased antimicrobial regimen could have been administered too early or too late with regards to pathogen identification and inoculum size. Influence of bacterial inoculum size on bactericidal activity of marbofloxacin has been demonstrated in several in vitro and in vivo studies, supporting the decrease dosage in the tested regimen (Ferran et al., 2011; Lhermie et al., 2015). However, in all these studies, the pathogen species and inoculum size at the time of treatment were known, but not in our field study. As hyperthermia and clinical signs monitored are not pathognomonic of bacterial pneumonia, it is possible that some YBs included presented a viral infection. However, bacteria from the *Pasteurellaceae* family (*M. haemolytica*, *Pasteurella. multocida* and *Histophilus somni*) are most frequently identified as pathogen agent of BRD in YB in France (Assié et al., 2009) and North America (Confer, 2009; Rice et al., 2007). It is also possible that our inclusion criteria partially failed to detect accurately early stage of BRD. Therefore, the decreased marbofloxacin dose could have been administered too early or too late with regards to pathogen identification and inoculum size. This could also explain the higher proportion of relapse treatments required in the E2 group. Our results suggest, at least, that improvement of BRD diagnosis, may lead to a decrease in antimicrobial consumption and avoid their misuse. As reported in a review (Taylor et al., 2010), our observations encourage development of additional tests at the animals' side.

Conclusions

Our data show that the combination of early detection of BRD treated with a lower marbofloxacin dose could be used to decrease antimicrobial consumption at the herd level without affecting treatment efficacy. However, to improve the efficiency of such protocol, increasing the accuracy of detection of diseased animals must be fulfilled. These findings illustrate a promising alternative to rationalize AMU in field conditions, limit the overall consumption of antimicrobials and their shedding in the environment.

Acknowledgements

The authors thank staff from the veterinary school of Nantes and Cornell University: Jean-Yves Audiart, Emmanuelle Blandin, Françoise Leray, Nadine Ravinet for technical assistance, Julia Hertl for English revision and Anne Lehebel for performing statistical analysis. They also thank the producers and the veterinarians for their help.

References

Aarestrup, F. 2012. Sustainable farming: Get pigs off antibiotics. *Nature* 486, 465–466. doi:10.1038/486465a.

Assié, S., Seegers, H., Makoschey, B., Desire-Bousquie, L., and Bareille, N. 2009. Exposure to pathogens and incidence of respiratory disease in young bulls on their arrival at fattening operations in France. *Vet. Rec.* 165, 195–199. doi:10.1136/vr.165.7.195.

Confer, A. W. 2009. Update on bacterial pathogenesis in BRD. *Anim. Heal. Res. Rev.* 10, 145–148. doi:10.1017/S1466252309990193.

Dowling, A., Hodgson, J. C., Schock, A., Donachie, W., Eckersall, P. D., and Mckendrick, I. J. 2002. Experimental induction of pneumonic pasteurellosis in calves by intratracheal infection with Pasteurella multocida biotype A:3. *Res. Vet. Sci.* 73, 37–44. doi:10.1016/S0034-5288(02)00037-1.

EMA. 2013. Revised ESVAC reflection paper on collecting data on consumption of antimicrobial agents per animal species, on technical units of measurement and indicators for reporting consumption of antimicrobial agents in animals. *EMA/286416/2012-Rev.1* 44, 1–29.

Ferran, A. A., Toutain, P. L., and Bousquet-Mélou, A. 2011. Impact of early versus later fluoroquinolone treatment on the clinical; microbiological and resistance outcomes in a mouse-lung model of *Pasteurella multocida* infection. *Vet. Microbiol.* 148, 292–297. doi:10.1016/j.vetmic.2010.09.005.

Fulton, R. W. 2009. Bovine respiratory disease research (1983-2009). *Anim. Heal. Res. Rev.* 10, 131–139.

Galyean, M.L., S. A. Gunter, and K. J. Malcolm-Callis. 1992. Effects of Arrival Medication Programs on Health and Performance of Newly Received Beef Steers. *J Anim Sci*. 73: 1219-1226.

Kesteman, A. S., Ferran, A. A., Perrin-Guyomard, A., Laurentie, M., Sanders, P., Toutain, P. L., et al. 2009. Influence of inoculum size and marbofloxacin plasma exposure on the amplification of resistant subpopulations of *Klebsiella pneumoniae* in a rat lung infection model. *Antimicrob. Agents Chemother.* 53, 4740–4748. doi:10.1128/AAC.00608-09.

Lhermie, G., El Garch, F., Toutain, P. L., Ferran, A. A., and Bousquet-Mélou, A. 2015. Bacterial species-specific activity of a fluoroquinolone against two closely related pasteurellaceae with similar mics: Differential In Vitro inoculum effects and In Vivo efficacies. *PLoS One* 10, 1–12. doi:10.1371/journal.pone.0141441.

Lhermie, G., Ferran, A. A., Assie, S., Cassard, H., El Garch, F., Schneider, M., et al. 2016. Impact of timing and dosage of a fluoroquinolone treatment on the microbiological, pathological, and clinical outcomes of calves challenged with *Mannheimia haemolytica*. *Front. Microbiol.* 7, 1–13. doi:10.3389/fmicb.2016.00237.

Mcewen, S. A., and Fedorka, P. J. 2002. Antimicrobial Use and Resistance in Animals. *Clin. Infect. Dis.* 34, 93–106. doi:10.1086/340246.

Potter, T., J. Illambas, L. Pelligand, A. Rycroft, and P. Lees. 2013. Pharmacokinetic and pharmacodynamic integration and modelling of marbofloxacin in calves for *Mannheimia haemolytica* and *Pasteurella multocida*. *Vet J*. 195: 53-58. doi: 10.1016/j.tvjl.2012.08.027

Rice, J. A., Carrasco-Medina, L., Hodgins, D. C., and Shewen, P. E. 2007. Mannheimia haemolytica and bovine respiratory disease. *Anim. Heal. Res. Rev.* 8, 117–128. doi:10.1017/S1466252307001375.

Schaefer, A. L., Cook, N. J., Church, J. S., Basarab, J., Perry, B., Miller, C., et al. 2007. The use of infrared thermography as an early indicator of bovine respiratory disease complex in calves. *Res. Vet. Sci.* 83, 376–384. doi:10.1016/j.rvsc.2007.01.008.

Taylor, J.D., R. W. Fulton, T. W. Lehenbauer, D. L. Step, and A. W. Confer. 2010. The epidemiology of bovine respiratory disease: what is the evidence for preventive measures? *Can Vet J*. 51: 1351-1359.

Timsit, E., Assié, S., Quiniou, R., Seegers, H., and Bareille, N. 2011a. Early detection of bovine respiratory disease in young bulls using reticulo-rumen temperature boluses. *Vet. J.* 190, 136–142. doi:10.1016/j.tvjl.2010.09.012.

Timsit, E., Bareille, N., Seegers, H., Lehebel, A., and Assié, S. 2011b. Visually undetected fever episodes in newly received beef bulls at a fattening operation: Occurrence, duration, and impact on performance. *J. Anim. Sci.* 89, 4272–4280. doi:10.2527/jas.2011-3892.

Vallé, M., Schneider, M., Galland, D., Giboin, H., and Woehrlé, F. 2012. Pharmacokinetic and pharmacodynamic testing of marbofloxacin administered as a single injection for the treatment of bovine respiratory disease. *J. Vet. Pharmacol. Ther.* 35, 519–528. doi:10.1111/j.1365-2885.2011.01350.x.

Early detection of ketosis monitoring cow's behavioural activities and milk yield

A. Peña Fernández[1], T. Norton[1], K. H. Sloth[2], S. Klimpel[3], D. Berckmans[1]
[1]*Department of Biosystems, Animal and Human Health Engineering Division, M3-BIORES Laboratory, KU Leuven, Kasteelpark Arenberg 30, 3001 Heverlee, Belgium.*
[2]*GEA Farm Technologies GmbH, Nørskovvej 1B, DK-8660 Skanderborg, Denmark*
[3]*GEA Farm Technologies GmbH, Siemensstrasse 25-27, D-59199 Bönen, Germany*
Daniel.Berckmans@kuleuven.be

Abstract

Cow's health status has an impact in the behavioural activities and milk production of dairy cows. This study shows the potential of using real-time monitoring of behavioural activities and milk yield production to get an early detection of a ketosis health event in individual dairy cows. The study was carried out on a commercial dairy farm, with approximately 280 lactating cows and equipped with milking robots. The CowView Real-Time-Location-System (GEA®) provides several behavioural activities in the form of the time spent performing each of them along with total distance travelled by each cow. Daily averages for a complete lactation period of the total distance walked by a cow, the time spent in the cubicles and at the feeding area were selected as behavioural activities to combine with the daily milk yield. An algorithm was developed to monitor the dynamics present in the time-series evolution of the behavioural activities and the milk yield from each individual cow. By monitoring sudden changes in the dynamic trends of the variables it was possible to detect a ketosis health event on average three days before it was diagnosed by the farmer. This technique worked in 72 % of the cows suffering from ketosis during the lactation period monitored. The continuous monitoring of these variables during a lactation period can provide farmers with a tool to assess the health status of each individual cow in their herds.

Keywords: cows, behaviour, milk yield, ketosis, precision livestock farming

Introduction

Cow's health status has an impact in the behavior and productivity of dairy cows. Health problems result in animal welfare reduction, production losses and

treatment costs, especially in the early lactation stage (Ingvartsen, 2006). Metabolic and digestive disorders impair cow's welfare and reduce farm profitability causing losses in milk production (Edwards and Tozer, 2004). Clinical ketosis is a health disorder in which cows show inappetence and depression along with elevated levels of ketone bodies, such as acetone, acetoacetate and BHB which can be found in body fluids. Some cows also show signs of nervous dysfunction, abnormal licking and aggression. Besides the clinical form, cows can suffer from subclinical ketosis or hyperketonemia, in which they show high blood concentration of ketone bodies but without the signs accompanying clinical ketosis (Enjalbert et al. 2001). Metabolic diseases usually happen in transition cows and early lactation, within the first 30 days in milk, due to the inability of the cows to cope with a negative energy balance to meet lactation demands (Rajala-Schultz et al., 1999; Ingvartsen, 2006; De Vries et al. 2010). Ketosis is associated with many transition cows' diseases and its subclinical form has been found to be a common condition in high production dairy cows. Between 30-50 % of cows develop a metabolic or infectious disease at the moment of calving and relations between subclinical or clinical ketosis and fresh cows diseases have been described (Berge and Vertenten, 2014).

The presence of diseases has an impact in cow's behavior. Sick animals become less active to conserve energy to recover themselves (Dantzer and Kelly, 2007). It has been reported that subclinical and clinical ketosis have an impact in cow's activity, for instance, cows suffering from ketosis showed a higher average activity 8 days before (Edwards and Tozer, 2004; Weary et al., 2009), a rapidly decay in feeding behaviour from 3 to 6 days before farm staff diagnosed the cow (Gonzalez et al., 2008; Goldhawk et al., 2009) and increasing standing time in the week before calving (Itle et al., 2015). Rajala-Schultz et al. (1999) showed that milk yield started to decrease between 2-4 weeks before the diagnosis of ketosis and kept decreasing for a varying period of time after it, depending especially on parity. Ospina et al. (2014) showed that hyperketonemia negatively affects milk yield. Rutherford et al. (2016) has determined that subclinical ketosis at estrus reduces both, activity, although this effect start to diminish as the cow goes further in lactation, and reproductive performance, which seems to be a more long-lasting effect.

The presence of health disorders in the dairy herds have increased, probably, due to an increase in milk yield and production stress (Fleischer et al., 2001). Besides, the management action of looking for sick cows can disturb other cow's behavioural routine and performance. Moreover, it is a time consuming process for the farmer (Steensels et al., 2016). Precision Livestock Farming (PLF) technologies can help farmers in their daily monitoring of their herd in an automated and non-invasive way. Nowadays, Real-Time-Positioning-Systems (RTLS) allow quantifying cows' location in the barn at all times (Tullo et al.,

2016). It is possible to use this information to develop detailed individual cow time budgets for each activity performed by the cows (Sloth et al., 2015). There are also several examples in literature in which systems to detect disease outbreaks in cows has been proposed. Steensels et al. (2016) proposed a decision-tree model to detect post-calving diseases based on rumination, activity, milk yield, body weight and voluntary visits to the milking robot. There are several approaches in which rumination and cow activities (Kayano and Kataoka, 2015) or milk yield and compositions (Stangaferro et al., 2016) are monitored in order to detect diseases. Mastitis and lameness are considered to be the most relevant diseases in dairy cows in terms of economic impact (Kossaibati and Esslemont, 1997). Metabolic diseases as ketosis produce moderate to large reductions in milk yield and feed intake over a short time (Rajala-Schultz et al., 1999). The prevalence in Europe for subclinical ketosis is 25% and its mean total cost per cow was estimated to be 257 Euros. When an early treatment is supplied to the cow, this is more effective and saves costs and time for the farmer (Raboisson et al., 2015).

Thus, the aim of this work is to develop an algorithm to monitor cow's activities, such as, distance walked and time at the feeding table or in the cubicles, as well as milk yield, in order to perform an early detection system for upcoming ketosis events.

Materials and methods

The data for this study was collected from December 2014 until December 2015, within the EU-PLF project (http://www.eu-plf.eu/), in a commercial dairy farm with approximately 280 lactating cows and equipped with milking robots. The barn is a loose housing system with cubicles with one milking-feeding group. The automatic milking system was a 5-box MiOne robot (GEA Farm Technologies GmbH, Bönen, Germany). The farmer also had the CowView Real-Time-Location-System (GEA®) (http://www.gea-farmtechnologies.com/hq/en/mediacenter/news/2012/dlgcowview.aspx) installed. This system is a real time positioning system for localising dairy cows indoors, with a precision of 50 cm, and for analysing animal behaviour based on their position. The position of the cow is allocated according to the topology of the barn and its activity is determined according to its location and its movements. The datasets consisted of hourly accumulated activities as determined by the CowView system, milk yield recordings and all events recorded by the farmer (interventions on the herd, oestrus, lameness, mastitis, accident, calving, respiratory problem, diarrhoea…).

For this study, data from a subsample of 55 cows showing metabolic disorders was selected. Daily values for a complete lactation period of the total distance

walked (DD), the times spent in the cubicles (DBD) and at the feeding area (DFD) for each individual cow were selected as behavioural activities to combine with the daily milk yield (MY). From the 55 cows, 35 showed reliable data (enough lactation time and with no gaps of missing data) to perform the analysis.

The time evolution of the behaviours studied and the milk yield were analysed by means of the Dynamic Auto-Regression (DAR) approach. This was performed using MATLAB® (The Mathworks, Inc) Software and the CAPTAIN Toolbox (Taylor et al. 2007). The basic DAR model is a simplification of the general transfer function model, in which the input variables are defined as past values of the output series. More formally, a DAR model may be formulated as:

$$y_t = \frac{1}{A(z^{-1})} e_t \qquad (1)$$

in which $A(z^{-1}, t) = 1 + a_{1,t}z^{-1} + a_{2,t}z^{-2} + \cdots + a_{n_a,t}z^{-n_a}$ is a time-variant parameter polynomial in the backward shift operator z^{-1}. On multiplying throughout by $A(z^{-1}, t)$, so that it operates on y_t , it is possible to obtain the DAR model in the discrete-time equation form:

$$y_t = -a_{1,t}y_{t-1} - a_{2,t}y_{t-2} - \cdots - a_{n_a,t}y_{t-n_a} + e_t \qquad (2)$$

In other words, y_t is dependent on past values of itself plus a random component in the form of white noise e_t.

Results and discussion

The main goal of this work was to check the ability of developing a DAR model which allows monitoring each individual variable gathered at the farm in real-time. The model allows forecasting the level expected the following day for a specific variable. Thus, deviations between the predicted and measured levels can be determined. In order to develop such a data-based model for each variable, the Dynamic Auto-Regression approach was tested in daily measurements of Milk Yield (MY), Daily Feed Duration (DFD), Daily Bed Duration (DBD) and Daily Distance (DD) data from 55 cows. Firstly, the model order needed to get reliable predictions from the model was evaluated. In order to do this, cows were grouped by lactation, to evaluate possible changes in the auto-regression order due to this factor. The results are displayed in Table 1.

Table 1. Auto-Regression (AR) orders of the DAR modelling approach for each one of the variables under study, Milk Yield (MY), Daily Feed Duration (DFD), Daily Bed Duration (DBD) and Daily Distance (DD).

Lactation	AR order MY	AR Order DFD	AR order DBD	AR order DD
1	5	6	5	5
2	5	5	5	5
3	5	5	5	4
4	4	5	4	4

It can be seen that at least 5-6 days are needed to develop the DAR model. Thus, it was decided to start with the monitoring after a week of data was gathered for each cow. Figures from 1 to 4 show an example of how the data gathered for DBD, DD, DFD and MY and the model performance for an individual cow look like before and after a recorded ketosis event. The monitoring of each individual variable with the DAR model leads to a performance of the algorithm in detecting in advance ketosis events of 60%. A deviation between the model output and the data collected raised an alert when it was higher than 2σ (2 standard deviations).

In this example, three out of the four variables monitored showed a deviation from the normal time evolution of the variable some days prior to the health event was recorded by the farm staff. On average, the deviations began (3 ± 1) (mean ± std) days in advance to the health event was noticed in the farm. Especially clear are the deviations in the time spent at the feeding table and the time spent in the cubicles. The rapid decay in the time spend at the feeding table was found in 80% of the cows in which the ketosis event was detected in advance. This is in accordance with previous studies, showing a rapidly decay in feeding behavior from 3 to 6 days before the cow was diagnosed with ketosis (Gonzalez et al., 2008; Goldhawk et al., 2009).

The deviations in the time spent in the cubicles are less consistent when analyzing together the 60% ketosis events detected by the algorithm. Half the cows showed an increase in the time spent in the cubicles while the other half showed a decrease. There were almost no deviations in the daily distance, although deviation was detected in the few cows due to an increase in the daily distance walked by the cow.

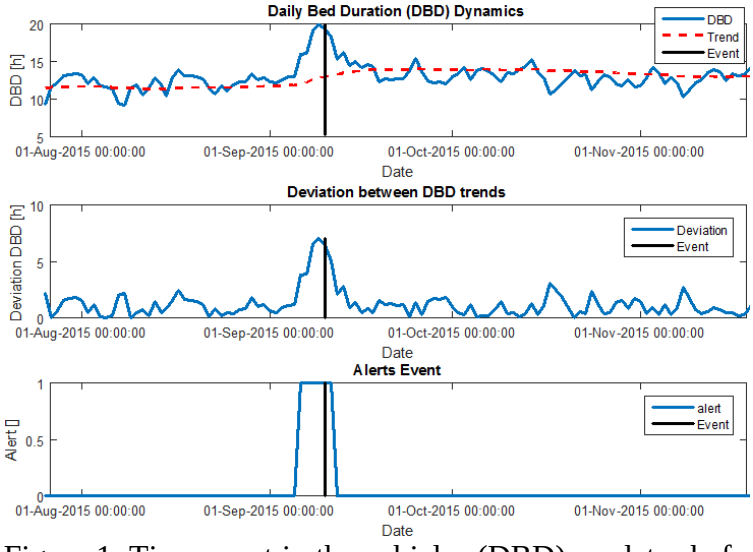


Figure 1. Time spent in the cubicles (DBD) on dates before and after a recorded ketosis health event in a cow. In the upper graph the data gathered for an individual cow (solid line) and the algorithm output (--) are shown. In the middle graph, the absolute difference between the data and the model is shown. In the lower graph the early warnings are shown. In all graphs the vertical lines indicate the recorded health event.

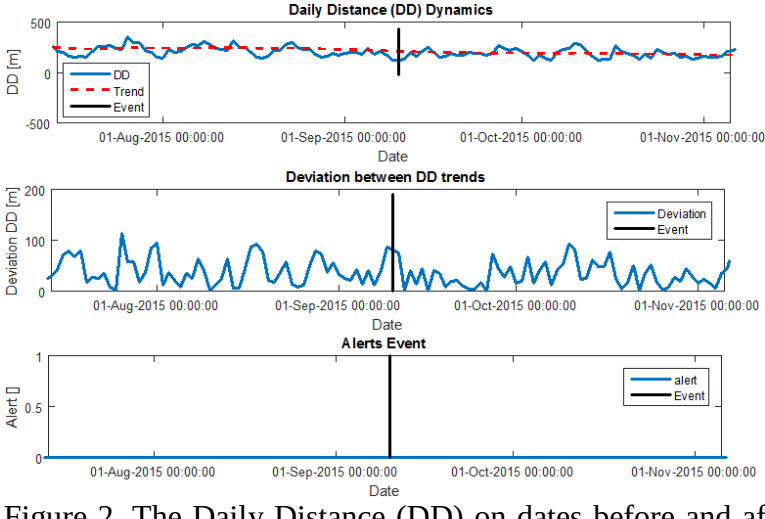


Figure 2. The Daily Distance (DD) on dates before and after a recorded ketosis health event in one cow. In the upper graph the data gathered for an individual cow (solid line) and the algorithm output (--) are shown. In the middle graph, the absolute difference between the data and the model is shown. In the lower graph the early warnings are shown. In all graphs the vertical lines indicate the recorded health event.

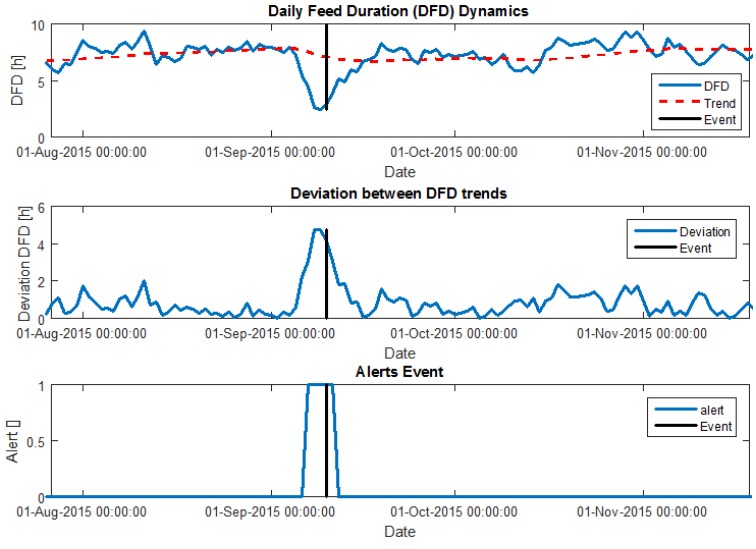


Figure 3. Time spend at the feeding table (DFD) on dates before and after a recorded ketosis health event in one cow. In the upper graph the data gathered for an individual cow (solid line) and the algorithm output (--) are shown. In the middle graph, the absolute difference between the data and the model is shown. In the lower graph the early warnings are shown. In all graphs the vertical lines indicate the recorded health event.

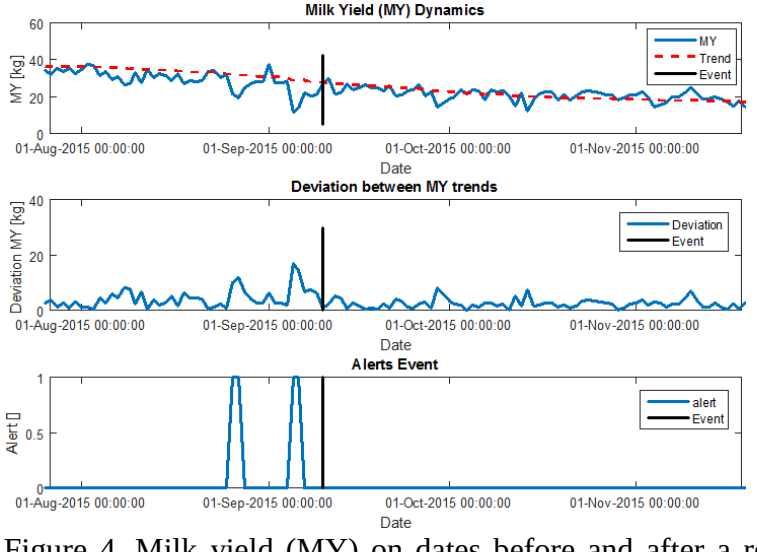


Figure 4. Milk yield (MY) on dates before and after a recorded ketosis health event in one cow. In the upper graph the data gathered for an individual cow (solid line) and the algorithm output (--) are shown. In the middle graph, the absolute difference between the data and the model is shown. In the lower graph the early warnings are shown. In all graphs the vertical lines indicate the recorded health event.

In order to improve the understanding of the model performance a close look to the ketosis events was performed. As described in the introduction, ketosis is a problem that affects cows especially in the early lactation period. From the 35 cows analysed in which a ketosis event was detected in the farm, 24 of them happened at the beginning of the lactation and 11 at a later stage.

Analysing the events happening at a later stage independently, the model performance for ketosis event detection raises to 72%. In all the events detected there is a drop in the daily time spent at the feeding table and a raise in the time spent in the cubicles. This raise in the time spend in the cubicles is consistent with the fact that cows suffering from a disease will rest more to save energy and help themselves to heal faster (Dantzer and Kelly, 2007).

The events detected in early lactation showed more variability. The model performance regarding the ketosis events detection dropped to only 54%. In the events detected, there was mainly a drop in the time spent at the feeding table, being consistent with the previous results. In 60% of the detected cases, there was a drop in the time spent in the cubicles and an increase in the daily distance. This is in accordance with the studies in which it was found that the average activity increased before a health event and increased standing time in the week before calving (Edwards and Tozer, 2004; Weary et al., 2009; Itle et al., 2015). The decrease in the algorithm's performance can be explained by the fact that in early lactation the transition cow's behavior is still adapting to the coming back to the lactation group from the dry period. This makes it harder for the model to define the normal behavior during the lactation period and discriminate between normal changes in behavior due to this change in environment and a deviation leading to the outbreak of a disease.

Finally, the deviations observed in milk yield are consistent with previous studies in which it was stated that milk yield started to decrease between 2-4 weeks before the diagnosis of ketosis and kept decreasing for a varying period of time after it (Rajala-Schultz et al., 1999).

Conclusion

The aim of this study was to develop an algorithm to monitor individual dairy cows' behaviour in real-time and link deviations between the gathered data at the farm and the model predictions to upcoming ketosis events.

Daily values for a complete lactation period of the total distance walked (DD), the times spent in the cubicles (DBD) and at the feeding table (DFD) by a dairy cow were selected as behavioural activities to combine with the daily milk yield (MY). A Dynamic Auto-Regression model was developed to monitor each one of these variables in real-time and forecast the level expected for that variable the next day. Deviations between these predictions and the data gathered at the farm

for each day were translated into alerts for an upcoming ketosis event when they were higher than 2σ. A total of 35 dairy cows showing a ketosis event during the lactation period were used in this study.

Taking all these cows into consideration, the model's performance to detect an upcoming health event was 60%, detecting them, on average, 3 days prior being noticed and logged by the farm staff. When the events are split in events at the beginning of the lactation period or at a later stage, the performance of the modelling approach was 54% and 72%, respectively. In an early stage cow's behaviour is still adapting to the change from the dry period to the new lactation, which makes it harder for the model to detect deviations due to health changes reliable.

An analysis of the deviations showed a consistent rapid decay in the time spent at the feeder by the cow in 80% of the events detected and a drop in milk yield. On the other hand, deviations in the time spent in the cubicles and the daily distance are less consistent. For the events detected at a later lactation stage, half of the cows showed an increase in the time spent in the cubicles, while the other half of the cows showed a decrease. The deviations in the daily distance were not significant to raise an alert in most cases. For the events detected at the beginning of the lactation, the deviations were more consistent, exhibiting a drop of the daily bed duration and an increase in the daily distance walked by the cow.

These results show the potential of monitoring cow's behaviour to detect upcoming disease problems. This may provide farmers with a tool to assess the health status of each individual cow in their herds.

These results should be taken as preliminary due to the small sample size of events analysed. More events are needed to validate these results and specially being able to discriminate between normal behavioural changes in the cows or deviations due to upcoming health events for transition dairy cows at the beginning of the lactation.

Acknowledgments

This project has received funding from the European Union's Seventh Programme for Research, Technological Development and Demonstration under Grant Agreement No 311825.

References

Berge, A. C., Vertenten, G. (2014). A field study to determine prevalence, dairy herd management systems and fresh cow clinical conditions associated with ketosis in western European dairy herds. *J. Dairy Sci.* 97, 2145–2154.

Dantzer, R., Kelley, K. W. (2007). Twenty years of research on cytokine-induced sickness behavior. *Brain Behav. Immun.* 21, 153–160. http://dx.doi.org/10.1016/j.bbi.2006.09.006.

De Vries, A., Olson, J. D., Pinedo, P. J. (2010). Reproductive risk factors for culling and productive life in large dairy herds in the eastern United States between 2001 and 2006. *J. Dairy Sci.* 93, 613–623.

Edwards, J. L., Tozer, P. R. (2004). Using activity and milk yield as predictors of fresh cow disorders. *Journal of Dairy Science*, *87*(2), 524–531. https://doi.org/10.3168/jds.S0022-0302(04)73192-6

Enjalbert, F., Nicot, M. C., Bayourthe, C., Moncoulon, R. (2001). Ketone bodies in milk and blood of dairy cows: Relationship between concentrations and utilization for detection of subclinical ketosis. *J. Dairy Sci.* 84, 583–589.

Fleischer, P., Metzner, M. , Beyerbach, M. , Hoedemaker, M., Klee. W. (2001). The relationship between milk yield and the incidence of some diseases in dairy cows. *J. Dairy Sci.*, 84, 2025–2035.

Goldhawk, C., Chapinal, N., Viera, D. M., Weary, D. M., von Keyserlingk, M. A. G. (2009). Prepartum feeding behavior is an early indicator of subclinical ketosis. *J. Dairy Sci.* 92, 4971–4977.

González, L. A., Tolkamp, B. J., Coffey, M. P., Ferret, A., Kyriazakis, I. (2008). Changes in feeding behavior as possible indicators for the automatic monitoring of health disorders in dairy cows. *Journal of Dairy Science*, *91*(3), 1017–28. https://doi.org/10.3168/jds.2007-0530

Ingvartsen, K.L. (2006). Feeding- and management-related diseases in the transition cow – physiological adaptations around calving and strategies to reduce feeding- related diseases. *Animal Feed Science and Technology* 126, 175–213.

Kayano, M., Kataoka, T. (2015). Screening for ketosis using multiple logistic regression based on milk yield and composition. *Journal of Veterinary Medical Science*, *77*(11),

1473–1478. https://doi.org/10.1292/jvms.14-0691 Kossaibati, M. A., Esslemont, R. J. (1997). The costs of production diseases in dairy herds in England. *Vet. J.* 154, 41–51.

Ospina, P. A., Nydam, D. V., Stokol, T., Overton, T. R. (2010). Association between the proportion of sampled transition cows with increased nonesterified fatty acids and β-hydroxybutyrate and disease incidence, pregnancy rate, and milk production at the herd level. *J. Dairy Sci.* 93, 3595–3601.

Raboisson, Mounié, D., Khenifar, M., Maigné, E. (2015). The economic impact of subclinical ketosis at the farm level: Tackling the challenge of over-

estimation due to multiple interactions. *Preventive Veterinary Medicine*, *122*(4), 417–425.https://doi.org/10.1016/j.prevetmed.2015.07.010

Rajala-Schultz, P. J., Gröhn, Y. T., McCulloch, C. E. (1999). Effects of milk fever, ketosis, and lameness on milk yield in dairy cows. *Journal of Dairy Science*, *82*(2), 288–294. https://doi.org/10.3168/jds.S0022-0302(99)75235-5

Rutherford, A. J., Oikonomou, G., Smith, R. F. (2016). The effect of subclinical ketosis on activity at estrus and reproductive performance in dairy cattle. *Journal of Dairy Science*, *99*(6), 4808–4815. https://doi.org/10.3168/jds.2015-10154

Sloth, K. H., Frederiksen, D., Klimpel, S. (2015). Estimated cow time-budgets using a Real Time Location System. Pages 740-748 in: *Proc. Precision Livestock Farming 2015, Posters, 7th European conference on Precision Livestock Farming*, September 15-18 2015, Milan, Italy.

Steensels, M., Antler, A., Bahr, C., Berckmans, D., Maltz, E., Halachmi, I., … Hillerton, J. E.(2016). A decision-tree model to detect post-calving diseases based on rumination, activity, milk yield, BW and voluntary visits to the milking robot. *Animal*, *10*(9), 1493–1500. https://doi.org/10.1017/S1751731116000744

Taylor, C.J., Pedregal, D.J., Young, P.C. and Tych, W. (2007). Environmental Time Series Analysis and Forecasting with the Captain Toolbox. *Environmental Modelling and Software*, 22, 797-814.

Tullo, E., Fontana, I., Gottardo, D., Sloth, K. H. , Guarino, M. (2016). Technical note: Validation of a commercial system for the continuous and automated monitoring of dairy cow activity. *J. Dairy Sci.* 99, 7489-7494.

Weary, D. M., Huzzey, J. M. , von Keyserlingk, M. A. G. (2009). Board-invited review: Using behavior to predict and identify ill health in animals. *J. Anim. Sci.* 87, 770–777. http://dx.doi.org/10.2527/jas.2008-1297.

Session 6

Ruminants and feeding

Effects of forage type and genotype on nutrient digestibility and energy utilisation efficiency in hill ewe lambs

Y.G. Zhao and T. Yan
Agri-Food and Biosciences institute, Hillsborough, BT26 6DR, United Kingdom
Tianhai.Yan@afbini.gov.uk

Abstract

Manipulation of forage type can alter rumen fermentation pattern and consequently influence nutrient degradability and methane (CH_4) emissions of the host animals. This study aimed to investigate how different forages and genotypes affected nutrient digestibility, energy utilisation and CH_4 production in lambs. Thirty-six hill ewe lambs (18 Scottish Blackface and 18 Texel × Scottish Blackface (50:50)) aged 10 months and weighing 37 ± 5.3 kg were offered 2 forages (grass nuts and grass silage) *ad libitum*. Grass nuts were pelleted dry ryegrass. Grass silage was made from the 2nd harvest of perennial ryegrass. The animals were offered experimental diets for 14 d before moving to individual calorimeter chambers for further 4 d with feed intake, faeces and urine outputs and CH_4 emissions measured. Data were analysed in a 2 × 2 factorial arrangement using ANOVA. There were no significant interactions between diets and genotypes on any variable measured. Lambs offered grass nuts had greater intakes of GE, DE and ME and energy outputs in faeces and CH_4, however lower DM, OM, NDF, ADF and energy digestibility and CH_4 energy output as a proportion of GE intake than those given grass silage ($P < 0.05$). Forages had no effect on nitrogen digestibility, urine energy output and ME/GE. No effect of genotypes was found on nutrient digestibility, energy utilisation or CH_4 emissions. Lambs offered grass nuts had lower CH_4 emission rate, leading to a higher ME/DE ratio than those given grass silage ($P < 0.001$).

Keywords: digestibility; energy utilisation; ewe lambs; grass nuts; grass silage; methane

Introduction

Methane (CH_4) is produced in ruminants as an unavoidable by-product of enteric fermentation, a digestive process by which nutrients are broken down by micro-organisms into simple molecules for absorption into the bloodstream in the rumen. Methane emissions from ruminant production systems are a major contributor to atmospheric greenhouse gas accumulation. The Tier 1 default emission factor of Intergovernmental Panel on Climate Change (IPCC, 2006) is used in the UK to estimate enteric CH_4 production for sheep with no consideration of effects of animal

and dietary factors (Brown et al., 2016). This may cause errors when developing national CH_4 emission inventories and mitigation strategies. For example, CH_4 emission factor for lowland sheep is also applied to hill sheep, despite their relatively smaller body size and different diet and behaviour, possibly resulting in an error of total CH_4 emissions. Therefore, emission factors specific to the representative breeds and forage types employed in the hill sheep sector are required to be quantified.

In addition, CH_4 energy loss from enteric fermentation accounts for 6.5% of total energy intake in sheep (IPCC, 2006). Accurate information of CH_4 emissions can thus help sheep producers identify management practices that increase energy utilisation efficiency and reduce environmental footprint, being of both environmental and economic interest. However, little information is available on CH_4 production in hill ewe lambs. Therefore, the objectives of the current study were to address the knowledge gap by investigating the effects of forage types (grass nuts vs. grass silage) and genotypes (Scottish Blackface vs. Texel × Scottish Blackface) on enteric CH_4 emissions and energy utilisation efficiency in hill ewe lambs.

Material and methods

The present study was conducted under the regulations of Department of Health, Social Services and Public Safety of Northern Ireland in accordance with the Animals (Scientific Procedures) Act 1986 (Home Office, 1986).

Animals, Experimental Design and Diets

Thirty-six hill ewe lambs (18 pure Scottish Blackface and 18 Texel × Scottish Blackface (50:50)) aged 10 months and weighing 37 ± 5.3 kg were allocated to 2 forage treatments balanced for genotype and live weight (LW). Each genotype was offered 2 forages (grass nuts and grass silage) *ad libitum* with 9 lambs for each of the 4 genotype × diet combination treatments. Grass nuts were pelleted dry ryegrass sourced from a commercial supplier (Drygrass South Western Ltd, Burrington, UK). Grass silage was made from the 2nd harvest of perennial ryegrass. The sheep were individually housed in pens in sequence with 6 sheep for each group in 6 groups according to their schedule in 6 respiration chambers and offered experimental diets for 14 d before being transferred to individual chambers for 4 d with feed intake, faeces and urine outputs, and CH_4 emissions measured. The sheep were housed in metabolic crates which were individually placed in each chamber with one sheep per chamber. Each crate contained a feed bin, drinking water container and separate trays to collect faeces and urine. The chambers were opened once daily at 0930 h to deliver diets and water and collect faeces and urine. The amount of forages offered

was adjusted based on average feed intake of the previous 2 d to ensure a 10% refusal. The chemical composition of the 2 forages is shown in Table 1. The measurements of chemical composition of forages, faeces and urine and CH_4 emissions using sheep respiration chambers were as described by Zhao et al. (2016).

Table 1. Chemical composition of the grass nuts and grass silage

Chemical composition	Grass nuts	Grass silage
DM (% as fed)	903	267
Ash (%, DM)	67	82
CP (%, DM)	164	101
NDF (%, DM)	590	597
GE (MJ/kg DM)	19.0	19.1
ME (MJ/kg DM)	10.9	11.2

Statistical Analyses

Data were analysed as a completely randomised design with a 2 (diet) × 2 (genotype) factorial arrangement of treatments using ANOVA for evaluation of the effects of forage type and genotype on feed intake, nutrient apparent digestibility and energy utilisation efficiency, with initial LW as a covariate. The statistical program used in the present study was Genstat statistical package (16th edition; Lawes Agricultural Trust, Rothamsted, UK) and the differences between treatment means were declared significant if $P \leq 0.05$.

Results and Discussion

Animal Performance and Nutrient Digestibility

The effects of forage type and animal genotype on dry matter intake (DMI) and nutrient digestibility are presented in Table 2. Lambs offered grass nuts had greater DMI and consequently greater LW, however less DM, organic matter (OM), digestible OM in DM (DOMD), neutral detergent fibre (NDF) and acid detergent fibre (ADF) digestibility than those given grass silage ($P < 0.05$). It is generally considered that intake is restricted by the capacity of the rumen, and that stretch and tension receptors in the rumen wall signal the degree of fill to the brain (McDonald et al., 2002). A voluminous, bulky feed, such as the grass silage in the current study would have filled the rumen to a greater degree than grass nuts and thus reduced the intake. However, increasing feed intake usually increases fractional passage rate in the rumen and therefore decreases nutrient digestibility because the rumen microorganisms have less time available to ferment the feedstuff. In the present study, grass nuts doubled DMI and reduced digestibility of the nutrients by a range from 5% - 14% when compared with grass silage. Therefore, the dietary factor such

as reducing grass density by pelleting can increase DMI of hill sheep, however high DMI can suppress digestibility on the other hand. There were no significant differences between the two genotypes of sheep on any variable of feed intake, LW or digestibility.

Table 2. Animal live weight, DM intake and nutrient digestibility (n = 36)

Item	Forage					Genotype			
	Grass Nuts	Grass Silage	s.e.	*P*		BF	T × BF	s.e.	*P*
DM intake (kg/d)	1.02	0.45	0.046	<0.001		0.79	0.69	0.058	0.237
Live weight (kg)	40.9	35.5	0.45	<0.001		37.7	38.7	0.570	0.225
Nutrient digestibility (kg/kg)									
DM	0.657	0.711	0.0173	0.032		0.665	0.702	0.0219	0.239
OM	0.674	0.734	0.0165	0.013		0.687	0.720	0.0209	0.268
DOMD	0.629	0.674	0.0155	0.044		0.638	0.665	0.0196	0.330
NDF	0.652	0.739	0.0181	0.002		0.673	0.718	0.0229	0.177
ADF	0.626	0.770	0.0184	<0.001		0.680	0.715	0.0233	0.297
Nitrogen	0.550	0.556	0.0238	0.833		0.535	0.570	0.0301	0.413

BF = Blackface; T × BF = Texel × Blackface

Energy utilisation efficiency and CH_4 emissions

The effects of forage type and animal genotype on energy utilisation efficiency and CH_4 emissions are presented in Table 3. Lambs offered grass nuts had greater gross energy (GE), digestible energy (DE) and metabolisable energy (ME) intakes and faecal energy output, however, less energy digestibility than those given grass silage ($P < 0.001$). Grass nuts produced more CH_4 emissions as MJ per day, however less CH_4 energy as a proportion of GE, DE and ME intake than grass silage, respectively ($P < 0.01$). Dry matter intake is a key driver of CH_4 emissions from animals and there is a positive relationship between CH_4 production and DMI (Ellis et al., 2007). Feeding grass nuts, rather than grass silage, increased feed intake and thus produced more CH_4 emissions (MJ/d). Meanwhile, increasing feed intake can reduce CH_4 emission rates (Zhao et al., 2016). Therefore, CH_4 production per MJ GE, DE and ME intake of sheep offered grass nuts were less than those given grass silage. Although there was no difference between the two forages on the ratio of ME/GE, the ratio of ME/DE was greater for grass nuts than grass silage ($P < 0.001$). This is possibly because grass nuts produced lower proportional CH_4 energy in DE ($P < 0.001$) and there was no significant difference on urine energy output between the two forages.

The CH_4 convention factors (CH_4-E/GE) for grass nuts (4.4%) in the current study was less than the recommendation (6.5%) of IPCC (2006). The use of the fixed value of IPCC (2006) to calculate CH_4 emissions does not take account of the effects

of dietary factors, such as the forage chemical composition and the depression in digestibility with increasing levels of feed consumption. The findings of the present study suggest that the default CH_4 convention factor of IPCC (2006) may overestimate the CH_4 production in the hill ewe lambs when offered grass nuts. Although there was no difference in CH_4 production between the two genotypes of hill ewes in the current study, CH_4 emission rate was reported to be linked to differential gene expression in the sheep rumen microbiome (Shi et al., 2014). Thus, the effect of genotype on CH_4 emissions and CH_4 mitigation strategies at the levels of microbiota composition require further investigation.

Table 3. Energy intake, outputs and utilisation efficiency (n =36)

Item	Forage				Genotype			
	Grass Nuts	Grass Silage	s.e.	*P*	BF	T × BF	s.e.	*P*
Energy intake and outputs (MJ/d)								
GE intake	19.4	8.5	0.87	<0.001	14.8	13.1	1.11	0.293
DE intake	12.3	5.9	0.62	<0.001	9.7	8.5	0.78	0.260
ME intake	11.1	5.1	0.60	<0.001	8.7	7.5	0.76	0.268
Faecal energy	7.1	2.6	0.42	<0.001	5.0	4.6	0.53	0.595
Urinary energy	0.32	0.27	0.019	0.078	0.29	0.29	0.024	0.962
Methane energy	0.83	0.58	0.033	<0.001	0.73	0.67	0.042	0.320
Energy utilisation efficiency (MJ/MJ)								
DE/GE	0.638	0.696	0.0180	0.027	0.647	0.687	0.0228	0.224
ME/GE	0.577	0.592	0.0194	0.542	0.565	0.604	0.0245	0.266
ME/DE	0.903	0.848	0.0087	<0.001	0.870	0.881	0.0111	0.469
CH_4-E/GE	0.044	0.070	0.0028	<0.001	0.058	0.057	0.0036	0.837
CH_4-E/DE	0.070	0.104	0.0064	<0.001	0.092	0.082	0.0081	0.368
CH_4-E/ME	0.078	0.125	0.0100	0.002	0.110	0.093	0.0127	0.368

BF = Blackface; T × BF = Texel × Blackface

Conclusions

The present study compared the effects of 2 contrasting forages on feed intake, digestibility and energy utilisation efficiency in 2 genotypes (Scottish Blackface vs. Texel × Scottish Blackface) of hill ewe lambs. In comparison with grass silage, feeding pelleted dry grass had greater dry matter and energy intakes and CH_4 emissions (MJ/d), however lower nutrient digestibility and CH_4 emission rates (MJ/MJ GE, DE and ME), resulting in a higher proportion of ME in DE. Moreover, the CH_4 conversion factor (CH_4-E/GE) of the grass nuts obtained in the current study was lower than that recommended by IPCC (2006), suggesting that using the default methodology of IPCC (2006) may overestimate the CH_4 production in the hill ewes when offered pelleted dry grass.

Acknowledgements

This work was funded by the Department for Environment, Food and Rural Affairs of UK, the Scottish Government, the Department of Agriculture, Environment and Rural Affairs of Northern Ireland, and the Welsh Government as part of the UK's Agricultural GHG Research Platform project – Methane emissions AC0115 (www.ghgplatform.org.uk). We thank the staff at the Agri-Food and Biosciences Institute, Hillsborough, Co. Down, UK, for assistance in animal management and chemical analysis.

References

Brown, P., Broomfield, M., Buys, G., Cardenas, L., Kilroy, E., MacCarthy, J., Murrells, T., Pang, Y., Passant, N., Ramirez Garcia, J., Thistlethwaite, G., and Webb, N. 2016. UK Greenhouse Gas Inventory 1990 to 2014: Annual Report for submission under the Framework Convention on Climate Change. https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/573172/UKnationalinventoryreport1990-2014.pdf. (Accessed 24 April, 2017.)

Ellis, J. L., Kebreab, E., Odongo, N. E., Mcbride, B. W., Okine, E. K., and France, J. 2007. Prediction of methane production from dairy and beef cattle. Journal of Dairy Science. 90: 3456-3466.

Home Office. 1986. Animal (Scientific Procedures) Act 1986. Her Majesty's Stationery Office, London, U.K.

Intergovernmental Panel on Climate Change (IPCC). 2006. Chapter 10. Emissions from livestock and manure management. In: Guidelines for national greenhouse inventories. Vol. 4. Agriculture, forestry and other land use, IPCC, Geneva, Switzerland.

McDonald, P., Edwards, R. A., Geenhalgh, J. F. D., and Morgan, C. A. 2002. Animal Nutrition. 6th ed. Pearson Education Limited, Essex, U.K.

Shi, W., Moon, C. D., Leahy, S. C., Kang, D., Froula, J., Kittelmann, S., Fan, C., Deutsch, S., Gagic, D., Seedorf, H., and Kelly, W. J. 2014. Methane yield phenotypes linked to differential gene expression in the sheep rumen microbiome. Genome Research. 24: 1517-1525.

Zhao, Y. G., Aubry, A., Annett, R., O'Connell, N. E., and Yan, T. 2016. Enteric methane emissions and nitrogen utilisation efficiency for two genotype of hill hoggets offered fresh, ensiled and pelleted ryegrass. Livestock Science. 188: 1-8.

Relationship between feeding behaviour, health, and performance in calves at high risk of developing respiratory disease

B. Vander Ley[1]
[1]*Great Plains Veterinary Educational Center, University of Nebraska-Lincoln, Clay Center, NE, United States of America*
Bvanderley2@unl.edu

Abstract

Feeding behaviour monitoring technology is rapidly developing and is available for use in cattle production systems. These monitoring systems have potential as data generation tools to guide livestock management; however, information about relationships between health and performance variables and feeding behaviour variables is lacking. To address this shortage, data from a cohort of cattle observed using a feed intake monitoring system were used to characterize relationships between respiratory disease, average daily gain (ADG), feed conversion (GF), feed intake (DMI), feeding time (DMIt), and feeding rate (DMIr). Data from 265 calves fed using a Growsafe® feed intake monitoring system for approximately 70 days were used. Pearson correlation statistics were calculated to describe relationships between continuous performance variables (ADG ,GF) and feeding parameters (DMI, DMIt, DMIr). One way analysis of variance was used to assess the impact of respiratory disease on DMI, DMIt, and DMIr. DMI was strongly correlated with ADG (Pearson's Correlation Coefficient [PCC]=0.68, $p<0.0001$). DMIt and DMIr were very weakly correlated with ADG (PCC=0.14, $p=0.023$; PCC=0.18, $p=0.004$; respectively). Calves with respiratory disease had reduced ADG (0.22 kg less, $p<0.0001$), decreased DMI (0.5 kg less, $p<0.0001$), and DMIr (0.9 g/s less, $p=0.008$) compared to healthy calves. Feeding time did not differ between calves treated for respiratory disease and untreated calves. These data show that feeding behaviour is significantly associated with health and performance of calves at high risk of respiratory disease.

Keywords: bovine respiratory disease, feeding behaviour, feed intake monitoring system

Introduction

Respiratory disease is a leading cause of morbidity and mortality in cattle in the United States and around the world and consequently impairs animal welfare, increases production costs, and decreases growth performance (Griffin, 1997). Prevention of bovine respiratory disease (BRD) remains the principal strategy to mitigate the deleterious effects associated with the disease; however, U.S. beef production is fragmented and implementing effective preventative strategies has proven difficult. Given that efforts to improve prevention of BRD are ongoing, timely diagnosis and early treatment of BRD remains the most effective means of mitigating BRD, especially in the post-weaning period of production. Diagnosis of BRD is currently based on subjective clinical signs of disease including attitude, respiratory effort and character, respiratory discharges, perceived appetite based on degree of rumen fill, and elevated rectal temperature. Many of the preceding signs are not only subjective, but also have many possible aetiologies besides the typical bronchopneumonia associated with BRD. White et al. used Bayesian statistical methods to estimate the accuracy of BRD diagnosis based on clinical signs and found very low diagnostic accuracy (White and Renter, 2009). Efforts aimed at using various forms of animal behaviour monitoring and measurement are in development for use as diagnostic aids for BRD (Mang et al., 2015; White et al., 2015; Wolfger et al., 2015). Despite advances in available diagnostic tools for BRD, significant gaps in knowledge exist regarding relationships between animal behaviour and disease status. The purpose of the research presented hereafter is to examine the feeding behaviour of beef calves at high risk of developing BRD and compare aspects of feeding behaviour between calves that had high growth performance and those that were suspected of having BRD.

Materials and Methods

Animals

A total of 300 beef calves were purchased from auction markets in Missouri. While the total number of producers represented in the group was unknown, it was assumed that a high degree of commingling had occurred. Calves were selected for purchase based on having no stated history of BRD preventative practices (e.g. vaccination, weaning) with the exception that all purchased calves were required to be castrated and healed prior to sale. These purchase criteria were implemented to provide a substantial natural challenge that would result in

moderate BRD morbidity as well as to provide data that would be generalizable to other groups of cattle considered to be at high risk of BRD.

Feeding and Husbandry

Animal research methods were approved by the University of Missouri Animal Care and Use Committee.

Following purchase, calves were held overnight at the auction market, then commingled and transported to the University of Missouri Beef Research and Teaching Farm (BRTF) the following morning. On arrival at the BRTF, calves were unloaded into holding pens and then moved through a processing facility and restrained in a squeeze chute. While in the chute, body weight was measured, an ear notch was collected for Bovine Viral Diarrhoea Virus persistent infection screening, a visual identification tag (Z-Tag, Temple, TX) was applied and a radio frequency identification tag (Allflex HDX, Dallas, TX) was applied to each calf. Additionally, coat colour, the presence of horns, and the presence of an existing visual ID tag were recorded. All information was recorded and stored in an electronic database (Microsoft Access). As calves left the chute, they were place in pens in order of processing until each pen contained 50 to 55 calves. Receiving diet and water was available as calves arrived in their pens. Immediately following arrival processing, ear notch samples were shipped via overnight courier service to a BVDV PI testing laboratory (Cattle Stats, Oklahoma City, OK).

The day following arrival, calves were brought back through the working facility. While restrained in the squeeze chute, each calf received a metaphylactic antibiotic (Micotil, Elanco Animal Health, Greenfield, IN), an antiparasitic drug (Cydectin Injectable, Boehringer-Ingelheim Vetmedica, Saint Joseph, MO), a clostridial 7-way vaccination (Alpha 7, Boehringer-Ingelheim Vetmedica, Saint Joseph, MO), a growth promoting implant (Component ES, Elanco Animal Health, Greenfield, IN) and one of two BRD vaccines (Pyramid 5 + Presponse or Bovishield Gold One Shot) that were assigned randomly as part of a vaccine clinical trial. A second bodyweight measurement was recorded. After leaving the squeeze chute, calves were sorted into randomly assigned pens. Feed was available to calves when they arrived in their assigned pens.

Throughout the experiment, feed was available to calves in a bunk system equipped to record individual feed intake (Growsafe, Airdrie, AB, Canada)

(FIMS). Each pen was equipped with 5 bunks, each of which allowed a single calf to eat at a time. Calves were provided with a receiving diet for the first 21 days and then a growing diet for the remainder of the experiment. Cumulative daily intakes for each pen were monitored via the FIMS and adjustments in feed delivery were made to achieve ad libitum feed intake. Feed was mixed and delivered each morning. On days when bodyweight was measured, feed delivery was delayed until after animals were removed from their pens to prevent variation in bodyweight attributable to differences in rumen fill.

Calves were observed at least once each day for signs illness. A clinical illness scoring system (CIS) was used to identify potential bovine respiratory disease (BRD) suspects. The scoring system is presented in table 1. Calves exhibiting mild depression and/or a cough were taken from their home pen to the working facility for rectal temperature measurement and further assessment. Calves with a rectal temperature greater than 39.7°C and a CIS of 2 or more were considered confirmed cases of BRD. Calves initially diagnosed with BRD were treated with enrofloxacin (Baytril, Bayer, Shawnee Mission, KS) at a dosage of 12.1 mg/kg bodyweight. A 3 day post treatment interval was observed for enrofloxacin after which calves were eligible for treatment again. If a calf met treatment criteria for BRD a second time, tulathromycin (Draxxin, Zoetis, Kalamazoo, MI) (2.4 mg/kg SQ) was administered and a post treatment interval of 10 days was observed. Calves meeting treatment criteria for BRD a third time were treated with oxytetracycline (Biomycin 200, Boehringer-Ingelheim Vetmedica, Saint Joseph, MO) (200 mg/ml, 18 mg/kg SQ). Following the third BRD treatment, calves were considered chronically affected by BRD and were no longer eligible for antimicrobial therapy.

Table 1. Clinical Illness Scoring

CIS Score	Description
0	Normal behaviour and attitude
1	Slight depression, treatment not warranted
2	Mild depression and/or cough
3	Moderate illness, severe depression, laboured breathing, and/or cough
4	Severe illness, potentially moribund, minimal response when approached

All calves were monitored visually and by means of the FIMS for feed intake. Calves that failed to eat at least 0.45 kg (as fed) of the diet on a day during the

first 7 days after arrival were removed from study pens and offered dry hay in a concrete bunk. Removed calves were maintained in groups based on home pen. Over a 3 day period, calves were offered increasing amounts of study diet presented first in the concrete bunk and then in the FIMS. Once calves were eating consistently from the FIMS, they were returned to their home pen. Intake and performance data from removed calves were excluded from statistical analysis. If calves failed to return to at least maintenance feed intake or were chronically affected by BRD, they were left in small groups containing no more than 3 animals per pen to minimize competition.

Calves were revaccinated 2 weeks following their initial vaccination with their assigned treatment vaccine, but without the bacterial component. Calves were reweighed at 2 week intervals following revaccination. At the conclusion of the study, calves were weighed on the second to last and last days. All cattle were shipped simultaneously to a finishing feedlot, resulting in a 69 or 70 day study period depending on arrival date.

Individual feed intake was corrected for dry matter content. Feed intake and weight gain were tallied for each calf and used to calculate average daily gain (ADG, kg), gain to feed ratio (GF, kg gain: kg feed). Average daily dry matter intake (DMI, g), average daily feeding time (DMIt, s), were calculated and used to generate an average daily feeding rate (DMIr, g feed: s feeding time).

Statistics

Pearson's correlation statistics were calculated using a statistics software program (Proc Corr, SAS 9.4, Cary, NC, USA) to describe relationships between performance variables (ADG, GF) and feeding parameters (DMI, DMIt, DMIr). Analysis of variance (Proc GLM, SAS 9.4, Cary, NC, USA) was used to compare mean daily DMI, DMIt, and DMIr as well as ADG and GF between calves affected by clinically diagnosed BRD and calves that remained undiagnosed.

Results and Discussion

In total, data from 265 calves was included in the analysis. Data from calves that died (n=11) and calves that failed to acclimated to eating from the FIMS (n=24) were removed from the analysis.

Correlations between performance data and feeding parameters are presented in table 2.

Table 2. Pearson's Correlation Coefficients	DMI	DMIt	DMIr
ADG	0.68 (p<0.0001)	0.14 (p=0.023)	0.179 (p=0.004)
GF	-0.074 (p=0.233)	-0.284 (p<0.0001)	0.362 (p<0.0001)

Differences in performance and feeding parameters between clinical BRD cases and apparently healthy cattle are presented in table 3.

Table 3.	Apparently Healthy	Clinical BRD	Difference	Lower 95% CL	Upper 95% CL	P-Value
ADG (kg/d)	1.903	1.683	0.219	0.208	0.231	<0.001
GF (kg gain: kg feed)	0.25	0.24	0.01	0.004	0.024	0.0071
DMI (kg/d)	7.52	7.0	0.53	0.24	0.81	0.0004
DMIt (s/d)	2,213.5	2,247.4	-34.0	-235.9	168.0	0.7409
DMIr (g/s)	6.4	5.5	0.92	0.25	1.58	0.0072

A commonly held understanding among livestock producers of all types is that sick animals consume little or no feed. The ability to exploit this decrease in feed consumption as an indicator of illness remains a promising technology. The purpose of this work was to measure performance and feeding behaviour parameters and compare them between cattle that were diagnosed with clinical respiratory disease and cattle that remained untreated.

Correlations between feeding parameters and performance outcomes were variable in strength. Dry matter intake was strongly correlated with ADG but was not related significantly to GF. Time spent eating (DMIt) was very weakly correlated with ADG and had a negative weak correlation with GF. Eating rate (DMIr) was weakly correlated with ADG and GF.

Comparisons of feeding and performance variables between sick and healthy cattle also produced significant results. In general, apparently healthy cattle grow faster, are slightly more efficient, eat more, and eat faster than cattle diagnosed with clinical BRD. Interestingly, there were no differences in time spent eating between apparently healthy cattle and clinical BRD cases. These data fit

commonly held theory regarding the performance of BRD-affected cattle. Average daily gain is expected to be less and dry matter intake is reduced compared to healthy cattle. A notable departure from conventional thought is that efficiency of sick cattle is expected to be reduced compared to healthy cattle. Our data reveals that while a statistically significant difference was present, the difference was small enough to be considered questionable in terms of biological relevance. Given the data, ADG was impacted more heavily by DMI and clinical BRD cases ate significantly less feed each day on average when compared to apparently health cattle.

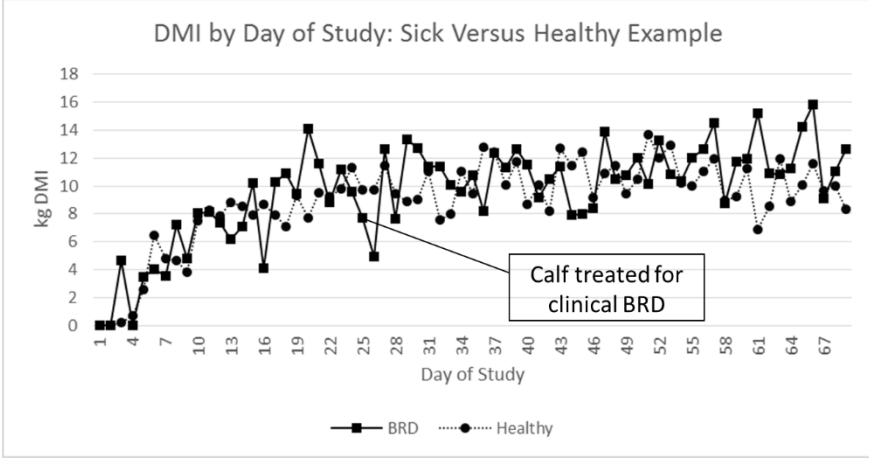


Figure 1. Comparison of DMI between a calf with clinical BRD and an apparently healthy calf.

Reasons for decreased feed intake are likely to be multifaceted. Early in the course of disease, malaise associated with inflammation is likely to suppress appetite. Figure 1 provides an example of DMI in a calf diagnosed with BRD compared to an apparently healthy calf. Dry matter intake remains approximately the same until day 43 of the study at which time, feed intake in the clinical BRD case decreased markedly. Following treatment, DMI recovers. These data are consistent with malaise-associated inappetance. Another possible explanation for differences seen in DMI between clinical BRD cases and apparently healthy cattle is that BRD cases may not compete as effectively for feed compared to healthy animals; however, our data suggest that clinical BRD cases spent about the same amount of time eating as did apparently healthy animals. Further, clinical cases ate at a significantly slower rate when compared to apparently healthy animals, perhaps suggesting that the rate of consumption was not

increased to account for decreased opportunities to access available feed. Taken together, similar DMIt and a slower DMIr for clinical BRD cases suggests but does not confirm that competition for feed was limited or absent.

At least two sources of bias may be affecting estimates of relationships presented in this report. First, despite reports on errors associated with classifying cattle as disease or healthy based on clinical signs, our classification was done based on clinical signs; hence, classification errors are probably and these data must be interpreted accordingly. Second, we excluded data from animals that died and failed to acclimate to the FIMS. In the case of mortalities, all of them were confirmed to have BRD by post-mortem examination. These fatal cases can be considered confirmed cases because of necropsy data; however, no performance relationships could be calculated because the animals failed to complete the study. Fatal cases will likely be useful in future investigations aimed and determining feeding patterns associated with the onset of BRD. In the case of animals that failed to acclimate to the FIMS, no definable evidence for failure to acclimate was collected. Because of this lack of information, it is possible that unknown factors that affect cattle's ability to acclimate to a FIMS also would have changed the estimates of relationships presented in this report.

Conclusions

Based on the data presented in this report, we can conclude that differences in performance and feeding behaviour exist between clinically determined BRD cases and apparently healthy controls. These data suggest that the most significant contributing factor to diminished performance in BRD cases in decreased DMI. Further research is necessary to elucidate the mechanism that results in decreased DMI. Further research is also necessary to correctly classify BRD cases and characterize their feeding behaviour.

References

Griffin, D. 1997. Economic impact associated with respiratory disease in beef cattle. Vet. Clin. N. Am.-Food Anim. Pract. 13(3):367-&. (Article)

Mang, A. V., S. Buczinski, C. W. Booker, and E. Timsit. 2015. Evaluation of a Computer-aided Lung Auscultation System for Diagnosis of Bovine Respiratory Disease in Feedlot Cattle. J. Vet. Intern. Med. 29(4):1112-1116. (Article) doi: 10.1111/jvim.12657

White, B. J., D. R. Goehl, and D. E. Amrine. 2015. Comparison of a Remote Early Disease Identification (REDI) System to Visual Observations to

Identify Cattle with Bovine Respiratory Diseases. Int. J. Appl. Res. Vet. Med. 13(1):23-30. (Article)

White, B. J., and D. G. Renter. 2009. Bayesian estimation of the performance of using clinical observations and harvest lung lesions for diagnosing bovine respiratory disease in post-weaned beef calves. J. Vet. Diagn. Invest. 21(4):446-453. (Article)

Wolfger, B., K. S. Schwartzkopf-Genswein, H. W. Barkema, E. A. Pajor, M. Levy, and K. Orsel. 2015. Feeding behavior as an early predictor of bovine respiratory disease in North American feedlot systems. J. Anim. Sci. 93(1):377-385. (Article) doi: 10.2527/jas2013-8030

Monitoring drops in rumination time and activity for the detection of health disorders in dairy cows

R. Guatteo[1], P. Clément[1], R. Quiniou[2], N. Bareille[1]
[1]*BIOEPAR, INRA, Oniris, La Chantrerie, 44307, Nantes, France*
[2]*INRIA Rennes Bretagne - Atlantique, campus de Beaulieu 35042 Rennes Cedex*
raphael.guatteo@oniris-nantes.fr

Abstract

The objective was to evaluate the detection of different health disorders (HD) in dairy cows by means of a one-sided cumulative sum (CUSUM) applied to data obtained from a rumination and activity sensor. Rumination and activity data were collected on 259 Holstein cows for 2.5 years on 2 French farms. The detection records were evaluated in comparison with HD detection by farm staff as the reference method. Sensitivity, specificity, and positive and negative predictive values were calculated for CUSUM settings, enabling a high specificity (97% and 90% for CUSUM on rumination time or on neck activity). The timing of detection was also evaluated. The most frequent HD were mastitis (n = 172), lameness (n = 129), impaired general condition without identified cause (n = 63) and diarrhoea (n=19). On average 40% of the HD detected by farm staff were detected by the CUSUM between 4 d before and 1 d after detection by farm staff, with sensitivities varying from 28% for mild lameness to 85% for severe mastitis. Sensitivities above 55% were obtained for impaired general condition episodes without identified cause, diarrhoea, and most of the rare but severe HD. The positive predictive values of CUSUM detections remained below 10% in our sample. Approximately 50% of the HD were detected at least 1 d before detection by farm staff, enabling early attention. Results suggest that, even if a large variety of HD were detected, the algorithms of this study would be useful for HD detection only in addition to visual appraisal.

Keywords: health monitoring, dairy cow, sensor, algorithm

Introduction

Recently, tools have been developed to assist dairy farmers in cow health or reproduction management, for instance for oestrus or calving detection (Rutten et al., 2013). Different types of sensor measuring for instance activity, milk conductivity, body temperature, ruminal pH, rumination time or feeding time have been used (Bewley, 2009) to detect cows with deviating values which

deserve special attention from the farmer. One of the characteristics of monitoring devices is the spectrum of events which they can detect. Some devices are dedicated primarily to the detection of one type of event, for instance mastitis, oestrus or lameness (Rutten et al., 2013), whereas others use sensors that measure a parameter which is potentially impacted by various reproduction or health disorders (temperature sensors (Adams et al., 2013), rumination or activity sensors (Chapinal et al., 2010)). For such "broad spectrum" tools, it is crucial to evaluate which events are likely to be detected and what is the performance of this detection. Indeed, a lack of sensitivity or specificity of the detections may (i) alter farmers' confidence in the tool and may lead to its underuse or to suboptimal use, (ii) impact farm profitability as non-optimal disease management results in economic losses due to decreased milk yield, increased treatment costs or increased risk of culling, (iii) compromise animal welfare if some cows are not detected as diseased or are detected late, and (iv) promote excessive use of antibiotic treatments if there is an excessive number of false alarms. However, the performance of the commercial devices in terms of detection quality is very often not stated by the manufacturers. Furthermore, few guidelines are available to determine the performance which can be considered as acceptable for health monitoring tools. For AMS, the International Standard ISO/FDIS 20966 recommends a sensitivity of 80% combined with a specificity of more than 99% for mastitis detection. However, it seems that commercial AMS usually do not attain such performance. In a recent review, only 3 out of 10 mastitis detection models achieved this performance (Rutten et al., 2013). Kamphuis et al. (2013a) recommend a sensitivity of 80%, with not more than 10 false alerts per 1,000 cow milkings. To our knowledge, no recommendations exist concerning minimal or acceptable performance for the detection of other health disorders.

Since 2009, a rumination and activity sensor (HR-Tag, SCR Engineers Ltd., Netanya, Israel) has been developed. This sensor is carried on a neck collar and continuously records rumination time (RT) and neck activity (NA) of each cow of the herd. Sensor data are used to generate lists of cows that need special attention with regard to oestrus (overactivity) or health (drops in activity or rumination time, or both). The performance of this automated system for oestrus detection has been evaluated elsewhere (Kamphuis et al., 2012).

The aim of this study was to evaluate the performance of a one-sided cumulative sum (CUSUM) (Luo et al., 2009) applied to RT and NA measured by HR-Tag, in detecting significant shifts related to different health disorders. The CUSUM test accumulates the difference (error) between a reference RT or NA and the observed RT or NA if this difference is positive (Figure 1). This method was chosen because it has been used successfully to monitor biological processes in animal production systems (De Vries and Reneau, 2010). Moreover, CUSUM is

able to detect progressive and moderate amplitude shifts (Huybrechts et al., 2014) as expected for RT or NA.

Materials and methods

Study sample and health disorder recording

The data used in this study were collected on 2 research farms in western France. Cows were milked twice daily and fed a maize silage based TMR or a pasture based diet, depending on the time of year. On farm 1 (Les Trinottières: Maine-et-Loire, France), 203 Holstein cows were studied between 1 September 2010 and 31 August 2013. Cows were managed in 2 batches: 1 (60 cows) fed a TMR containing 75% maize silage and 25% concentrate (zero-grazing) and the other batch fed the same TMR from November to April and a diet containing 50% grass and 50% maize silage from April to November. On farm 2 (Trevarez: Brittany, France), 56 Holstein cows were studied between 4 November 2009 and 11 January 2012. Cows were fed a maize silage based TMR during winter or a pasture based diet from spring to autumn. During the winter cows were housed in cubicles on both farms, and average milk yield was 30.6 kg/d (farm 1) and 25.9 kg/d (farm 2). Throughout the study, all cows were monitored daily by farm staff for signs of disease. Nature, severity and date of occurrence of HD detected were recorded by farm staff on a standardised form. Raw data on rumination and activity were not available to farm staff.

Sensor data and algorithms for the detection of drops in RT and NA

Three weeks before the theoretical date of calving, cows were fitted with a neck collar carrying a NA and RT logger (HR-Tag, SCR Engineers Ltd., Netanya, Israel). The logger contains a microphone which records RT continuously and summarises it into 2 h blocks (Schirmann et al., 2009). It also contains an accelerometer which, after algorithmic treatment, summarises NA into 2 h blocks (Kamphuis et al., 2012). RT and NA data were stored in the logger and transmitted to a computer (DataFlow software, SCR Engineers Ltd., Netanya, Israel) when cows walked below an infrared antenna located in the milking parlour or over a trough. Thus, new data were typically available twice a day after milking and data were not available during the early dry period.

As the commercial algorithms developed by the manufacturer for HD detection with the device used in this study were confidential, the authors of the present study developed their own algorithms. The algorithms were retrospectively applied to the sensor data.

A method based on a one-sided cumulative sum (CUSUM) test (Luo et al., 2009) was used to detect drops in RT or NA. The CUSUM test accumulates the difference (error) between the reference RT or NA and the observed RT or NA if

this difference is positive. First, a reference RT and NA was calculated for each cow and for each 2 h block of the day (12 blocks/d) as the mean RT and NA, respectively, recorded for this cow for the same 2 h time block of the day during the past 7 d. Secondly, an alarm was triggered when the CUSUM value exceeded a given decision interval (h). The CUSUM used in this study was computed for each cow as:

$$\begin{cases} C_0 = 0 \\ C_t = max\ (0\ ;\ C_{t-1} + \varepsilon_t - k) \end{cases}$$

where Ct is the CUSUM value at time t, ε_t is the difference between the reference RT or NA values and the observed values at time t, k is equal to b x σ(ref-obs)7d, where b is a constant and σ(ref-obs)7d is the standard deviation of the error (difference between observed and reference values) calculated for RT or NA for each cow on all the values of the last 7 d, whatever the time block of the day. This last parameter was added to take into account the high variability of RT and NA between cows. In order to limit the number of very short alarms, often corresponding to irrelevant events, detection was triggered only if the CUSUM exceeded the decision interval (h) during at least 2 x 2 h blocks consecutively. The CUSUM value was reset to 0 if more than 12 successive values of RT or of NA were missing.

Performance of the algorithms and predictive values of CUSUM detections

As a monitoring tool may detect a HD a few hours or a few days before or after detection by farm staff, it is necessary to define a time-window in which the HD is likely to cause a detection by the tool for informative value calculation. The exact time of detection of HD was not known in our data set, so detection by farm staff was arbitrarily positioned at 1200 h on the day of detection. For sensitivity calculations, a 5 d time-window starting 96 h (4 d) before the time of detection of the HD by farm staff and ending 24 h (1 d) after was defined. This 5 d time-window was called the validation time-window. For each CUSUM setting of interest, a HD was considered as a True Positive (**TP**) if a detection was triggered during the validation time-window containing this HD. An HD was considered as a False Negative (**FN**) if no detection was triggered during the validation time-window containing this HD. The sensitivity of the CUSUM detections was calculated for each type and severity of HD as **Se** = TP/(TP + FN). Distinct specificity calculations were carried out for the peripartum period and for the lactation or late dry period. For the period prior to 5 d before calving or after 11 DIM (lactation-dry period), three 5 d control time-windows were randomly sampled (proc surveyselect, SAS 9.2) for each cow with sufficient sensor data (more than 3.5 months of data). For each CUSUM setting of interest, a control time-window was considered as a False Positive (**FP**) if a detection was triggered during this time-window (Figure 1).

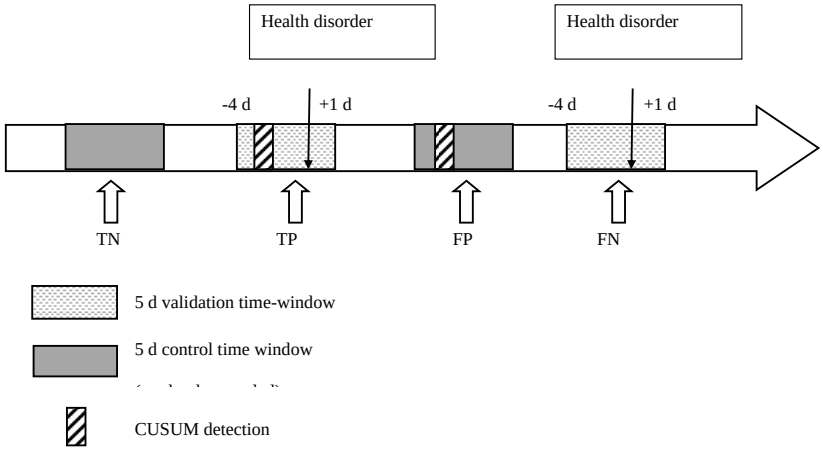


Figure 1. Example of rumination time measured for one cow around a health disorder (solid line). The reference rumination time (dotted line), computed as the mean rumination time measured for that cow in the same 2 h time block of the day during the past 7 d is also shown. One significant difference (horizontal arrow) between measured and reference rumination time was identified just after a mastitis detection (vertical arrow), using a method based on the cumulative sum test.

A control time-window was considered as a True Negative (**TN**) if no detection was triggered during this time-window. The specificity of the CUSUM detections during lactation and dry period (**Sp**) was calculated as Sp = TN/(TN + FP). Among the 222 cows in the study with more than 3.5 months of data, control time windows could be successfully sampled on 213 cows due to the constraints imposed on validation of the control time-windows. Thus, specificity calculations were made on 639 (3 x 213) 5 d control time-windows. In order to propose a user-friendly measure of specificity, an indicator linked to specificity was calculated as follows. For each cow and for each day with sufficient sensor data (i.e. with less than 6 out of 12 RT or NA values missing daily) outside the validation time-windows, a dichotomous variable (Y) was created. For one day d, the value Y(d) was set to 0 if no detection was triggered by the CUSUM between 0000 h and 2359 h, and was set to 1 if at least 1 detection was triggered by the CUSUM during the same time-window. In the case of long-lasting detections or repeated detections for a cow, the variable was set to 1 for every day in which the cow triggered a detection. The mean number of cows triggering a detection/day was then calculated for different CUSUM settings as the false positive rate = (number of cow days where Y = 1)/(number of cow days where Y

= 1 or Y = 0) x 100. It represents, for 100 cows present in the herd, the mean number of detections triggered daily by the CUSUM outside validation time-windows i.e. when no HD were detected by farm staff.
Predictive values are operational values which are of major importance in evaluating the usability of a detection tool. Therefore, PPV and NPV were calculated for a range of prevalence, from 0.5% of diseased cows each day to 4.5% of diseased cows each day (1.5% of diseased cows each day in our sample) to evaluate the performance of CUSUM algorithms in different HD prevalence conditions. Calculations were made for the combined algorithm, using the mean Se and Sp found for each HD type over the 2 farms in the study. For the most frequent HD, the time-lag between the first detection by the CUSUM algorithm on RT data or on NA data in the validation time-window and detection by farm staff was calculated. Calculations were made for the detection by the combined algorithm with the settings which produced a specificity of 97% or 90% for CUSUM algorithms on RT and on NA.

Results

The most frequent HD were mastitis (n = 172), lameness (n = 129), impaired general condition without identified cause (n = 63) and diarrhoea (n=19). With settings producing less than 4 false positive alerts/100 cows, 23% and 30% of HD were detected based respectively on rumination and activity drops (Table 1). When both were combined, sensitivity reached 40%. Moreover, HD were detected between 4 d before and 1 d after detection by farmers, with sensitivities from 28% for mild lameness to 85% for severe mastitis. As a consequence, the positive predictive values of CUSUM detections remained below 23% (Table 2). Approximately 50% of the HD were detected at least 1 d before detection by farmers, enabling early attention (Figure 2).

Figure 2. Distribution of the time of first detection by the combined algorithm compared to detection by farm staff for the main health disorders (striped bars = farm 1, black bars = farm 2).

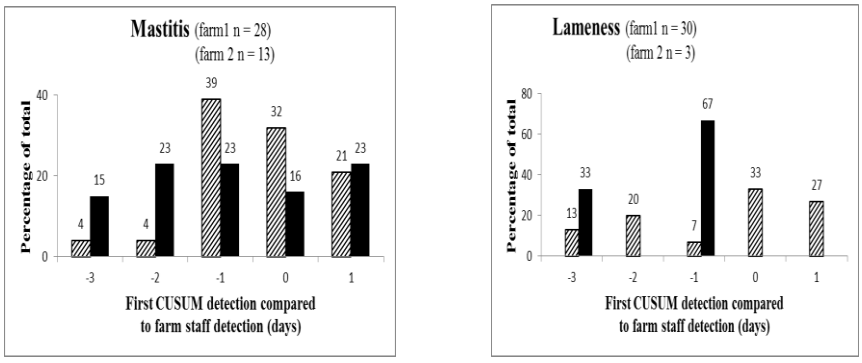


Table 1. Sensitivity of CUSUM algorithms applied to Rumination Time (RT), Neck Activity (NA) or (RT or NA) for 2 CUSUM settings, for the main health disorders detected by farm staff

		Sensitivity of CUSUM settings 1[1] (%) (Sp 97%)					Sensitivity of CUSUM settings 2[2] (%) (Sp=90%)				
	CUSUM	RT	NA	RT or NA			RT	NA	RT or NA		
HD	Severity	Overall[3]		Overall	Farm 1	Farm 2	Overall		Overall	Farm 1	Farm 2
Mastitis	mild (n = 111)	9	6	14	12	24	14	20	30	27	43
	moderate (n = 48)	10	6	10	3	22	17	25	33	30	39
	severe (n = 13)	31	38	46	54	0	54	61	85	91	50
	Total (n = 172)	11	9	16	14	22	18	24	35	33	41
Lameness	moderate (n = 94)	4	4	7	7	10	10	21	28	26	40
	severe (n = 35)	11	17	23	23	-	20	31	37	37	-
	Total (n = 129)	6	8	12	12	10	12	24	30	29	40
Impaired general condition	mild (n = 39)	46	28	51	50	100	54	44	61	60	100
	severe (n = 24)	33	46	46	46	-	46	62	67	67	-
	Total (n = 63)	41	35	49	48	100	51	51	63	63	100
Diarrhoea	(n = 19)	32	21	37	25	100	47	32	58	50	100
Acute metritis	(n = 3)	0	33	33	33	-	0	33	33	33	-
Retained placenta	(n = 3)	0	0	0	0	-	0	0	0	0	-
Milk fever	mild (n = 1)	0	0	0	0	-	0	0	0	0	-
	severe (n = 2)	100	0	100	100	100	100	50	100	100	100
	Total (n = 3)	67	0	67	50	100	67	33	67	50	100

[1]CUSUM parameters (b, h) : $b_{RT} = b_{NA} = 0,7$, $h_{RT} = 100$, $h_{NA} = 75$
[2]CUSUM parameters (b, h) : $b_{RT} = b_{NA} = 0,7$, $h_{RT} = 75$, $h_{NA} = 36$
[3]Overall = on farm 1 and farm 2

Discussion

To our knowledge, our study is the first to evaluate the informative value of CUSUM algorithms applied to raw RT and NA data provided by HR-Tag for the detection of a large variety of HD. In our opinion, CUSUM settings 2 should be used in practice, as this gives the best trade-off between overall sensitivity of detection (38 to 46% for the combined algorithm), the PPV (6%) and the false positive rate (3 to 4 detections/d for 100 cows). With these settings, the sensitivity ranged from 28 to 85%, depending on the type and severity of the HD considered.

Table 2. Positive predictive values of combined algorithm detections for different HD prevalences.

Prevalence (%)	Health disorder	CUSUM settings 1 (Sp = 97%)	CUSUM settings 2 (Sp = 90%)
0.5	Health disorder	PPV = 3% NPV[3] > 99%	PPV = 2% NPV > 99%
1.5	Health disorder	PPV = 9% NPV = 99%	PPV = 6% NPV = 99%
4.5	Health disorder	PPV = 23% NPV = 96%	PPV = 15% NPV = 97%

Mastitis with impaired general condition, impaired general conditions without identified cause, diarrhoea and most of the rare but severe HD were detected with a sensitivity above 55%. This makes our algorithms useful for detecting the more severe HD in dairy herds. However, with the moderate level of sensitivity achieved, the monitoring device must be seen as complementary to visual appraisal by the farmer for HD detection. Indeed, some HD included in the analysis and which should be detected in practice, such as local mastitis, rarely provoked a detectable drop in RT or NA. Our results underline the benefit of combining two measures (RT and NA) for the detection of HD. This is consistent with the results of other studies which have demonstrated the benefit of combining data from different sensors and milk yield recording systems for the detection of mastitis or lameness, for instance (Kamphuis et al., 2008, Kamphuis et al., 2013b, Van Hertem et al., 2013).

The PPV obtained were below 10% in our sample. Firstly, this may be due to a lack of specificity of the detections. Many events, such as a change in management routine (feeding, milking, changing pen), may have influenced the behaviour of the cows and provoked FP detections. Another source of FP detections might be the lack of sensitivity of farm staff detections. For instance, Leach et al. (2010) found that, on average, farm staff underestimated lameness

prevalence by 30% compared with standard notation by researchers on a 222 dairy farm sample in the UK. Thus, the reference method used to classify an animal as diseased or healthy is far from ideal. A third reason for low PPV was the low frequency of HD.

Finally, due to the low PPV found in general for health monitoring systems (Kamphuis et al., 2008), in practice farmers have to bring together information from their information system, such as milk yield, visual observations and data from their reproduction and health management tools, before deciding to make a clinical examination of a cow that has triggered a detection. Thus for health monitoring tools, the decision to examine an animal will rarely be based on detection by the monitoring tool. Moreover, performance of health disorder detection models is generally highly variable across farms (Kamphuis et al., 2010). Thus, even though all farmers must be offered standard algorithm settings based on acceptable mean performance of these algorithms, it would be beneficial to enable farmers to parameterise personal algorithm settings (e.g. CUSUM decision limit "h" for instance) in order to optimise use of the tool.

Our results indicate that approximately 50% of the detected events would be detected before detection by farm staff, with 4 to 17% of HD detections occurring 3 d before. Similarly, Adams et al. (2013) found that 86% and 65% of mastitis and pneumonia cases, respectively, were detected within 2 d before diagnosis. If these HD were detected earlier, a better cure rate might be obtained after treatment, compared with the situation where no monitoring tool is used. These early detections might help to improve animal welfare and to limit the economic impact of HD.

Conclusion

The present study shows that monitoring drops in RT and in NA could be useful for the detection of a large variety of HD. For an acceptable level of specificity (90%), on average 40% of the HD observed by farm staff were detected. However, most of the HD of high severity were detected with a sensitivity higher than 55%. In spite of this, automated detection would only supplement visual observation for HD detection. Future work will focus on the development of an appropriate reference method to evaluate such a monitoring tool.

Acknowledgements

We acknowledge the contributions made by farm staff in gathering the data used in this research. We are also grateful to Milkline srl (Podenzano, Piacenza, Italy) for financial and technical support. This research was supported by Evolution (Rennes, France).

References

Adams, A. E., F. J. Olea-Popelka, and I. N. Roman-Muniz. 2013. Using temperature-sensing reticular boluses to aid in the detection of production diseases in dairy cows. J Dairy Sci 96:1549-1555.

Chapinal, N., A. M. de Passille, J. Rushen, and S. Wagner. 2010. Automated methods for detecting lameness and measuring analgesia in dairy cattle. J Dairy Sci 93:2007-2013.

De Vries A., J.K. Reneau. 2010. Application of statistical process control charts to monitor changes in animal production systems. J Anim Sci 88:E11-24.

Huybrechts T., K. Mertens, J. De Baerdemaeker, B. De Ketelaere, W. Saeys. 2014. Early warnings from automatic milk yield monitoring with online synergistic control. J Dairy Sci 97:371-81.

Kamphuis, C., R. Sherlock, J. Jago, G. Mein, and H. Hogeveen. 2008. Automatic detection of clinical mastitis is improved by in-line monitoring of somatic cell count. J Dairy Sci 91:4560-4570.

Kamphuis, C., B. DelaRue, C. R. Burke, and J. Jago. 2012. Field evaluation of 2 collar-mounted activity meters for detecting cows in estrus on a large pasture-grazed dairy farm. J Dairy Sci 95:3045-3056.

Kamphuis C., B. Dela Rue, G. Mein, J. Jago. 2013a. Development of protocols to evaluate in-line mastitis-detection systems. J Dairy Sci. 96:4047-58.

Kamphuis C., E. Frank, J. K. Burke, G. A. Verkerk, J. G. Jago. 2013b. Applying additive logistic regression to data derived from sensors monitoring behavioral and physiological characteristics of dairy cows to detect lameness. J Dairy Sci 96:7043-53.

Leach, K. A., H. R. Whay, C. M. Maggs, Z. E. Barker, E. S. Paul, A. K. Bell, and D. C. Main. 2010. Working towards a reduction in cattle lameness: 1. Understanding barriers to lameness control on dairy farms. Res Vet Sci 89:311-317.

Luo, Y., Z. Li, and Z. Wang. 2009. Adaptive CUSUM control chart with variable sampling intervals. Comput. Stat. Data Anal. 53:2693-2701.

Rutten, C. J., A. G. Velthuis, W. Steeneveld, and H. Hogeveen. 2013. Invited review: sensors to support health management on dairy farms. J Dairy Sci 96:1928-195

Differentiating pre- and post-grazing pasture heights using a 3D camera: a prospective approach

A.L.H. Andriamandroso[1,2,4¥*], E. Castro Muñoz[3*], Y. Blaise[2,4], J. Bindelle [1,2], F. Lebeau[4]

[1]*AgricultureIsLife, TERRA teaching and research center, Gembloux Agro-Bio Tech, University of Liège, Passage des Déportés 2, 5030 Gembloux, Belgium*

[2] *Precision Livestock and Nutrition Unit, AgroBioChem, Gembloux Agro-Bio Tech, University of Liège, Passage des Déportés 2, 5030 Gembloux, Belgium*

[3]*Universidad Central del Ecuador, Facultad de Ciencias Agrícolas, Jerónimo Leiton y Av. La Gasca s/n. Ciudadela Universitaria. 170521, Quito, Ecuador.*

[4]*Biosystems Dynamics and Exchanges Unit, Gembloux Agro-Bio Tech, University of Liège, Passage des Déportés 2, 5030 Gembloux, Belgium*

**These authors contributed equally to this publication*

[¥] *naina.andriam@gmail.com, jerome.bindelle@ulg.ac.be*

Abstract

Grasslands management involves the monitoring of both animal and plant components. Recent precision livestock farming developments have focused on high-rate monitoring of grazing animals to enhance livestock productivity and welfare. The evolution of grass resource during the grazing process is not being overlooked by graziers and researchers, but grass characteristics, such as height, dry matter content, productivity or density, are still measured using low frequency and sometimes destructive and time-consuming methods; such as quadrat, sward-sticks, rising plate meters.

This study investigated the potential of using 3D cameras to assess sward physical characteristics. Main objectives were: (1) to define the correct way to capture images, particularly the camera position above the ground and, (2) to assess if differences in sward height were detectable. Couples of images differing in grass height were captured on the same spot with a 3D camera at different above-ground heights (30, 40, 50 cm) on a ryegrass-white clover pasture. Pre-grazing height was 15cm and post-grazing sward was simulated by cutting at 2 cm. Histograms of intensity performed on greyscale images showed differences between pre- and post-grazing sward. As expected, overall darker pixels were observed for pre-grazing images ($p<0.01$) and whiter pixels for post-grazing images ($p<0.01$), indicating longer distances consistent with lower forage biomass. Images taken at a distance of 30 and 40 cm could identify these differences. Further developments require improving the calibration of the camera and developing image analysis method to estimate more plant characteristics such as density or dry matter content.

Keywords: pasture heights, grazing, 3D camera.

Introduction

Feeding animals is a challenge that farmers face in the search of the optimal animal weight gain or milk production and at the lowest cost (Castro et al., 2017). Grasslands constitute the best and cheapest source of feed to ensure milk or meat productions (Boval and Dixon, 2012; O'Mara, 2012). Grasslands characteristics and animal grazing behaviors are in close relationship. For an efficient grazing management the plant-animal interface should be considered at the spatial and the temporal scales on the pasture, besides the monitoring of grazing behaviors (Gregorini et al., 2017). Nevertheless, with regular weighing or daily milking, the monitoring of animals is performed at a higher rate than that of the plant component in the pastoral system. There is a strong need for a better monitoring of the pasture vegetation (Nadimi et al., 2008).

Moreover, on the one hand, since the emergence of precision livestock farming over the past two decades, the monitoring of individuals, using different kinds of sensors, has become more accurate and has offered the possibility to detect behaviors at different scales, from the pasture scale to the finest scale of bites for grazing animals (Gibb, 1996; Carvalho, 2013; Andriamandroso et al., 2016). On the other hand, the different tools used to measure physical characteristics of grass, among which the grass height is the most important, lag still behind in terms of possible application for precision livestock research and farming uses. Measurements of grass height before and after the passage of animals are one method to estimate the intake (Macoon et al., 2003; Smit et al., 2005). Traditionally, pasture height is measured using a sward stick, an electronic capacitance meter or a rising plate meter. The measured height is then used to estimate forage biomass availability via a calibration with cut samples. Calibration errors with these tools average 10% in terms of pasture yields (Sanderson et al., 2001). This technique is mostly used by farmers to have an idea of the importance of biomass that they have on pasture. Recent developments showed that it is possible to automatically monitor the biting pattern of animals (Andriamandroso et al., 2015) and in order to be able to assess simultaneously the intake during the biting process, a rapid method with high temporal and spatial resolution characterizing pasture biomass availability is called for research applications investigating the grazing behavior of animals at the plant-animal interface. Thus, the use of sensors, similarly to what is done with animals, could be one solution to palliate this problem. For example, using a simple digital camera, Bonesmo et al. (2004) developed an image processing system to estimate white clover coverage in a grass–clover mixture, based on clover color and its morphological properties achieving a great correlation with

the reality. The seasonal growth status of ryegrass was also detectable using a logistic model on color intensities and indices parameter (Fan et al., 2016). The use of depth cameras in precision agriculture has increased in recent years enabling plant structure characterization and species differentiation (Andújar et al. 2016). In this work, a depth camera was used to assess the difference between grass height before and after a simulated grazing.

Material and Methods

The experiment was carried out in one pasture of Gembloux Agro-Bio Tech (University of Liège, Belgium). An Intel RealSense F200 depth camera (Intel Corporation, Santa Clara, CA, USA) was fixed on a monopod (Figure 1) to take pictures of pasture before (pre-grazing) and after (post-grazing) the simulated passage of the animals done by manual cuts. Three different heights (30 cm, 40 cm, and 50 cm) were tested to define which one was the most suitable for capturing images at the different grass height. The camera objective focused on a 30 × 30 cm² quadrat where the height of the grass was taken with a rising plate meter and a sward stick on 5 random locations within the same quadrat. Five couples of images, corresponding to pre- and post-grazing grass, were taken on five different quadrats.

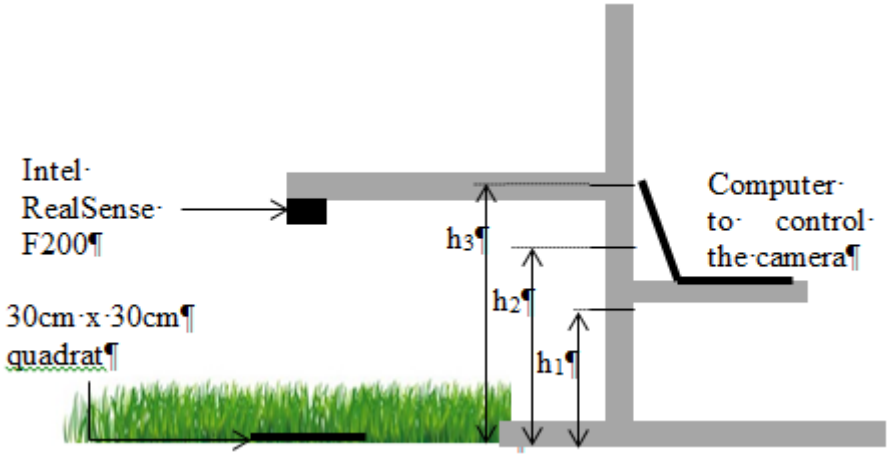


Figure 1: Image acquisition device using an Intel RealSense F200 depth camera, placed at modular heights (h_1: 30 cm, h_2: 40 cm, h_3: 50 cm) on the grass and controllable with a personal computer. A shade tent should be put around the camera to avoid sunlight disturbance.

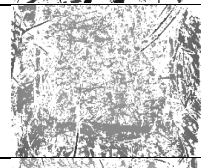
For the data processing, only greyscale images were taken into account and compared using histogram function of Matlab R2015a (Mathworks, NL). Ten groups of pixel color, named image greyscale intensity class (IGIC, ranging from 0-255) were created to class the different range of pixels of each photo where the

group 1 contained the lightest pixels and the group 10 the darkest pixels. The number of pixels present in each of the 10 greyscale groups were then counted and compared on a frequency basis using a general linear model with the GLM procedure in SAS (Cary, North Carolina, USA) with grass height (pre-, post-grazing), height of the camera (30, 40, 50 cm) and their interaction as fixed class variables. The quadrats were used as experimental units.

Results and Discussion

For one sample (sample n°1), pictures taken by the camera are displayed in Table 1 in color and greyscale formats for each camera height and each grazing status. From these tables, it is already possible to see that taking pictures at 50 cm above the ground involved the presence of grasses outside of the quadrat.
Over the ten greyscale intensity classes (IGIC), less differences were shown between pre-grazing and post-grazing grass for images taken at 50 cm (Table 2) confirming the possibility of confusion with grasses outside the quadrat viewed in Table 1.

Table 1: Color and greyscale photos taken by the camera at 30, 40 and 50 cm of heights from the ground and for pre- and post-grazing grass status for sample n°1.

Camera height	Grass status	Colored photo	Greyscale photo
30 cm	Pre-grazing		
	Post-grazing		
40 cm	Pre-grazing		
	Post-grazing		

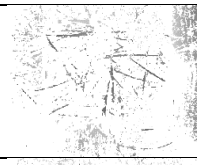
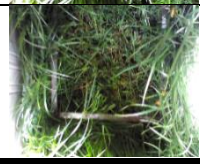
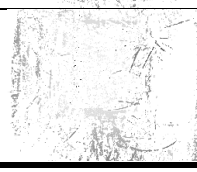
50 cm	Pre-grazing		
	Post-grazing		

Table 2: Comparison of pre-grazing and post-grazing greyscale images taken at 30, 40 and 50 cm above ground considering ten classes of image greyscale intensity class (IGIC) using analysis of variance method.

IGIC	Source	Degree of freedom	p-value
Class 1	Camera height	2	0.308
	Grass status	1	0.358
	Interaction	2	0.589
Class 2	Camera height	2	0.000
	Grass status	1	0.000
	Interaction	2	0.005
Class 3	Camera height	2	0.003
	Grass status	1	0.036
	Interaction	2	0.367
Class 4	Camera height	2	0.019
	Grass status	1	0.752
	Interaction	2	0.019
Class 5	Camera height	2	0.024
	Grass status	1	0.150
	Interaction	2	0.004
Class 6	Camera height	2	0.954
	Grass status	1	0.199
	Interaction	2	0.007
Class 7	Camera height	2	0.732
	Grass status	1	0.048
	Interaction	2	0.370

Class 8	Camera height	2	0.020
	Grass status	1	0.006
	Interaction	2	0.029
Class 9	Camera height	2	0.017
	Grass status	1	0.007
	Interaction	2	0.153
Class 10	Camera height	2	0.003
	Grass status	1	0.001
	Interaction	2	0.004

Only with the greyscale images, differences were directly identifiable on the histograms of each image (example of sample n°1 on Figure 2).
However for images taken at 30 cm and 40 cm, significant differences were visible (Table 2) for classes between 2 and 8. Intense dark pixels were more visible for grass before the cut, which is normal because of the presence of grass ($p<0.0001$). Although it was not significant, one can see that lighter pixels are present after the cuts simulating the passage of the animals (class 6 to class 9).

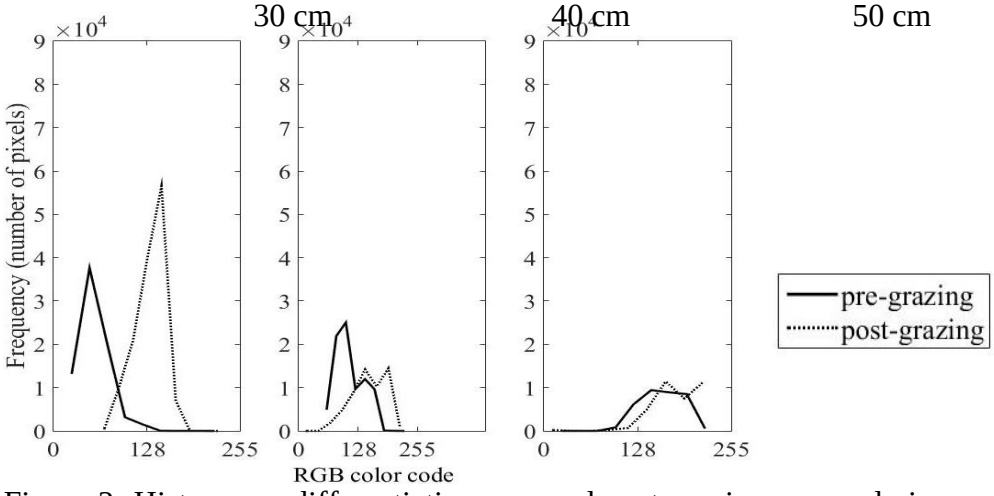


Figure 2: Histograms differentiating pre- and post-grazing greyscale images for sample n°1 at 30, 40 and 50 cm of heights above the ground.

This method has the advantage to be non-destructive as well as to be able to characterize the sward structure in details. However, to cover the whole pasture, it would be time-consuming unless representative samples would be taken into account. Hence, it does not seem quite feasible to use it as the vegetation counterpart to high rate animal biting monitoring. The other limit of this

technique is sunlight as it was not possible to take good quality images without a shade tent. Finally, if the slope of the ground is high, biases might appear on the images taken at different place on the pasture. The use of tools enabling image acquisition at a high frequency could cope with this problem knowing that nowadays devices like drones are fitted with more sophisticated cameras. Coupled with an accurate location sensor the data could cover in one shot the whole pasture and improve the determination of the spatial distribution of the grass.

Conclusions

Histograms of intensity performed on greyscale images could detect differences between pre- and post-grazing sward. As expected, overall darker pixels were observed for pre-grazing images and whiter pixels for post-grazing images, indicating longer distances consistent with lower forage biomass. It could be concluded that use of camera would be a helpful tool for assessing the grass heights on pasture. Nevertheless, more automated methods should be investigated in order to accelerate the image acquisition and to sweep the whole pasture area reducing the duration of the measurements.

Acknowledgements

This work was initiated by the Precision Agriculture Unit of Gembloux Agro-Bio Tech (University of Liege, ULg), and performed with the help of all technical and scientific staff, with a special acknowledgement to Dylan Ruelle for his great contribution and dedication in the accomplishment of this research.

References

Andriamandroso, A. L. H., Bindelle, J., Mercatoris, B., & Lebeau F. 2016. A review on the use of sensors to monitor cattle jaw movements and behavior when grazing. *Biotechnology, Agronomy, Society and Environment*, 20(S1).

Andriamandroso, A., Lebeau, F., & Bindelle, J. 2015. Changes in biting characteristics recorded using the inertial measurement unit of a smartphone reflect differences in sward attributes. *Precision Livestock Farming'15*, 283-289.

Andújar, D., Dorado, J., Fernández-Quintanilla, C., & Ribeiro, A., 2016. An Approach to the Use of Depth Cameras for Weed Volume Estimation. *Sensors*, 16(7), 972.

Bonesmo, H., Kaspersen, K., & Bakken, A. K., 2004. Evaluating an image analysis system for mapping white clover pastures. *Acta Agriculturae Scandinavica, Section B–Soil and Plant Science, 54, 76–82.*

Boval, M., & Dixon, R. M. 2012. The importance of grasslands for animal production and other functions: a review on management and methodological progress in the tropics. Animal, 6(05), 748-762.

Carvalho, P. C. F., 2013. Harry Stobbs Memorial Lecture: Can grazing behavior support innovations in grassland management? *Tropical Grasslands-Forrajes Tropicales*, 1(2), 137-155.

Castro, E., Pérez, C., Ortega, C. A., Vizuete, D. S., & González, J. P. 2017. Evaluation of two hormonal stimulants for fattening Brahman bulls under grazing and supplementary multinutritional blocks. *SIEMBRA, 3(1), 101-104.*

Ehlert, D. Adamek, R. Und Horn, H.-J., 2009. Laser rangefinder-based measuring of crop biomass under field conditions. - *Precision Agriculture '10,* 395–408

Fan, X., Kawamura, K., Lim, J., Yoshitoshi, R., Yuba, N., Lee, H. J., Tsumiyama, Y., 2016. Spring growth stage detection in Italian ryegrass field using a ground-based camera system. *Grassland Science*, 62(3), 188-193.

Gebhardt, S., Schellberg, J., Lock, R. Kühbauch, W. "Identification of broad-leaved dock (Rumex obtusifolius *L.*) on grassland by means of digital image processing". *Precision Agriculture* 2006, 7, 165.

Gregorini, P., Villalba, J. J., Chilibroste, P., Provenza, F. D., 2017. Grazing management: setting the table, designing the menu and influencing the diner. *Animal Production Science*, in press.

Gibb, M. J. 1996. Animal grazing/intake terminology and definitions. *Pasture ecology and animal intake* 3, 21-37.

Girma, K., Martin, K. L., Anderson, R. H., Arnall, D. B., Brixey, K. D., Casillas, M. A., Chung, B., Dobey, B. C., Kamenidou, S. K., Kariuki, S. K., Katsalirou, E. E., Morris, J. C., Moss, J. Q., Rohla, C. T., Sudbury, B. J., Tubana, B. S., Raun, W. R., 2006. Mid-Season Prediction of Wheat-Grain Yield Potential Using Plant, Soil, and Sensor Measurements. *Journal of Plant Nutrition* 29, 873 – 897

Hodgson, J., 1985. The control of herbage intake in the grazing ruminant. *The Proceedings of the Nutrition Society* **44**, 339–346.

Macoon, B., Sollenberger, L. E., Moore, J. E., Staples, C. R., Fike, J. H., Portier, K. M. 2003. Comparison of three techniques for estimating the forage intake of lactating dairy cows on pasture. *Journal of Animal Science*, 81, 2357-2366.

Nadimi, E.S., Søgaard, H.T., Bak, T., Oudshoorn, F.W., 2008. ZigBee-based wireless sensor networks for monitoring animal presence and pasture time in a strip of new grass. *Computers and Electronics in Agriculture*, **61**, 79–87

O'Mara, F. P., 2012. The role of grasslands in food security and climate change. *Annals of botany*, 110, 1263-1270.

Porter, M.G., Barton, D., 1997. A comparison of methods for the determination of dry matter concentration in grass silage including an extraction method for water. *Animal Feed Science and Technology*, 68, 67-76.

Robert, F., Barnes, C., Jerry, N., Kenneth, J. M., Michael, C. 2007. *Forages: The science of grassland agriculture*. 808 p.

Sanderson, M. A., Rotz, C. A., Fultz, S. W., Rayburn, E. B., 2001. Estimating forage mass with a commercial capacitance meter, rising plate meter, and pasture ruler. *Agronomy Journal*, 93, 1281-1286.

Smit, H. J., Taweel, H. Z., Tas, B. M., Tamminga, S., Elgersma, A., 2005. Comparison of techniques for estimating herbage intake of grazing dairy cows. *Journal of Dairy Science*, 88, 1827-1836.

Yin, X., McClure, M.A. Jaja, N. Tyler, D.D., Hayes, R.M., 2011. In-Season Prediction of Corn Yield Using Plant Height under Major Production Systems. - *Agronomy Journal* 103, 923-929.

Zhang, L., Grift, T. E., 2012, A LIDAR-Based Crop Height Measurement System for Miscanthus giganteus. *Computers and Electronics in Agriculture* 85, 70-76.

Session 7

Information technology in PLF

Wireless network monitoring system for pig farm based on a mobile coordinator and borrowed address routing algorithm

W. Zhu, Y. Si, J. Zhang, X. Li
School of Electrical Information Engineering, Jiangsu University, Zhenjiang, China
wxzhu@ujs.edu.cn, zwxbest@126.com

Abstract

An environmental control system for pig farms, based on a mobile coordinator and borrowed address routing algorithm, was designed to address the characteristics of large pig farms, such as the complex environment, numerous control objects and messy wiring. This system consisted of the control centre with ARM-LINUX, the remote control terminal and the wireless networks composed of various devices and sensors. In order to improve the success rate of orphan nodes connecting to the wireless sensor networks, and collect the piggery environment parameters accurately, the type of destination node would be assessed by the router to reduce the packet transmission delay. The coordinator node and the controller were installed on a patrol car with a battery to provide power. Experimental results showed that the success rates of network address assignment were improved by using the borrowed address algorithm. Remote real-time control of environmental parameters was implemented, and this system will find wide application in modern precision livestock farming.

Keywords: borrowed address; mobile coordinator; wireless sensor network; monitoring system; ZigBee

Introduction

The pig production industry in China is developing very quickly. Improvements to monitoring systems are the development trend in the pig production industry. At present, the goal of the monitoring system is to collect environmental parameters accurately in real time. The distributed address assignment mechanism (DAAM) is used in the wireless sensor network which is based on the ZigBee communication protocol (Sun, Kong, 2011). However, the DAAM would cause the orphan node problem, which affects the stability and reliability of the monitoring system.

There have been some related research advances in relation to the orphan node. In 2011, Yang converted the terminal device into the router and increased the depth of the network. The coverage range of the network was extended, but the

complexity of the terminal device was also increased (Yang, Xu and Qiu, 2011). In 2012, Yukun Yao designed an efficient address assignment algorithm based on a borrowed address. The parent node borrowed the address first from the descendant nodes in the same branch to improve the detouring problem (Yao, Chen, 2012). In 2014, Hu proposed a distributed address assignment algorithm with borrowed address for ZigBee networks. The parent node could borrow a subtree of address space from a neighbour to alleviate the orphan node problem (Hu, Lin, 2014). The borrowed address routing algorithm defaults to the one-hop-neighbour for the borrowed address. This causes some network problems, such as a large time requirement and energy loss. On the other hand, a routing node has problems looking for the proper node which could borrow the address. In this paper, a wireless network monitoring system is designed for a pig farm based on a mobile coordinator and a borrowed address routing algorithm. The coordinator node and the controller were installed on the patrol car with a battery to provide power. Because the mobile coordination node could reliably form a network with flexible orphan node connection, the video and sound information as well as the environmental parameters could be delivered to the controller in real time. The coordination node is directly powered by the battery and the lifetime is prolonged. In addition, the borrowed address range of the parent node is set to two-hop-neighbour, making it easy for the coordination node to form a network connecting new nodes flexibly. Therefore, the temperature, humidity and carbon dioxide concentration could be collected and controlled accurately by the pig farm monitoring system.

Materials and methods

The overall design of the system

The site of the experiment was Jiangsu Danyang Rongxin pig farm. The monitoring system based on a S3C6410 development board was installed in the pig farm. The CC2430 wireless module was used as a platform for a wireless sensor network to collect the environmental parameters in the piggery. The coordinator node and controller were installed on the patrol car and formed a network which connected the orphan nodes and improved the transmission efficiency of video and other information during the control process. The personal computer was used as the remote control centre. This paper describes the design of a wireless network monitoring system for a pig farm based on a mobile coordinator and a borrowed address routing algorithm.

The wireless network monitoring system for a pig farm, based on the borrowed address routing algorithm, is composed of three parts: the wireless sensor network with mobile coordinator, embedded site controller and remote control centre. The overall design of the system is shown in Figure 1.

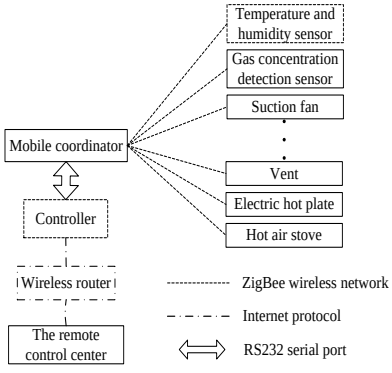


Figure 1
The overall design of the system

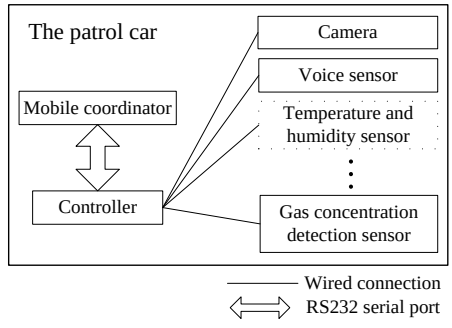


Figure 2
Design of the mobile node on the patrol car

The wireless sensor network for the piggery is composed of ZigBee nodes. The temperature, humidity and harmful gas concentration in the piggery are monitored in real time by placing the sensor nodes in different areas of the farm. The collected data are sent to the coordinator through the ZigBee wireless network, and then to the embedded site controller S3C6410 through the RS232 serial port. The database and server are transplanted onto the S3C6410. Users can read the real-time data remotely over the internet. A patrol car could also be used in the monitoring system. On the patrol car there are voice sensors, environmental parameter sensors, cameras, a coordinator and controller. A magnetic track was laid in the piggery, and designed so that the patrol car could follow the magnetic track to move around the piggery. The patrol car could also be used as the mobile coordinator node in the wireless network. The design of the mobile node on the patrol car is shown in Figure 2.

ZigBee wireless sensor network

According to the different functions of the network equipment, the ZigBee nodes are classified into coordinator node, router nodes and end device nodes. The coordinator and router are the full function device (FFD) and the end device is the reduced function device (RFD) (Zhu, Dai and Huang, 2012).

Distributed address assignment mechanism

Two address assignment protocols for the ZigBee network were defined: the stochastic address assignment mechanism (SAAM) and distributed address assignment mechanism (DAAM) (Wu, Chang, 2013). The DAAM is mostly used in the cluster-tree networks. Assuming that the number of parent nodes connecting up to the child nodes is C_m, the maximum number of the child router node is R_m, the maximum depth of the network is L_m (Wu, Wang, 2013). The

C_{skip} is used by the distributed address assignment mechanism to assign a unique network address for each node (Giri, Roy, 2009). The assignable address space of the parent node could be computed by the formula (1):

$$C_{skip}(d) = \begin{cases} 1 + C_m(L_m - d - 1) & R_m = 1 \\ \dfrac{1 + C_m - R_m - C_m \times R_m^{L_m - d - 1}}{1 - R_m} & R_m \neq 1 \end{cases} \quad (1)$$

If we suppose that the current address of the parent node is A_{parent}, then the address of the end device should be assigned by the formula (2):

$$A_{end} = A_{parent} + C_{skip}(d) \times R_n + n \quad (2)$$

The address of the router should be assigned by the formula (3):

$$A_{router} = A_{parent} + n(-1) \times C_{skip}(d) + 1 \quad (3)$$

The pig farm sensor networks with mobile coordinator

A coordinator and a controller are installed on the patrol car. The video information from cameras is delivered to the controller in real-time, and the mobile coordinator can establish networks with the orphan nodes flexibly. The coordinator is directly powered by a battery with a long life. During the wireless sensor network setup process, ZigBee technology was used to form the wireless network, as shown in Figure 3.

Users could monitor the pig farm in real time by means of the environmental parameter sensors and cameras. Because the transmission range of the ZigBee protocol is generally between 10 and 75m, the network node connected to the coordinator would disconnect from the tree network when it is outside the transmission range (Zheng, Shi, 2010). In order to ensure real-time collection of the environmental parameters of the pig farm, it was necessary to join the disconnected nodes to the network using the improved borrowed address routing algorithm.

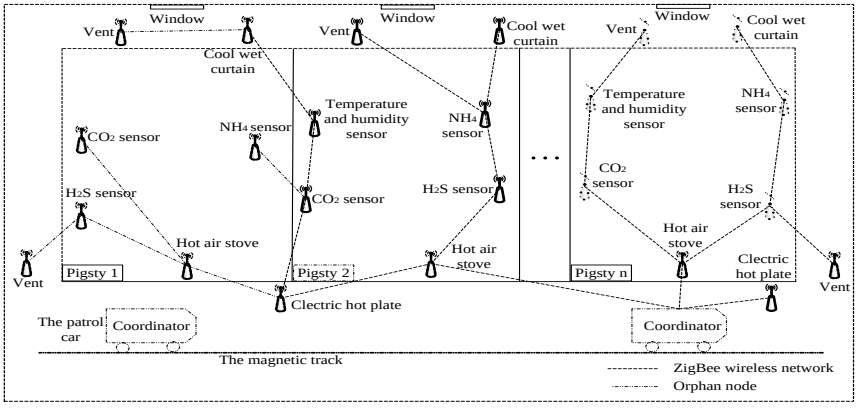


Figure 3 ZigBee node distribution map

The improved borrowed address algorithm

The borrowed address assignment algorithm based on a two-hop neighbourhood

In the DAAM the borrowed address range of the routing node is a one-hop neighbour node. In order to increase the success rate of the borrowed address, the information range of two-hop neighbour nodes could be obtained by the parent node, and the parent node would borrow the address first from the descendant nodes in the same branch. As an improvement to the routing algorithm, the borrowed address assignment algorithm based on a two-hop neighbourhood (BAAA-2) is proposed. The detailed steps of the algorithm are as follows.

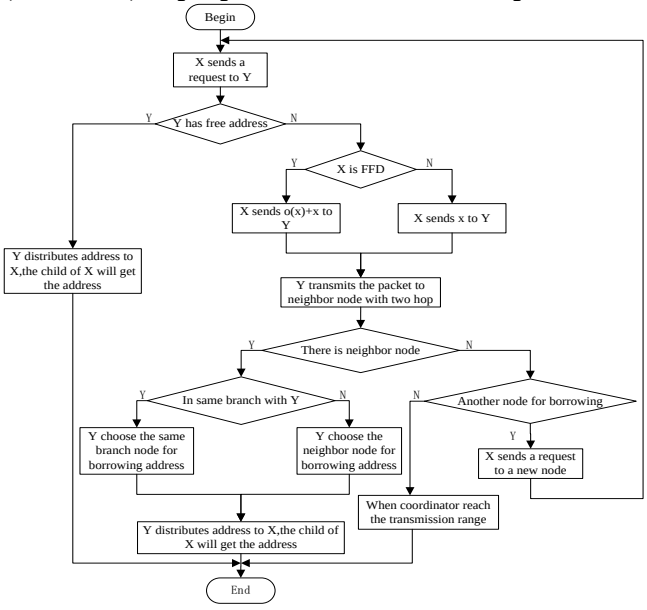


Figure 4 The BAAA-2 algorithm flow chart

Step 1: Node X sends a request to router Y to apply the free address. Router Y judges whether it has a free address. If so, the address is assigned to node X; otherwise, the router Y starts the borrowed address operation.

Step 2: Router Y sends a message to node X which contains the dy of the network depth. Node X sets the dx as dy+1, and joins as the child node of router Y.

Step 3: Router Y sends a response to node X to calculate the size of the address space of its application. If node X was FFD, then the address space of the child node would be calculated as o(x), and o(x)+x as the borrowed packet is sent to the router Y. If node X is RFD, then the address space of the child node is o(x)=0, and the borrowed packet x is sent to the router Y.

Step 4: Router Y transmits the borrowed address packet to neighbour nodes with two hops. The neighbour node that receives the borrowed address packet replies to the router Y. If no neighbour nodes satisfy the requirement for the borrowed address packet, the node X judges whether there is another neighbour node for

borrowing. If so, then X returns to step (1); otherwise, the orphan nodes connect to the mobile coordinator if it can be reached within the transmission range.
Step 5: After router Y receives the reply packet from the neighbour node, Y judges whether there is a descendant node in the same branch. If so, Y chooses the node which has more free address as the borrowed node; otherwise, a neighbour node is chosen as the borrowed node which had more free address. Then router Y distributes the borrowed address to node X, and the child node of X also receives the free address. The BAAA-2 algorithm flow chart is shown in Figure 4.

The routing process of BAAA-2
In the wireless sensor networks for the pig farm, the address of the router Y is A, the network depth is d. When Y receives a data packet with destination address D, the process followed by the cluster-tree routing algorithm is as follows.
①If the destination node is the router Y, that is A=D, the Y accepts the packet and stops forwarding.
② If the destination node is the child router node of the Y, that is $A < D \le A + R_{\max} \cdot C_{skip}(d-1)$, the next hop address is $A+1+\{[D-(A+1)]/C_{\text{skip}}(d)\} \cdot C_{skip}(d)$. Y sends the packet to the next hop address.
③ If the destination node is the end device node of the Y, that is $A + R_{\max} \cdot C_{skip}(d) < A < A + C_{\text{skip}}(d-1)$, the packet is transmitted to the end device node.
④Otherwise, the Y transmits the packet to its parent node, and the process is complete.

Experimental results and analysis

The simulation of routing algorithm
The simulation results for DAAM, BAAA-1 and BAAA-2 were compared using the NS2 simulation platform (Wang, Chen, 2011). Real-time data acquisition and accuracy of the pig farm monitoring system were the important criteria for measuring the intelligence of the monitoring system. This simulation therefore focused on analysing the impacts of different algorithms on the average address assignment time and address assignment success rate when they were used in the same network parameters. It proved that the improved borrowed address was superior to other routing algorithms.
In the NS2 simulation, setting a circular area of radius 200 metres as the node scene, the number of nodes was 50, 100, 150, 200 and 250 respectively, the node communication range was 40 metres, network parameters C_{m}, R_m and L_m

were set to 5, 3, 8, and the simulation results were as follows.

Figure 5 compares the results for the success rate of orphan node address assignment. At less than 200 nodes, the success rate of address assignment of the BAAA-1 and the DAAM was similar, but from the 250th node onwards, the performance of BAAA-1 was better than the DAAM. The improved borrowed address algorithm proposed in this paper was used to set the range of the parent node borrowed address in two-hop-neighbour nodes, while also giving priority to the borrowed address from the descendant node of the same branch. The mobile coordinator node could create a new network with the orphan node flexibly, and the orphan node problem of networks was solved successfully. At the 50th node, the address assignment success rate of the BAAA-2 was higher than the other two algorithms, and at the 250th node the address assignment success rate of this algorithm increased quickly, so, compared with the other two algorithms, the higher the node number of BAAA-2, the higher the address assignment success rate.

Figure 6 compares the results for average time of orphan node address assignment. There were no big differences between these three routing algorithms, but the type of access node was judged in the BAAA-2 algorithm, and the borrowed address from the descendant node of the same branch reduced the average time. So the BAAA-2 algorithm is better than the other two algorithms which could allocate address space more quickly. Before the 200th node, the BAAA-2 and the DAAM had a similar average address assignment time, but after the 250th node, in the BAAA-2 the address allocation rate gradually accelerated.

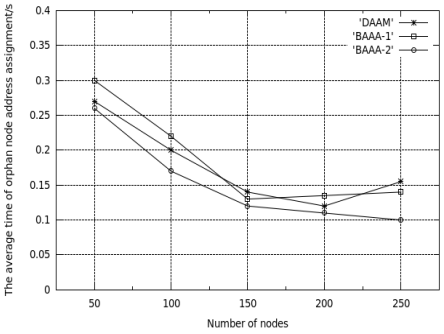


Figure 5
The comparison of success rate

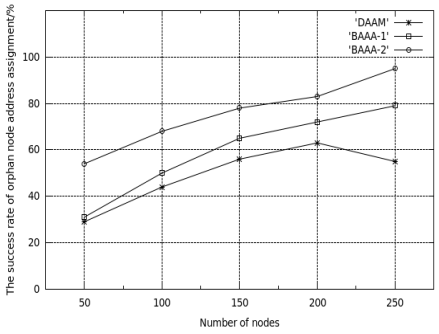


Figure 6
The comparison of average time

Environmental parameters test on the pig farm

The experimental site was the Jiangsu Danyang Dongxin Pig Farm. The pig barn was 90 metres long, 8 metres wide and 3.5 metres high to the roof. There were 40 router nodes and 10 end device nodes in the piggery. The coordinator node and controller were installed on the patrol car, and a magnetic track was laid on

the piggery floor. A personal computer was used as a remote control centre in the equipment control room (office). The experimental data was collected on 1 March 2016, between 05:00 and 14:30. The temperature, humidity and carbon dioxide concentration were collected every half hour and saved in the database.

The temperature was chosen as the experimental object. The internal and external temperature values for piggery were recorded, as shown in Table 1. Table 1 shows that there was a large difference between the internal and external temperature of the pig farm. The sensor nodes of the wireless sensor networks could collect the real-time temperature values, and the environment monitoring system kept the internal temperature at about 21°C. The system maintained the internal environmental parameters of the piggery in a stable range over time.

Table 1 Temperature values

Time	Internal	External	Time	Internal	External
05:00	20.1	3.1	05:30	20.3	3.0
06:00	20.5	3.3	06:30	20.2	3.5
07:00	20.2	3.6	07:30	20.4	4.1
08:00	20.6	4.6	08:30	20.5	5.5
09:00	20.7	5.7	09:30	20.8	5.7
10:00	21.1	6.2	10:30	21.0	6.5
11:00	21.5	7.0	11:30	21.4	7.2
12:00	21.4	7.2	12:30	21.6	8.4
13:00	22.0	9.5	13:30	22.2	10.0
14:00	21.8	10.2	14:30	21.7	10.1

The DAAM and the BAAA-2 were used in the wireless sensor network to collect the environmental parameters. The DAAM collected 683 records and the BAAA-2 collected 751, but the number of data records collected by 40 sensor nodes was 40×2×10=800. If the data packet loss rate of the network was not included, the BAAA-2 improved the success rate of address assignment. At the same time, the accuracy and real-time performance of data acquisition by the system was improved. However, there is a need to further improve the data packet loss rate of the network.

Conclusions

In this system, the coordinator and controller are installed on the patrol car. The coordinator node could be powered directly by the car battery which had a long operating time. Additionally, this mobile coordinator node can easily create a new network with the orphan node flexibly. On the other hand, the video information from the camera nodes could be easily delivered to the controller in real time. Using the improved borrowed address algorithm proposed, the

cluster-tree network could be formed flexibly. The system reduced the time consumption and energy loss of the network. The temperature, humidity and carbon dioxide concentration could be collected accurately with the system. However, there is a need to further improve the data packet loss rate of the network. The address reassignment strategy of the mobile nodes and the borrowed address algorithm should be improved in order to increase the operating efficiency.

Acknowledgment

This project was supported by the National Natural Science Foundation of China (Grant No. 31172243) and a project funded by the Priority Academic Program Development of Jiangsu Higher Education Institutions.

References

Giri DU, Roy K 2009. Address Borrowing in Wireless Personal Area Network, 2009IEEE International Advance Computing Conference, India, 181-186.

Hu SC, Lin CK 2014. Distributed Address Assignment with Address Borrowing for ZigBee Networks, International Conference on Communications Workshops, Sydney, 454-459.

Sun Q, Kong L 2011. Construction of wireless sensor network monitoring system based on zigbee, Instrument technology 6 7-9.

Wang Q, Chen H 2011. Design and implementation of simulation platform for network control systems based on NS2, Journal of system simulation 32 270-274.

Wu C, Chang R 2013. An innovative scheme for increasing connectivity and life of ZigBee networks, The Journal of Supercomputing 65 136-153.

Wu X, Wang Y 2013. Borrowed address assignment algorithm in zigbee networks based on two-hop neighborhood, Science technology and engineering 13 8333-8338.

Yang X, Xu Y, Qiu S 2011. A Solution of Orphan Problem in ZigBee Tree Network, Networking and Mobile Computing, Wuhan 1-4.

Yao Y, Chen Y 2012. A borrowed address-based on-efficient distributed address assignment algorithm in zigbee networks. Journal of chongqing university 35 151-158.

Zheng J, Shi M 2010. Research on wireless sensor network tree routing based on zigbee technology, Journal of Xi'An university of posts and telecommunications 15 23-26.

Zhu W, Dai C, Huang P 2012. Environmental control system based on IOT for nursery pig house, Transactions of the Chinese society of agricultural engineering 28 177-182.

Development of a traceability system for the animal product supply chain based on blockchain technology

F. Marinello[1], M. Atzori[2], L. Lisi[1], D. Boscaro[1], and A. Pezzuolo[1]
[1]*Department of Land, Environment, Agriculture, and Forestry, University of Padova, Viale dell'Università 16, 35020 Legnaro (PD), Italy.*
[2]*Research Center for Blockchain Technologies, University College of London, United Kingdom.*
andrea.pezzuolo@unipd.it

Abstract

The agri-food supply-chain has been studied extensively in recent years and many researchers are now considering the application of advanced technologies in supply-chain management. Technological developments in the areas of networking devices, sensors and communication technology can play a significant role in the sustainability of animal products. In particular, the blockchain has attracted considerable attention as a technology with disruptive applications in many different domains. The blockchain consists of a distributed database which maintains a continuously-growing list of data records, secured from tampering and revision thanks to algorithmic procedures. This paper therefore discusses the potential for establishing a conceptual framework for an animal product supply-chain traceability system based on blockchain technology, in order to enhance food safety and quality and significantly reduce losses during the logistics process. This approach covers the whole data gathering and information management process for every link in the animal product supply chain, including monitoring, tracing and traceability management for quality and safety of the animal product "from farm to fork". Specifically, the study considers supply chains with different levels of complexity and analyses strengths, weaknesses, limits and opportunities in the implementation of this new technique. The study also shows possible benefits related to both direct supply chains (one supplier to one customer) and multi-entry-exit chains (multiple suppliers to multiple customers).

Keywords: livestock management, supply chain, food safety, traceability system, blockchain.

Introduction

Over the past 20 years, customers and EU institutions have increasingly demanded higher quality, safety and confidence in food, along with a reduction

in information asymmetry across food supply chains (Schwägele, 2005; Van Wezemael *et al.*, 2011; Min Aung and Seok Chang, 2014). Traceability and animal identification are essential in order to meet those demands (Golan *et al.*, 2004). Traceability means "the ability to trace and follow a food, feed, food producing animal or ingredient through all stages of production and distribution" – and was first proposed by the EU as a key solution after the BSE problem occurred (European Commission, 2000).

The traditional methods of animal and product identification in small farms are usually body marks, ear shears, ear tags and normal labels (Eradus, 1999; Bosona and Gebresenbet, 2013). With the development of technology, new animal identification methods such as RFID, one-dimensional barcodes, two-dimensional barcodes or DNA fingerprints and retina scans (Voulodimos *et al.*, 2010; Wang *et al.*, 2010; Dabbene and Gay, 2011) have gradually been introduced.

RFID utilises wireless electromagnetic fields to transfer data and write and read the information it contains multiple times. The superiority of RFID lies in automated high precision reading, since there is no direct contact (Kumar *et al.*, 2009). A one-dimensional barcode is the typical barcode placed on the meat packaging, and it offers a good way of including a reference code or a small amount of information. A two-dimensional barcode looks like a square, with many dots. A single two-dimensional bar code can hold a clear message and represents more data per unit area than a one-dimensional barcode (Mainetti *et al.*, 2013). The Quick Response (QR) code is the most commonly used two-dimensional barcode and it can contain traceability information about the product. Consumers, for example, can use their smartphone to scan the QR code and instantly trace the origin of the product with multimedia information (Costa *et al.*, 2013). Unfortunately, since the system does not necessarily include curation, it is easy to introduce forged data in the absence of adequate control during such operations (Bai *et al.*, 2017)

The blockchain is a new emerging technology which has drawn much attention from researchers in many different domains (Crosby *et al.*, 2016; Sikorski *et al.*, 2017), and may provide a valid solution to the problem. A blockchain is a distributed database which maintains a continuously-growing list of data records that are secured against tampering and revision (Nakamoto, 2008). It consists of blocks containing batches of individual transactions (Zyskind *et al.*, 2015). Each block contains a timestamp and a link to a previous block. Blockchain could guarantee the security of the whole network by using a mathematical algorithm mechanism (Kosba et al., 2016).

The blockchain is essentially a public ledger, in which all committed transactions are stored in a list (or a chain) (Lewemberg *et al.*, 2015). The chain grows continuously as new transactions are confirmed. Every compatible client can

verify any transaction. Blockchain technology allows transactions to be safely verified in a decentralised way, without the need of a central intermediary (Tian, 2016). The blockchain can hence result in increased time- and cost-effectiveness if applied to the management of livestock farming. It can be used to increase the fight against food safety violations and improve the efficiency of animal health checks, based on unambiguous and high-speed information.

This work follows a feasibility study conducted by the authors and discusses the potential for establishing a conceptual framework for an animal product supply-chain traceability system based on blockchain technology to enhance food safety and quality, while at the same time significantly reducing losses of time, product and resources during the logistics process. This approach covers the whole data gathering and information management process for every link in the animal product supply chain, including monitoring, tracing and traceability management for quality and safety of the animal product "from farm to fork". Specifically, the study considers supply chains with different levels of complexity and analyses strengths, weaknesses, limits and opportunities in the implementation of this new technique.

Materials and methods

Blockchain technology

Blockchain is a sequence of blocks which holds a complete list of transaction records like a conventional public ledger. Each block points to the immediately previous block via a reference that is essentially a hash value of the previous block, known as the parent block. The first block in a blockchain is known as the genesis block and has no parent.

A block consists of the block header and the block body. In particular, the block header includes: (i) block version, (ii) previous block header hash, (iii) Merkle tree root hash, (iv) timestamp, (v) nBits, (vi) the nonce. The Merkle tree root is the hash value of all the transactions in the block. The time stamp field represents the current time stamp as seconds in universal time. The nBits is the target threshold of a valid block hash.

Figure 1 shows how the digital signature (based on asymmetric cryptography) is used in the blockchain.

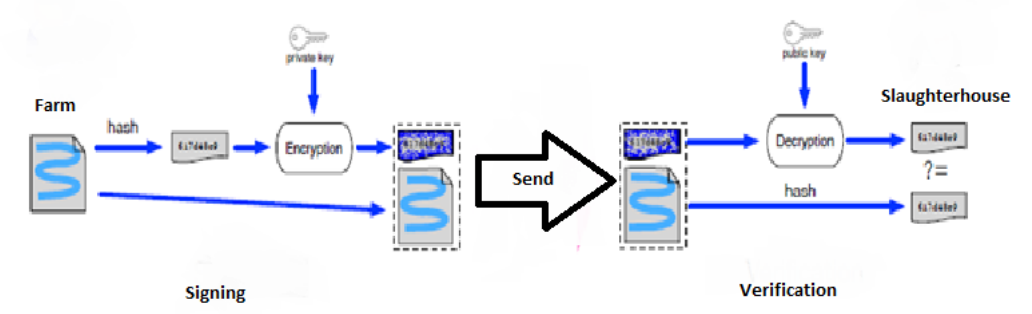


Figure 1. Example of a digital signature used in a blockchain.

Each user interacts with the blockchain network via a dedicated node in which a blockchain client is installed. When a node receives data from another node, it verifies the authentication of the data. It then broadcasts the validated data to every other node connected to it. In this way, the data is spread across the whole network. One of the benefits of such decentralised systems is the independence of the central server or the third party, which can greatly reduce costs.
Since each of the transactions on the blockchain is validated and recorded with a timestamp, it provides a global truth so that users can easily verify and trace the previous records by accessing any node in the distributed network. It significantly improves the traceability and transparency of the data stored in the blockchain.
The reputation of a node can be evaluated on the basis of its previous transactions and interactions with the community. There is a rising number of cases of falsification of personal reputation records. For example, in e-commerce, many service providers enrol a huge number of fake customers in order to achieve a high reputation (i.e. Sybil attack).
In the meat production supply chain, the blockchain could help to evaluate the information. It will be possible to analyse the transaction and therefore identify whether there are suspicious movements in the chain.

Animal product supply chain

The proposed analysis follows a feasibility study carried out in the north of Italy, and considers different livestock supply chains, with different complexities in terms of number of foreign and national livestock farms, slaughterhouses, grading plants and final dealers.
Table 1 below describes the typical supply chain in the Italian meat production system. A typical characteristic is that the supply chain starts in a country other than Italy, generally an EU country, where the calves are born and spend the first few weeks before being moved to Italy for the rest of the rearing period. Another typical characteristic of Italian meat production is control by a government

supervisory body (USL) which holds information about the health and movements of each calf throughout its life.
The main players in a typical supply chain are:

- *Foreign farm*: frequently located in an EU country where the calves are born and spend the first few weeks.
- *Livestock farm*: Italian farms buy the calves from a foreign farm, including them in the farming process and the rules imposed in order to comply with the required standards.
- *Slaughterhouse*: receives the cows that are ready for slaughter and normally produces half-carcases which are classified by quality.
- *Carcass selection and grading plant*: the half-carcases arrive and are selected and divided in cuts, depending on the requirements of the supermarket chains.
- *Supermarket chains*: normally these only carry out final cutting, packing and labelling, also adding quality brands and traceability codes.

With regard to traceability, all the stakeholders are actively engaged in the information flow: they participate by communicating the obligatory information to the USL and, if the supply chain is authorised by the Ministry of Agriculture, every stakeholder communicates all the additional information to the farmers' association or to the independent control agency, such as: feed characteristics, any additional animal welfare information, other specific features of the animal or the meat, etc.
Table 1. Description of the main stages in the supply chain with particular attention to distribution of the information flow.

Process stage	**Obligatory information**	**Additional information**	**Geographic competence**
Foreign farm	Animal ID number	Antibiotic/immunisation treatments	Transnational
Livestock farm	Arrival and exit dates.	Feeding and type of feed. Antibiotic/immunisation treatments	National
Slaughterhouse	Arrival date and ante-mortem inspections	Quality of carcass and meat	National
Carcass selection and grading plant	ID code to record the identity of every cut of meat.	ID code to maintain the traceability chain	National
Supermarket chains	Arrival date, date of packaging/labelling.	Labelling with bar code that links to the description of the individual animal.	National
Customer			

In Italy, the information flow (Figure 2) typically converges on three big data holders: USL, farmer association and the certifying organisation. The USL is a government body which stores general information related to movements and characteristics of the individual animals. This information may be used for health inspections and in the event of health problems. In a typical case, the farmer association uses the public information from the USL database in order to upload information about every animal they are interested in tracking, always referring to the ID number of each animal. The certification body is backed up by checks by public authorities and verifies every step of the workflow and the information related to animals and meat, from the herd owner to the supermarket. The main task of the certification body is to verify the correctness of the information and supervise compliance with production requirements in every area.

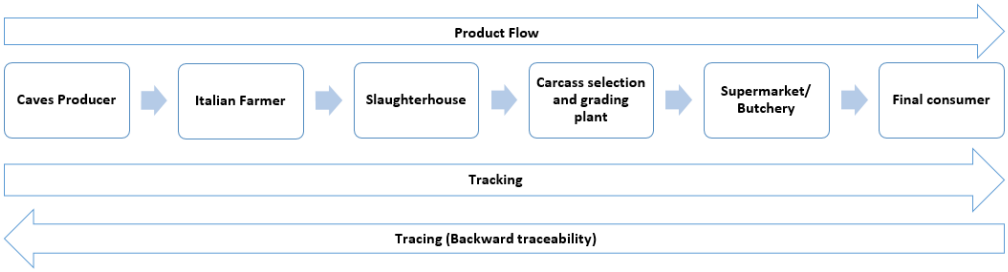


Fig. 2 – Typical supply chain occurring nowadays in Italy.

Results and discussion

Improving the animal product supply chain

Along with many technical requirements, the animal supply chain typically requires the verification and storage of a large amount of information.

Blockchain technology can be deployed effectively as a database which connects all the stakeholders involved, creating a network of reliable information which is verified by tamper-resistant, algorithmic procedures. The blockchain may prevent many of the information errors which often occur between those responsible for checking and validating key information, mainly due to the use of paper records. The blockchain would also significantly improve time efficiency throughout the chain and cut red tape, with benefits for the animals themselves. Under the current system, for example, when an Italian stockman receives a calf, it could take up to a month for all the relevant information to be fully recorded by the supervisory bodies, and understandably, this would prevent proper and immediate action in the event of a health emergency.

Blockchain technology allows for efficient verification and storage of information, so that bodies responsible for controls can easily detect any fraud or

malpractice in real time. While it may be easy to tamper with paper records, data stored in the blockchain are immutable, completely reliable, and distributed to each node of the network. This makes it possible to track, in a secure, timely and tamper-proof manner, for example, the number of animals sent from one farm to another, or to the slaughterhouse, without any room for error or illegal acts.
Moreover, thanks to its decentralised structure (Fig. 3) and trustless architecture, a blockchain-based supply chain would not need any certifying body or third party to manage and verify the information flow. Decentralisation makes the workflow more efficient, since authority checks may concentrate on specific information only and verify it, instead of keeping track of the whole information flow.
The deployment of the blockchain in the industry can thus lead to significant benefits, in terms of better quality and improved efficiency of meat production.

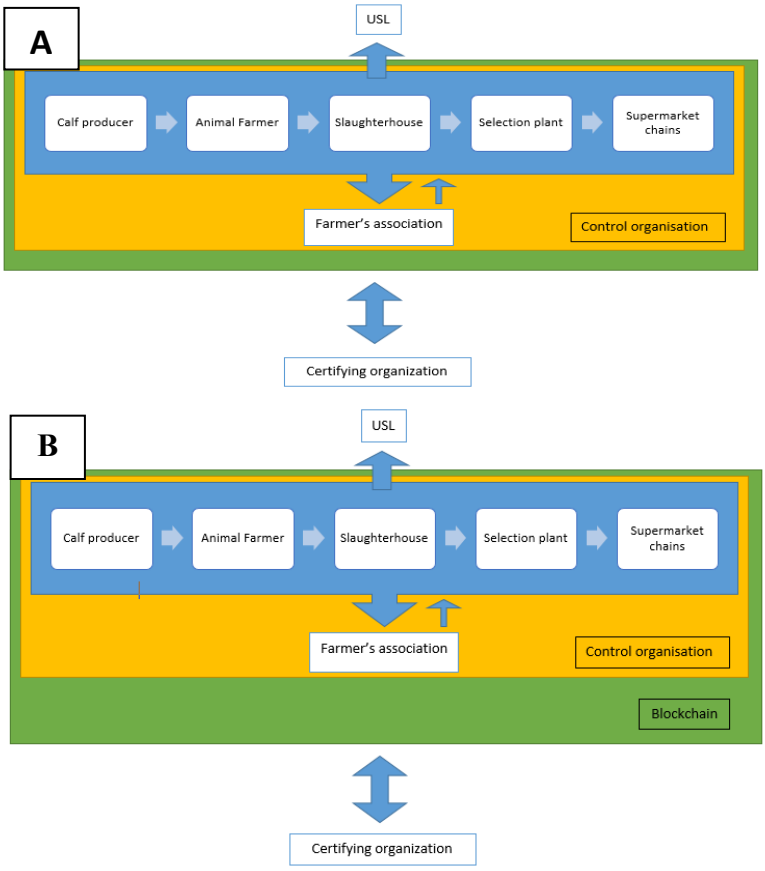


Figure 3. Example of information flow and control in a typical Italian meat production supply chain (A) and representation of a typical supply chain improved by the blockchain (B)

Different supply-chain scenarios

This application may prove to be even more effective as supply chain workflows become more complex, as highlighted by the different scenarios summarised in the current supply chains in Italian meat production (Table 2). As the number of stakeholders increases, such as farms, slaughterhouses, etc., information flow and transactions tend to grow exponentially, causing major problems in poorly digitised systems (Figure 4).

The blockchain also makes it possible to access information regardless of geographical boundaries, linking different countries or continents. It can also be successfully deployed in a small supply chain, especially as a protection against fraud and malpractice relating to European products with a registered designation of origin or other specific production protocols.

While blockchain-based and tamper-proof product certification may entail additional costs, it is likely to result in significant benefits, such as greater product credibility and better consumer perception of their quality, so it may prove a wise investment.

Table 2 This table shows six possible cases, which differ in terms of the number of parties involved in each node of the supply chain.

Process stage	**Supply chain scenario**					
	A	B	C	D	E	F
Foreign farm	0	1	1	2	2	2
Livestock farm	1	1	2	4	6	8
Slaughterhouse	1	1	1	1	2	2
Grading plant	0	1	1	2	2	2
Supermarket chains	1	1	3	4	5	6

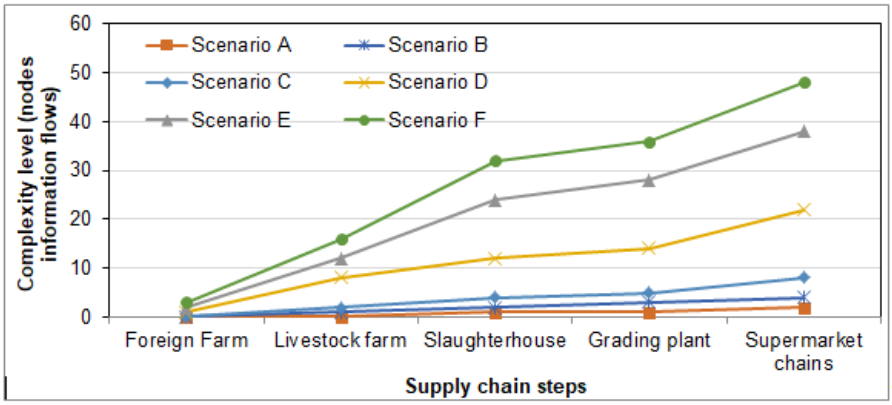


Figure 4. The graph shows different types of supply chain, based on the level of complexity in terms of the number of parties involved in each node

Conclusions

In the present work, we propose implementation of a supply chain in the meat production based on blockchain technology.
Blockchain can serve as a decentralised and tamper-proof information repository, significantly improving the efficiency, security and accountability of supply chain information, and also reducing fraud and accidental errors associated with the use of paper records. The blockchain can also be successfully used to verify food quality marks, making them highly reliable through tamper-proof, algorithmic procedures.
Experimental tests also demonstrate that blockchain-based applications can be even more effective when the supply chain complexity scales up, growing exponentially in terms of the number of parties involved and the volume of information flow and transactions.
Although blockchain technology is an emerging technology which needs further development before widespread adoption, its deployment can have a significant, positive impact on management of the entire supply chain.

References

Bai, H., Zhou, G., Hu, Y., Sun, A., Xu, X., Liu, X., Lu, C. 2017. Traceability technologies for farm animals and their products in China. *Food Control*, **79**, 35-43.

Bosona, T., Gebresenbet, G. 2013. Food traceability as an integral part of logistics management in food and agricultural supply chain. *Food Control*, **33**, 32-48.

Costa, C., Antonucci, F., Pallottino, F., Aguzzi, J., Sarriá, D., Menesatti, P., 2013. A review on agri-food supply chain traceability by means of RFID technology. *Food and Bioprocess Technology* **6**, 353–366.

Crosby, M., Nachiappan Pattanayak, P., Verma, S., Kalyanaraman, V. 2016. Blockchain technology: Beyond bitcoin. *Appl Innov Rev*, **2**, 6–19

Dabbene, F., Gay, P., 2011. Food traceability systems: performance evaluation and optimization. *Computers and Electronics in Agriculture* **75**, 139–146.

Eradus, W.J., Jansen, M.B., 1999. Animal identification and monitoring. *Computers and Electronics in Agriculture* **24**, 91–98.

European Commission. 2000. Regulation (EC) No 1760/2000 of the European Parliament and of the Council of 17 July 2000, establishing a system for the identification and registration of bovine animals and regarding the labeling of beef and beef products and repealing Council Regulation (EC) No 820/97 (16/03/2012).

Golan, E., Krissof, B., Kuchler, F., Calvin, L., Nelson, K., & Price, G. 2004. Traceability in the US food supply: Economic theory and industry studies. Agricultural Economic Report, Number 830. Washington, DC: Economic Research Service, US Department of Agriculture.

Kosba, A., Miller, A., Shi, E., Wen, Z., Papamanthou, C. 2016. Hawk: The blockchain model of cryptography and privacy-preserving smart contracts. *IEEE Symposium on Security and Privacy* (SP), 839–858

Kumar, P., Reinitz, H.W, Simunovic, J., Sandeep, K.P., Franzon, P.D. 2009. Overview of RFID technology and its applications in the food industry. *Journal of Food Science*, **74**, 101 – 105.

Lewenberg, Y., Sompolinsky, Y., Zohar, A. 2015. Inclusive block chain protocols. In: International Conference on Financial Cryptography and Data Security. Springer, Heidelberg, 528–547

Mainetti, L., Patrono, L., Stefanizzi, M. L., Vergallo, R. 2013. An innovative and low-cost gapless traceability system of fresh vegetable products using RF technologies and EPCglobal standard. Computers and Electronics in Agriculture, **98**, 146-157.

Min Aung, M., Seok Chang, Y. 2014. Traceability in a food supply chain: safety and quality perspectives. *Food Control*, **39**, 172-184.

Nakamoto, S. 2008. Bitcoin: a peer-to-peer electronic cash system. Available at: https://bitcoin.org/bitcoin.pdf

Schwägele, F. 2005. Traceability from a European perspective. *Meat Science*, **71**, 164-173.

Sikorski, J.J. Haughton, J., Kraft, M. 2017. Blockchain technology in the chemical industry: machine-to-machine electricity market. *Applied Energy*, **19**5, 234-246.

Tian, F., 2016. An agri-food supply chain traceability system for China based on RFID & blockchain technology, in: Service Systems and Service Management (ICSSSM), 2016 13th International Conference on. IEEE, pp. 1–6.

Van Wezemael, L., Verbeke, W., Kügler, J. O., & Scholderer, J. 2011. European consumer acceptance of safety-improving interventions in the beef chain. *Food Control*, **22**, 1776-1784.

Voulodimos, A.S., Patrikakis, C.Z., Sideridis, A.B., Ntafis, V.A., Xylouri, E.M. 2010. A complete farm management system based on animal identification using RFID technology. *Computers and Electronics in Agriculture* **70**, 380–388

Wang, L., Kwok, S.K., Ip, W.H., 2010. A radio frequency identification and sensor based system for the transportation of food. *Journal of Food Engineering*, **101**, 120-129.

Zyskind, G., Nathan, O., Pentland, A. 2015. Decentralizing privacy: Using blockchain to protect personal data. In Security and Privacy Workshops (SPW), IEEE 180–184.

PhenoLab: automatic recording of location, activity and proximity in group-housed laying hens

T.B. Rodenburg[1,2], J.A.J. van der Eijk[1,2], K. Pichová[1,3], B. van Mil[4], E.N. de Haas[1,2]
[1]*Behavioural Ecology Group,* [2] *Adaptation Physiology Group, Wageningen University & Research, P.O. Box 338, 6700 AH Wageningen, The Netherlands*
[3]*Slovak Academy of Sciences, Institute of Animal Biochemistry and Genetics, Moyzesova 61900 28 Ivanka pri Dunaji, Slovak Republic*
[4]*Noldus Information Technology, Nieuwe Kanaal 5, 6709 PA Wageningen, The Netherlands*
bas.rodenburg@wur.nl

Abstract

With the transition to larger group housing systems in farm animals, it is becoming increasingly important to be able to automatically record the performance of individual animals housed in groups. This is especially important to record damaging behaviours, such as feather pecking in laying hens, or related traits. With traditional methods, such as live and video observations this is difficult and time consuming. Recent developments in sensor technology offer new possibilities for automatic tracking of behaviour of individuals. The aim of the PhenoLab project is to develop methods for automatic recording of location, activity and proximity in group-housed laying hens. Hundred thirty one laying hens from three feather pecking selection lines (high and low feather pecking (n = 45 and 41) and an unselected control line (n = 45)) were tracked using two different tracking systems: video-tracking using EthoVision and ultra-wideband tracking using TrackLab. Birds were tracked in three different situations: individually in a barren test-room (individual novel environment test), in a group in a barren test-room (group novel environment test) and in a group in a room offering four different functional areas (preference test). Preliminary results indicated that distance moved using TrackLab yielded up to 96% accuracy, when compared to video-tracking using EthoVision. For the group tests, ultra-wideband tracking seems the better option, as this method is better able to distinguish between individuals compared with video-tracking, as it relies on individual tags. Previously found line differences in activity, with the high feather pecking line showing higher activity levels than both other lines, were confirmed by the ultra-wideband tracking system. Furthermore, ultra-wideband tracking provides valuable information on the behaviour of specific individuals within a group, allowing us to investigate differences in activity patterns between feather peckers, victims and neutrals.

Keywords: Animal behaviour, Laying hen, Tracking, Ultra-wide band, Sensors, Activity

Introduction

Since the European ban on battery cage housing for laying hens in 2012, the percentage of laying hens kept in non-cage systems is increasing in the EU. Also in the United States, the laying hen industry is changing from cage to non-cage systems, in response to societal pressures. On the one hand, the change to non-cage systems is positive for laying hen welfare, as hens have more space and can perform more natural behaviours in these systems. On the other hand, the large flock size in non-cage systems poses a risk for outbreaks of feather pecking and cannibalism (Rodenburg et al., 2005). Feather pecking (FP), the pecking and plucking feathers of conspecifics, occurs regularly in large flocks, and can cause feather damage and increased mortality rates (Lambton et al., 2010; Gilani et al., 2013; de Haas et al., 2014). Identifying individuals that perform FP, i.e. feather peckers, is extremely difficult in large groups and relies on traditional behavioural observations. It may be more realistic to identify feather peckers by measuring related characteristics, such as activity level (Kjaer, 2009), but even that may be difficult and time consuming using traditional observation methods. Recent developments in sensor technology offer new possibilities for automatic tracking of behaviour of individuals (Banerjee et al., 2014; Nakarmi et al., 2014; Rodenburg and Naguib, 2014; Zaninelli et al., 2016). To develop methodology for automatic tracking of individual laying hens, the PhenoLab project was initiated. The aim of the PhenoLab project was to develop methods for automatic recording of location, activity and proximity in group-housed laying hens. Ultra-wideband tracking using TrackLab and video-tracking using EthoVision were used to explore differences between three lines divergently selected on feather pecking (unselected control, high and low feather pecking lines) and between phenotypes within lines (feather peckers, neutrals and victims).

Material and Methods

Animals and housing

Hundred thirty one adult laying hens from three feather pecking selection lines (high (HFP, n=45) and low feather pecking (LFP, n=41) and an unselected control line (control, n = 45)) were used for this experiment. They were kept in 2 m^2 floor pens in groups of maximum eight birds per pen, with ad libitum feed and water. These feather pecking lines have previously been found to differ in activity levels, with the high feather pecking line showing signs of hyperactivity (Kjaer, 2009). This difference in activity indicates that individuals with a

tendency to develop FP might be detected on the basis of their activity levels, potentially prior to the development of FP. Apart from the comparison of the three lines, we also assessed differences in activity of birds characterized as feather pecker, neutral or victim. Data here represents preliminary data of activity of birds based on one batch of 131 animals.

Tracking in the PhenoLab test-room

For testing, birds were transferred to the PhenoLab test-room and tracked using two different tracking systems: video-tracking using EthoVision (Noldus, Wageningen, The Netherlands) and ultra-wideband tracking using TrackLab (Noldus, Wageningen, The Netherlands). Birds were tracked in three different situations: individually in a barren test-room (individual novel environment test), in a group in a barren test-room (group novel environment test) and in a group in a room offering four different functional areas (preference test with 1) perches, 2) feed and water, 3) litter and 4) feathers). The ultra-wideband tracking system consists of active tags that are placed on the birds. The location of each bird is calculated based on triangulation between four beacons, based on time of arrival and angle of arrival of the signal. A test-room (Figure 1, left panel: 7*6m) at the research facility of the Wageningen University (The Netherlands) was equipped with four Ubisense beacons (Figure 1, middle panel). An active sending tag of Ubisense containing a 12V battery (3.5 * 3.5 cm, ± 29 grams) was used for tracking (Figure 1, right panel). Battery life was approximately five weeks when continuously active. Tags were placed in a backpack on an adult White Leghorn laying hen. Sampling rate was set to twice per second in Ubisense. During and after tracking TrackLab provided the following data, per sample point; x, y, z location, x-y distance (cm), x-y speed (m/s), acceleration (cm/s^2), x-y heading (degree), x-y turning angle (degree), and x-y angular velocity (degree/s^2). These data were further processed by TrackLab to provide a statistical overview per track. For validation of the ultra-wideband tracking method, we compared data of TrackLab with video-tracking using EthoVision (Noldus, Wageningen, The Netherlands). Data was collected on 24 hens which were tested individually for five minutes in a barren test-room and compared between systems, based on distance moved. Eight non-moving, eight highly moving and eight randomly chosen birds were selected.

Figure 1. Test-room at Wageningen University (left panel), TrackLab beacon (middle panel), Active sending tag (right panel).

Three different behavioural tests

First, an individual test was conducted in the barren test-room. Hens were placed in the middle of the test-room in darkness. This procedure was needed to assure that all hens started at the same position and tracking started directly after the light was switched on. TrackLab and EthoVision were linked to start exactly at the same time point by one command. For five minutes video and ultra-wide band tracking took place. Distance moved of the HFP, LFP and control lines were compared at an individual level. Second, a group test was performed in the barren test-room. Hens were taken per pen and placed in the middle of the test-room and individual hens were tracked using TrackLab for 15 minutes. Distance moved was compared at an individual level. Finally, hens were tested in a group test with four functional areas. Hens were taken per pen and placed in the middle of the test-room. This test was conducted in the morning and in the afternoon for all groups to assess and correct for potential time effects. The test-room was divided in four equal zones, with each zone offering a different feature 1) wood shavings, 2) feathers, 3) feed and water or 4) a perch). Time spent and distance moved in each zone was recorded using TrackLab. After exactly 3.5 hours programs were terminated. Time spent in different zones was compared between HFP, LFP and control lines.

Results and discussion

Individual ultra-wideband tracking vs. video-tracking

Data on distance moved was initially not comparable between TrackLab and EthoVision due to a large overestimation of distance moved in TrackLab, caused by outliers and small detection errors when tags were not moving. Corrections were applied to the TrackLab data to exclude outliers by 1) outlier removal of data points having an acceleration over $10m/s^2$, 2) maximum smoothing of 29 sample points and 3) virtually cutting of 125cm of each corner of the test-room (x and y), where fluctuations in tracking were recorded due to wall reflections. After correction, distance moved using TrackLab yielded up to 96% accuracy of

all 24 tracks, when compared to video-tracking using EthoVision. The same correction of TrackLab data was used when analysing the group tests.

Differences in activity between lines and phenotypes

Distance moved was compared for all three tests using the TrackLab data. Distance moved was higher for HFP than for LFP and control birds in the individual test (Figure 2, left panel). In the group tests, birds characterised as feather peckers had a higher distance moved in the group test than victims (Figure 2, right panel). The finding that birds from the HFP were more active is consistent with previous studies using the same lines (Kjaer, 2009; de Haas et al., 2010). Kjaer (2009) actually suggested that hyperactive birds are more at risk to develop feather pecking. Our data on the phenotypes support that idea, as also birds characterised as feather peckers were more active than victims.

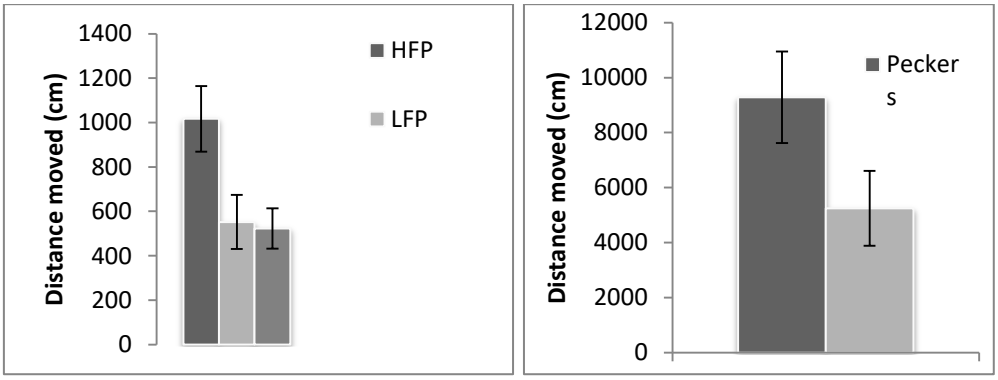


Figure 2. Distance moved in the individual test in birds from the HFP, LFP and control line (left panel) and the group test in the birds characterised as peckers or victims (right panel).

When the lines were compared regarding the use of the four different functional areas, we found that HFP birds spent more time in the foraging zone than LFP and CON birds (Figure 3). This result also corresponds with previous findings: when offered novel foraging opportunities in a foraging maze, HFP birds were faster to explore these opportunities and pecked more at the foraging materials offered (de Haas et al., 2010). This underlines the strong relationship between foraging behaviour and feather pecking. Contrary to our expectations, HFP birds did not spent much time in the feather zone. This could be because the loose back feathers offered may not have been attractive enough for feather pecking or feather eating (Harlander-Matauschek and Feise, 2009).

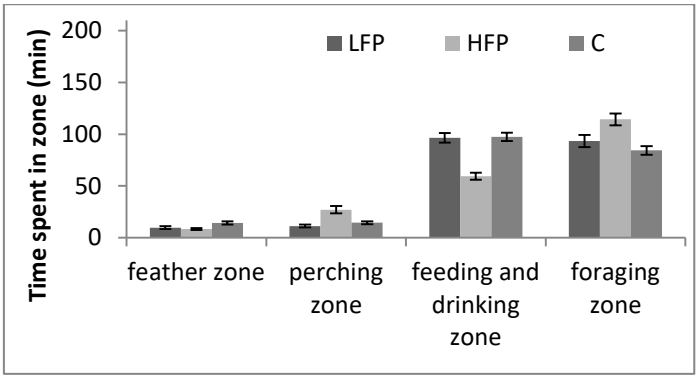


Figure 3. Time spent in the feather zone, perching zone, feeding and drinking zone and foraging zone for birds from the LFP, HFP and Control lines.

Conclusions

The aim of the PhenoLab project was to develop methods for automatic recording of location, activity and proximity in group-housed laying hens. By comparing the ultra-wideband data collected with TrackLab to the video-tracking data collected with EthoVision, we were able to calibrate the TrackLab system and reach a 96% accuracy compared with the video track. The group tests show that the TrackLab system can be used to track individual laying hens in groups. We were able to confirm previously found line differences in activity and use of space between the HFP, LFP and control line. Moreover, using the TrackLab system we were able to analyse differences between individuals within the same group, allowing us to focus on space use of individual birds with different phenotypes. This revealed that, similar to the line differences, birds characterised as feather peckers were more active. Future work will focus on proximity analysis and combination with other sensing methods (RFID, video-tracking).

Acknowledgements

The PhenoLab project was financially supported by the Dutch Ministry of Economic Affairs (project TKI-AF12018) and the Breed4Food partners Cobb-Europe, CRV, Hendrix Genetics and Topigs Norsvin. Katarina Pichová's contribution was financed by the COST Action CA 15134 GroupHouseNet, supported by COST (European Cooperation in Science and Technology), through funding for a short-term scientific mission to Wageningen University.

References

Banerjee, D., Daigle, C.L., Dong, B., Wurtz, K., Newberry, R.C., Siegford, J.M., Biswas, S., 2014. Detection of jumping and landing force in laying hens using wireless wearable sensors. *Poultry Science* **93**, 2724-2733.

de Haas, E.N., Bolhuis, J.E., de Jong, I.C., Kemp, B., Janczak, A.M., Rodenburg, T.B., 2014. Predicting feather damage in laying hens during the laying period. Is it the past or is it the present? *Applied Animal Behaviour Science* **160**, 75-85.

de Haas, E.N., Nielsen, B.L., Buitenhuis, A.J., Rodenburg, T.B., 2010. Selection on feather pecking affects response to novelty and foraging behaviour in laying hens. *Applied Animal Behaviour Science* **124**, 90-96.

Gilani, A.-M., Knowles, T.G., Nicol, C.J., 2013. The effect of rearing environment on feather pecking in young and adult laying hens. *Applied Animal Behaviour Science* **148**, 54-63.

Harlander-Matauschek, A., Feise, U., 2009. Physical characteristics of feathers play a role in feather eating behavior. *Poultry Science* **88**, 1800-1804.

Kjaer, J.B., 2009. Feather pecking in domestic fowl is genetically related to locomotor activity levels: implications for a hyperactivity model of feather pecking. *Behavior Genetics* **39**, 564-570.

Lambton, S.L., Knowles, T.G., Yorke, C., Nicol, C.J., 2010. The risk factors affecting the development of gentle and severe feather pecking in loose housed laying hens. *Applied Animal Behaviour Science* **123**, 32-42.

Nakarmi, A.D., Tang, L., Xin, H., 2014. Automated tracking and behavior quantification of laying hens using 3D computer vision and radio frequency identification technologies. *Transactions of the Asabe* **57,** 1455-1472.

Rodenburg, T.B., Naguib, M., 2014. Tracking individual laying hens in group housing, In: Spink, A.J., Loijens, L.W.S., Woloszynowska-Fraser, M., Noldus, L.P.J.J. (Eds.), *Measuring Behavior*, Wageningen, The Netherlands.

Rodenburg, T.B., Tuyttens, F.A.M., De Reu, K., Herman, L., Zoons, J., Sonck, B., 2005. Welfare, health and hygiene of laying hens housed in furnished cages and in alternative housing systems. *Journal of Applied Animal Welfare Science* **8**, 211-226.

Zaninelli, M., Redaelli, V., Tirloni, E., Bernardi, C., Dell'Orto, V., Savoini, G., 2016. First Results of a Detection Sensor for the Monitoring of Laying Hens Reared in a Commercial Organic Egg Production Farm Based on the Use of Infrared Technology. *Sensors* **16**, 13.

New open-source software tools using accelerometer data for the discrimination of cow behavioural activities in free-stall barns

C. Arcidiacono[1], S.M.C. Porto[1], M. Mancino[1], F. Valenti[1], G. Cascone[1]
[1]*Department of Food, Agriculture and Environment (Di3A), University of Catania, via S. Sofia n.100, 95123, Catania (Italy)*
siporto@unict.it

Abstract

Among the automated systems used to monitor animal behaviour in real time, those based on wearable inertial sensors are widely used for dairy cows housed in free-stall barns. However, the technical specifications of these systems and the code of the implemented algorithms are seldom included in the literature. The overall aim of this study was to fill these gaps by proposing new open-source software tools, i.e. an algorithm and a classifier, to be adopted in a low-cost automated monitoring system based on accelerometers for discriminating dairy cow behavioural activities.
Firstly, a novel algorithm characterised by a linear computational time was used for real-time monitoring and analysis of walking behaviour. An innovative classifier was then proposed to detect cow feeding and standing behavioural activities. Both these software tools were based on statistically defined thresholds computed from accelerometer data acquired during the animals' daily routine by a new data acquisition system operating with a sampling frequency of 4 Hz. It required simple installation into the building and did not need any preliminary calibration.
In this study, an overall algorithm for the recognition of dairy cows' behavioural activities (i.e., *lying*, *standing*, *walking*, and *feeding*) was also proposed.
With regard to the accuracy of the algorithm for walking, the total error was 9.5% and the relative measurement error ranged between 2.4% and 4.8%. The misclassification rate of the algorithm, which discriminates feeding from standing, was 5.56%. Testing of the whole algorithm for cow behaviour recognition showed relatively lower performance in discrimination of standing from walking. The performance of the data acquisition system was evaluated by the stored data index which achieved 83%.
The application of the proposed tools allowed cow behaviour recognition with a high level of accuracy, using low-cost devices and open-source software.

Keywords: cow behaviour, precision livestock farming, dairy farming, wearable sensors

Introduction

In recent years, new methods based on wearable sensors (Alsaaod et al., 2015; Porto et al., 2014), computer vision systems (Carreira et al., 2009; Porto et al., 2015), or combinations of these systems (Van Hertem et al., 2015), have been studied to automate the monitoring of cow behavioural activities with the ultimate aim of early detection of illness or a specific physiological status. With reference to wearable sensors, most of the studies in this field have focused on hardware improvement (Pastell et al., 2009), while few research studies have been conducted to improve algorithms and implement the related software (Alsaaod et al., 2015). Among wearable sensors, accelerometers are widely used because of their low cost and ease of integration with other ICT devices. They were first used in smart devices to monitor human health and behaviour, then they were also used in automated systems for animal monitoring. Within dairy cow barns, accelerometers are mainly used in pedometers which count cow steps. They often work offline and data collected are downloaded two to three times a day, during the milking process. Recently, pedometers based on wireless technologies have been developed because of the need to count cow steps in real time (Yoshioka et al., 2010). The real-time feature of these devices facilitates the early detection of cow oestrus, which is a relevant concern for dairy farmers. However, the technical specifications of this kind of system and the code for the step counting algorithm are seldom included in the literature.

Among the methods used in the literature to process data from accelerometers, those based on acceleration threshold values are valuable because they do not require a training phase, as for SVM-based systems (Martiskainen et al., 2009), they are not invasive for animals if attached to the collar and, once the threshold values are determined, the computational cost of the behaviour classifier is lower.

However, in the literature few research papers have considered the definition of threshold values for classifying cow behavioural activities. More specifically, the classification of standing and lying has already been successfully assessed using an accelerometer fixed to the cow's leg (Arcidiacono et al., 2015). In fact, an acceleration threshold value of 0.5 g was found to be suitable for differentiating between standing and lying. Different walking and feeding recognition systems are still currently under study.

This paper describes an automated monitoring system based on acceleration thresholds which had the main objective of monitoring dairy cow behaviour by using low cost devices and open-source software.

Materials and methods

The experiment took place in June 2015 within the central box of a free-stall barn located in Sicily (Italy). The monitoring system consisted of a data acquisition system, located in the centre of the box at 2.5 m above the floor of the stalls, and 10 wearable sensors embedded with accelerometers. The technical specifications of the data acquisition system are reported in Figure 1 and in Arcidiacono et al. 2017a, 2017b. Moreover, a video recording system previously installed in the barn was used to assess the accuracy of the automated system. An operator carried out offline visual recognition of the behavioural activities studied in this research.
Five cows, randomly selected from the 14 cows reared in the box, were monitored using the wearable sensors. The data acquisition systems operated within the time interval 13:00 – 18:00 when which was characterised by the highest occurrence of the behavioural activities studied in this research, i.e. walking and feeding. Samples of accelerometer signals were selected for each behavioural activity (Figure 1).

<u>The step counting software tool</u>
In the literature, different variables have been considered to study accelerometer signals. In this research Signal Vector Magnitude, referred to here as *mod*, and Signal Magnitude

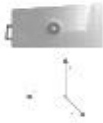
Data acquisition system	Wearable sensor	Feeding/standing behavioural activity					
		Sensor position	Number of monitored cows	Data acquisition time interval	Feeding/standing samples		
					Number	Duration per sample [s]	Variables
Hardware Raspberry Pi - SDHC (8 Gbyte) - USB-BLE (adaptor) - USB-WiFi (adaptor) *Software* - Raspbian Operating System - Python v3.3 - BLUEZ v5.4 libreries - Perspect v3.3 module *Position* Centre of the monitored area height: 2.5 m above floor	Type: SensorTags Developer: Texas Instruments (USA) Range: ± 8g Frequency: 4 Hz Connectivity: Bluetooth Low Energy Coordinate system: 	Collar 	5	13:00-18:00	150 (feeding)	5	acc_x *x*-axis acceleration
					150 (standing)	5	acc_x *x*-axis acceleration
		Walking/standing behavioural activity					
		Sensor position	Number of monitored cows	Data acquisition time interval	Walking samples		
					Number	Duration per sample [s]	Variables
		Hind leg 	5	13:00-18:00	153 (walking)	5	Signal Vector Magnitude Signal Magnitude Area

Figure 1: Main features of data acquisition system and wearable sensors used for automatic recognition of walking and feeding behavioural activities; basic information about the experimental activities

Area (*sma*), which were applied by Robert et al. (2009) were considered:

$$mod_{xy} = \sqrt{acc_x^2 + acc_y^2} \qquad (1)$$

$$sma_{xy} = |acc_x| + |acc_y| \qquad (2)$$

These two variables were used in two different versions, Alg_{mod} and Alg_{sma}, of the algorithm reported in Figure 2 in order to count cow steps. Datasets were used in the analysis and testing phases of the algorithms: 75% of the walking samples made up the analysis datasets and the remaining 25% formed the test datasets. More details on walking sample selection are reported in Arcidiacono et al., 2017a.

The Kruskal-Wallis statistical method was used to test the equality of acceleration medians for the reference populations, i.e. the walking periods of the cows in the sample. This procedure was useful for choosing acceleration values which were common to all the cows in the sample. The thresholds were then computed as the maximum of the acceleration medians in their respective analysis dataset.

In the testing phase, the number of cow steps (N_{step}^{c}) computed by the algorithm was compared with the number of steps observed in the video recordings (N_{step}^{v}). The indicators used to assess the accuracy were as follows:

$$E = \frac{\sum_i^k \left(N_{step_i}^{c-} + N_{step_i}^{c+}\right)}{\sum_i^k N_{step_i}^{v}} \times 100\% \qquad (3)$$

$$RME = \frac{\left|\sum_i^k N_{step_i}^{v} - \sum_i^k N_{step_i}^{c}\right|}{\sum_i^k N_{step_i}^{v}} \times 100\% \qquad (4)$$

where k is the number of walking samples in the test datasets of both the variables.

The first indicator (E) takes into account the total error when an overestimation (N_{step}^{c+}) or an underestimation (N_{step}^{c-}) of the number of steps occurred. The second indicator, named *Relative Measurement Error* (*RME*), takes into account the compensation between N_{step}^{c+} and N_{step}^{c-} and allowed comparison with another study (Alsaaod et al., 2015).

```
START

input:     sample, set of n records
           th_mod, accelerometric threshold
           th_offset, offset threshold
output:    step_counter, calculated steps in sample

    current_observation <- 0;
    last_peak <- 0;

    step_counter <- 0;

    for row in sample do

          acc_x <- row['acc_x'];
          acc_y <- row['acc_y'];

          mod_xy <- sqrt(acc_x^2 + acc_y^2);

          current_observation <- current_observation + 1;

          if mod_xy > th_mod then
                if last_peak = 0 then
                      step_counter <- step_counter + 1;
                else
                      if current_observation - last_peak > th_offset then
                            step_counter <- step_counter + 1;
                last_peak <- current_observation;


    write step_counter;

END
```

Figure 2: Threshold-based algorithm used to count cow steps

<u>The feeding classifier software tool</u>

For each cow, analysis datasets containing samples of feeding and standing activity were defined (Arcidiacono et al., 2017b). After verifying that the variable acc_x did not follow a normal distribution, parametric tests were applied to obtain statistical information on the acceleration medians computed on the analysis datasets. The *Kruskall-Wallis Test* showed a low robustness since the z-value was highly variable even when computed on samples of the same activity. By contrast, the non-parametric *Mood's Median Test* was suitable for providing information on each of the analysis datasets. For each dataset, this test computed the 'overall median' (i.e. the median of the whole dataset) and for each sample it provided both the number of observations having acc_x values lower than or equal to the 'overall median' and the number of observations with higher values. The mean of the 'overall medians', named th_{feed} in this report, was proposed as the acceleration threshold in order to discern feeding from standing. The indicators *Misclassification Rate* (*MR*), *Sensitivity*, *Precision*, *Specificity*, *Quality Percentage* (*QP*), *Branching Factor* (*BF*), and *Miss Factor* (*MF*) were considered with the aim of assessing the classifier accuracy and comparing the results with those obtained in other research studies (Porto et al., 2015).

<u>Design of an automated system for the recognition of cow behavioural activities</u>

A novel automated system for recognition of dairy cows' behavioural activities (i.e., *lying*, *standing*, *walking*, and *feeding*) was designed on the basis of the acceleration thresholds computed in this study and those reported in the

literature. The algorithm of this automated system is illustrated in the flow chart presented in Figure 3.

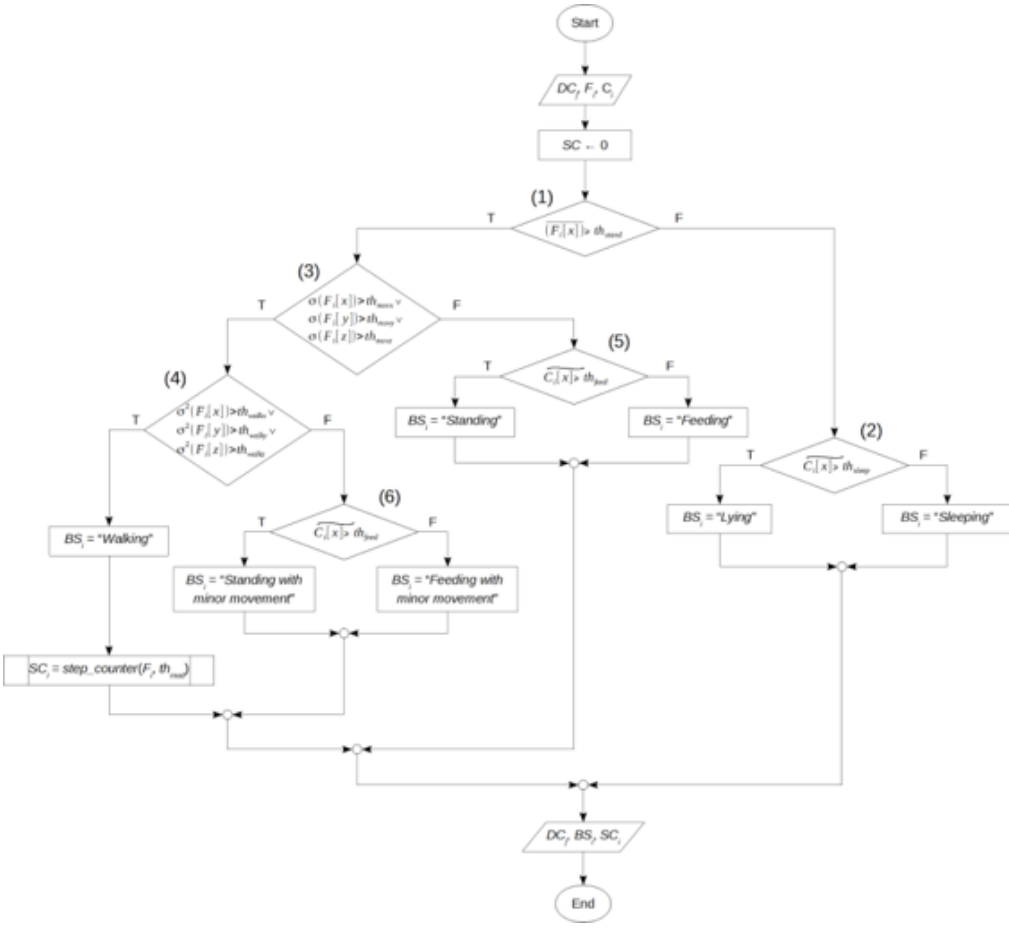


Figure 3: Algorithm of the automated system for the recognition of cow behaviours

Let m the number of cows bred in the free-stall barn and DC_j, $j = 1 \ldots m$, the j-th dairy cow of the herd. The algorithm required two 5-s samples as input for each DC_j, i.e. the F_i sample (i-th acceleration sample acquired by the sensor fixed to the cow's leg) and C_i sample (i-th acceleration sample acquired by the sensor fixed to the cow's collar), where $i = 1 \ldots n$ and n is the number of samples acquired during one day (24 h). When the algorithm ends its computation, it gives two outputs. These are the *behavioural state* (*BS*), attributed to DC_j during the 5-s sample (i.e., '*lying*', '*standing*', '*standing with minor movement*', '*feeding*', '*feeding with minor movement*', and '*walking*') and the *step count*, *SC*, if the '*walking*' behavioural state (*BS* = '*walking*') was recognised.

The check of the condition (1) in Figure 3, where $\overline{(F_i[x])}$ is the mean value of the accelerations along the *x*-axis and th_{stand} is equal to 0.5 g, determines whether the cow is standing or lying. If the cow is *lying*, the subsequent condition (2) is also verified. In this case, $\widetilde{C_i[x]}$ is the median value of the accelerations along the *x*-axis and th_{sleep} is a suitable threshold to determine whether the cow is *sleeping* or not. This threshold was defined but has not been computed yet.
If the cow is standing, the condition (3) is used to detect minor movement of the leg, and the condition (4) is used to detect walking. In this last case, the behaviour state was set to '*walking*' (*BS* = "*walking*") and the step counting algorithm was used to obtain the step count, *SC*, of the cow DC_j during the sample F_i by using th_{mod} equal to 1.198 g. Finally, again in the case of a standing still posture, the conditions (5) and (6) were used to recognise the feeding activity by using th_{feed}.
The algorithm of the automated system for the recognition of cow behavioural activities was tested by using a dataset of 30 samples for each behaviour of one cow. Further work is in progress to validate the algorithm for within-cow variability and between-cow variability.
Finally, the performance of the data acquisition system was computed using the total quantity of data stored on the SD Card of the single board computer at the end of the acquisition process. This criterion was expressed by the indicator:

$$SDI = \frac{\sum_1^n sd_i}{TSD} \times 100 \qquad (5)$$

where sd_i is the amount of *stored data* during the data acquisition process from the *i-th* SensorTag and *TSD* is the *Theoretical Storable Data*, which is the maximum amount of data that *DAS* can acquire during the time interval of the acquisition process. A *SDI* (*Stored Data Index*) equal to 100% means that no disconnection and neither system latencies nor system delays occurred during the process.

Results and discussion

The application of the Kruskal-Wallis test allowed the computation of thresholds which produced the minimum error in the cow step count. They were equal to 1.198 g for the variable *mod*, and 1.75 g for the variable *sma*. Both versions of the algorithm, Alg_{mod} and Alg_{sma}, which were executed on two different test datasets, produced the same accuracy, since they made an error *E* = 9.5% (Table 1). For Alg_{mod}, 75.0% of the total errors *E* corresponded to an overestimation of the number of steps while the remaining 25.0% corresponded to an underestimation. For Alg_{sma}, by contrast, 62.5% of the total errors were an underestimation of the number of steps and 37.5% an overestimation. From the

visual analysis of the video recordings it was found that Alg_{mod} gave a higher number of N_{step}^{c+} , which were caused by small movements of the leg slightly before or after the walking activity. Alg_{sma}, by contrast, produced a higher number of N_{step}^{c-}, which occurred when the cow's walking activity was characterised by steps having an acceleration intensity that did not exceed the fixed threshold. For Alg_{sma}, the best compensation between N_{step}^{c-} and N_{step}^{c+} produced a value of the relative error *RME* = 2.4%, which is lower than that of Alg_{mod}, equal to 4.8%.

Application of the Mood's Median test allowed computation of the acceleration threshold th_{feed}, equal to 0.276 g, which makes it possible to distinguish feeding behaviour from standing. With regard to the test datasets, a 'score' was computed for each sample (i.e. 45 feeding samples and 45 standing samples). The classifier correctly detected 42 samples out of 45 for feeding, whereas 3 samples were recognised as standing. The classifier correctly detected 43 samples out of 45 for standing, whereas 2 samples were recognised as feeding. Moreover, the values of the accuracy indicators were computed and compared with those of video-recorded data (Table 2).

Table 1. Performance of Alg_{mod} and Alg_{sma} algorithms in comparison with video recorded data.

	N_{step}^{v}	N_{step}^{c}	N_{step}^{c+}	N_{step}^{c-}	*Total errors*	*E*	*RME*
Alg_{mod}	84	88	6	2	8	9.5%	4.8%
Alg_{sma}	84	82	3	5	8	9.5%	2.4%

Table 2. Performance of the feeding algorithm in comparison with video recorded data.

	Sensitivity	*QP*	*BF*	*MF*	*Precision*	*Specificity*	*MR*
Video recorded data	87.00%	81.00%	0.08	0.15	91.97%	-	-
Feeding algorithm	93.33%	89.36%	0.05	0.07	95.45%	95.56%	5.56%

Since the lying activity affected communication between the foot sensor and the single board computer for long periods, the indicator SDI of the performance of

the data acquisition system was calculated by considering only the data originating from the collar sensors. The value of SDI was equal to 83%.
Table 3 shows the performance of the algorithm of the automated system for the recognition of cow behaviours reported in Figure 3.
The results in Table 3 show that all the samples related to lying and walking behaviours were correctly recognised by the algorithm. With regard to the standing activity, 27 samples were classified as 'standing with minor movements', and 3 samples were misclassified as walking. Specifically, the step counting module calculated one step in three samples out of the 30 samples recognised as standing. This occurrence was due to movement of the cow's leg while standing. The performance of the feeding and step counting modules of the software is reported in Tables 1 and Table 2.
Further analyses are in progress to validate the algorithm by using sample datasets relating to a number of cows from the group considered. Other improvements could include definition of the threshold for sleeping behaviour and corresponding assessment of its discrimination from lying.

Table 3. Performance of the algorithm of the automated system for the recognition of cow behaviours

Cow behaviour	*Number of samples analysed*	*Number of samples recognised*	*Performance*
Lying	30	30	100 %
Standing	30	27	90 %
Feeding vs Standing	Fig. 1		Table 2
Walking	30	30	100 %
Step counting	Fig. 1		Table 1

Conclusions

A new automated system, which was based on accelerometer sensors fixed to the dairy cow's body (i.e. neck and hind leg), was developed and assessed in a free-stall barn located in Sicily (Italy) with the aim of detecting lying, walking, standing and feeding activities. It allowed data acquisition from different sensors (accelerometer, gyroscope and barometer), with a sampling frequency of 4 Hz, during the animals' daily routine. A specific algorithm of the automated system, which was based on statistically defined thresholds and implemented in specially developed software tools, was proposed and assessed. Good results were obtained for discrimination of lying from the other behaviours, feeding from standing activity, and step counting. Testing of the whole algorithm for cow

behaviour recognition showed relatively lower performance in the discrimination of standing from walking due to cow leg movements.
The automated system proposed was easily installed in the building and did not need any preliminary calibration. Furthermore, it was designed using low-cost devices, such as wearable sensors and single board computers, and open source software. This last feature of the system would have a crucial relevance in developing countries.

Acknowledgements

This research activity is part of the research project FIR 2014 “Development of an automatic monitoring system for the study of individual dairy cow behaviour in a free housing system” - University of Catania (Italy), coordinated by PhD Eng. Simona M.C. Porto

References

Alsaaod, M., Niederhauser, J. J., Beer, G., Zehner, N., Schuepbach-Regula, G., & Steiner, a. (2015). Development and validation of a novel pedometer algorithm to quantify extended characteristics of the locomotor behavior of dairy cows. *Journal of Dairy Science*, *98*(9), 6236–6242.

Arcidiacono, C., Cascone, G., Catania, V., Di Natale, R., Intilisano, A. R., Mancino, M., … Porto, S. M. C. (2015). Feasibility study on the development of a real-time inertial sensor-based system for dairy cow behaviour detection in free stall barns. *Precision Livestock Farming 2015 - Papers Presented at the 7th European Conference on Precision Livestock Farming, ECPLF 2015*.

Arcidiacono, C., Porto, S. M. C., Mancino, M., & Cascone, G. (2017a). A threshold-based algorithm for the development of inertial sensor-based systems to perform real-time cow step counting in free-stall barns. *Biosystems Engineering*, *153*.

Arcidiacono, C., Porto, S. M. C., Mancino, M., & Cascone, G. (2017b). Development of a threshold-based classifier for real-time recognition of cow feeding and standing behavioural activities from accelerometer data. *Computers and Electronics in Agriculture*, *134*, 124–134.

Carreira, X. C., Fernández, M. E., & Mariño, R. A. (2009). Indices for estimation of dairy free-stall occupancy. *Applied Animal Behaviour Science*, *119*(1–2), 23–31.

Martiskainen, P., Järvinen, M., Skön, J.-P., Tiirikainen, J., Kolehmainen, M., & Mononen, J. (2009). Cow behaviour pattern recognition using a three-dimensional accelerometer and support vector machines. *Applied Animal*

Behaviour Science, *119*(1–2), 32–38.
Pastell, M., Tiusanen, J., Hakojärvi, M., & Hänninen, L. (2009). A wireless accelerometer system with wavelet analysis for assessing lameness in cattle. *Biosystems Engineering*, *104*(4), 545–551.
Porto, S. M. C., Arcidiacono, C., Anguzza, U., & Cascone, G. (2015). The automatic detection of dairy cow feeding and standing behaviours in free-stall barns by a computer vision-based system. *Biosystems Engineering*, *133*, 46–55.
Porto, S. M. C., Arcidiacono, C., Giummarra, A., Anguzza, U., & Cascone, G. (2014). Localisation and identification performances of a real-time location system based on ultra wide band technology for monitoring and tracking dairy cow behaviour in a semi-open free-stall barn. *Computers and Electronics in Agriculture*, *108*.
Robert, B., White, B.J., Renter, D.G., Larson, R.L., 2009. Evaluation of three-dimensional accelerometers to monitor and classify behavior patterns in cattle. Computers and Electronics in Agriculture 67, 80–84.
Van Hertem, T., Bahr, C., Schlageter Tello, A., Viazzi, S., Steensels, M., Romanini, C. E. B., … Berckmans, D. (2015). Lameness detection in dairy cattle: single predictor v. multivariate analysis of image-based posture processing and behaviour and performance sensing. *Animal : an international journal of animal bioscience*, 1–8.
Yoshioka, H., Ito, M., & Tanimoto, Y. (2010). Effectiveness of a real-time radiotelemetric pedometer for estrus detection and insemination in Japanese Black cows. *The Journal of Reproduction and Development*, *56*(3), 351–355.

Session 8

Dust and ventilation for pigs/chickens

Identification of key factors for dust generation in mechanically and naturally ventilated broiler houses

G. Park[1], K. S. Kwon[2], I.-B. Lee[1]
[1]*Department of Rural Systems Engineering, Research Institute for Agriculture and Life Sciences, College of Agriculture and Life Sciences, Seoul National University, 599, Gwanakno, Gwanakgum Seoul 08826, Republic of Korea*
[2]*Animal Environment Division, National Institute of Animal Science, 1500, Kongjwipatjwi-ro, Jeollabuk-do, 55365, Republic of Korea*
kskwon0512@korea.kr

Abstract

The evaluation of dust level is of concern because it can result in poorer indoor air quality (IAQ) within livestock houses, which is associated with the respiratory welfare of both livestock workers and animals. To create an adequate IAQ inside broiler houses, an understanding of the mechanisms of dust generation according to a complicated combination of variables is very important. However, most investigations conducted to date have focused on the single correlation between dust concentration and environmental factors. There have been few comprehensive and detailed studies that have statistically investigated various dust generation factors simultaneously. In this study, intensive dust monitoring was carried out for 13 months in mechanically and naturally ventilated broiler houses. For the multiple regression analyses to evaluate the key factor for dust generation, various factors were also simultaneously monitored. Among them, the ventilation rate of the facilities was numerically evaluated using computational fluid dynamics with tracer gas decay (TGD). The observations showed that dust concentrations which were seven times higher than normal occurred when farmers entered the facility, due to an increase in broiler activity. In terms of the applicability of each variable under practical conditions, controlling the humidity level was the significant factor in the generation of inhalable dust. However, increased humidity in the facility is strongly related to the proliferation of micro-organisms. Therefore, careful approaches are needed to ensure biological safety with regard to the outbreak of animal disease.

Keywords: aerosol, broiler house, inhalable dust, PM10, respirable dust, TSP

Introduction

Organic dust generated in livestock production facilities is the major factor causing environmental degradation for both animals and workers. The dust is

mainly generated by feed, hair, faeces and bedding materials inside the livestock house (Hartung & Saleh, 2007). Substances attached to the surface of the dust, such as micro-organisms, endotoxins and toxic gases, can cause negative health effects for both livestock and workers. High dust concentrations could decrease productivity by causing allergic reactions, and carry livestock disease pathogens such as HPAI or Newcastle disease (Hugh-Jones et al., 1973; Power, 2005). Many studies have reported that workers on livestock farms have a high prevalence of respiratory symptoms, such as allergic rhinitis, chronic decline in lung function, organic dust toxic syndrome (ODTS) and bronchitis (Tucker, 2000; Rosentrater, 2004). The dust generation rate inside the livestock house is influenced by various factors, including animal species, age, rearing density, ventilation, micro-climatic conditions, feeding method and so on. However, most existing studies have shown a single correlation between the measured aerial dust concentration and one experimental environmental factor. Only a few have conducted comprehensive and detailed studies with statistical analysis of multiple dust generation factors simultaneously. Banhazi et al. (2008) conducted a statistical investigation to determine the key factors for the generation of airborne pollutants in pig houses. However, there is insufficient long-term and comprehensive research on poultry facilities. In this study, dust concentration and environmental conditions were monitored and statistically analysed to determine key dust generation factors inside broiler houses.

Materials and methods

Experimental broiler houses

Mechanically and naturally ventilated broiler houses on a farm located in Jeongeup city, South Korea, were selected for the experiment. For the mechanically ventilated (MV) broiler house, a tunnel ventilation system with 14 tunnel exhaust fans (1.27 m diameter, 26,500 CMH) and two plate openings (24.45 m long, 1.58 m high) was used during the summer, and a cross-ventilation system using three side fans (0.88 m diameter, 33,000 CMH) and slot-openings (1.25 m long, 0.43 m high) during the winter. The experimental MV broiler house was 15 m wide, 85 m long, 3.2 m high at the eaves and 6.3 m high at the ridge, and a total of 30,000 broilers were raised in the facility.

The naturally ventilated (NV) broiler house used a combination of natural ventilation with two winch curtain openings (85.5 m long, 1.2 m high) and mechanical ventilation with eight exhaust fans (0.51 m diameter, 6,020 CMH) during the summer. During the winter and the early stages of broiler rearing, mechanical ventilation with exhaust fans and pipe inlets (0.1 m diameter, 1.95 m long) along the roof slope was used. The of the experimental NV broiler house was 11 m wide, 85.5 m long, 1.5 m high at the eaves and 4.5 m high at the ridge,

and a total of 25,000 broilers were raised in this facility. Schematic diagrams of the experimental broiler houses are shown in Figure 1.

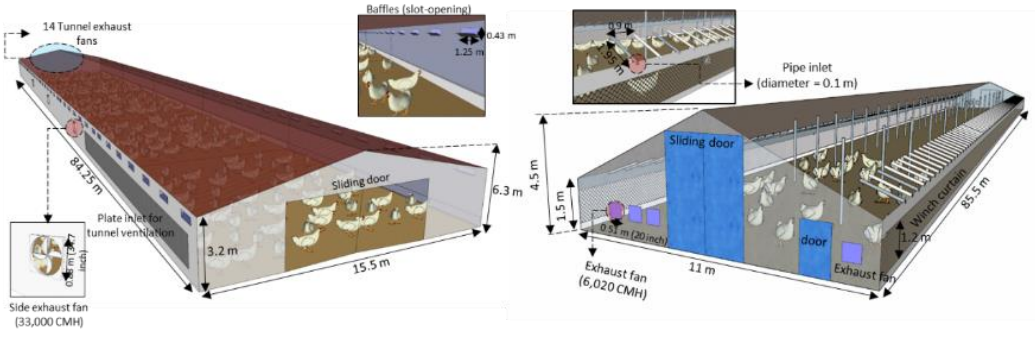


Figure 1: Schematic diagram of the experimental mechanically ventilated broiler house (left) and naturally ventilated broiler house (right)

Experimental equipment

A polytetrafluoroethylene (PTFE) membrane filter (SKC Inc., Eighty Four, PA, USA, 2.0 µm pore size, 37 mm diameter) was used to sample aerial TSP and PM10. PTFE membrane filters were inserted into a 3-stage polystyrene cassette (SKC Inc.) for TSP while a Personal Environmental Monitor (PEM) (SKC Inc.) sampler was used for PM10. Aerial dust was collected using an air sampler (AirChek XR5000; SKC Inc.), which was connected to the 3-stage polystyrene cassette and PEM sampler. Gravimetric measurement of the filters with sampled dust particulates was carried out using an electronic balance device (Ohaus Discovery balance DVG214C; Ohaus Co.).

An Aerosol spectrometer (Model 1.109; GRIMM Aerosol Technik GmbH & Co.) was used to measure the concentration and particle numbers of inhalable and respirable dust based on a laser light scattering method. Dust was measured in the range of 0.001~100 mg/m3, with a detection sensitivity of 0.001 mg in real time. Measurements of the dust concentration and the particle numbers were taken every 6 seconds.

For comprehensive analyses of dust generation inside the livestock houses, various experimental instruments for monitoring the environmental factors were also used. T-type thermocouples (Omega Engineering Inc., Stamford, CT, USA) and a data-logger (GL-820; Graphtec Inc., Jessup, MD, USA) were used to record the internal thermal distributions of the experimental broiler houses. HOBO sensors (UX100-003; Onset Computer Co., Bourne, MA, USA) were used to measure indoor air temperature and relative humidity in the experimental livestock houses. A portable weather station (WatchDog 2700; Spectrum Tech, Inc., Aurora, IL, USA) was used to monitor outdoor environmental conditions

such as wind speed, wind direction, solar radiation, rainfall, air temperature and humidity near the experimental livestock buildings.

Experimental procedure

In this study, long-term and intensive monitoring of aerial dust including TSP, PM10, and inhalable and respirable dust was conducted regularly in a mechanically ventilated broiler house and naturally ventilated broiler house, respectively. To investigate any correlation between the dust concentration and various experimental variables, indoor and outdoor climates were also measured. Monitoring in the experimental facilities took place 12 times, according to the rearing stage of the broilers, over 13 months from September 2013 to September 2014.

PTFE filters were fully desiccated for 24 hours and the pre-weighed and measured filter was then housed in a 3-stage polystyrene cassette for TSP while sampling PM10 in the PEM. The flow rates for TSP and PM10 sampling were 2 and 4 l/min for 8 hours, respectively. Dust sampling instruments were installed at a height of 1.5 m above the broiler zone to reflect the average height of a broiler farmer's respiratory intake. Five experimental regional sampling locations were selected for each experimental broiler house. When sampling was complete, the filters were completely desiccated again for 24 hours in the laboratory and then weighed to determine the particle mass based on the gravimetric method.

The concentration of inhalable and respirable dust was measured using the Aerosol spectrometer at a height of 0.2 and 1.5 m, reflecting the average respiratory height of broilers and farmers. Measurements were taken at locations near the entrance and in the middle of the facility. The concentration of these occupational dusts was measured in two experimental situations: i) when broilers were very calm and ii) when broilers showed active and vigorous movement due to the work activity of the staff. Measurements of the target dust concentration in the MV broiler house are shown in Figure 2.

Figure 2: Measurement of TSP and PM10 (left) and inhalable and respirable dust (right) concentration in an experimental mechanically ventilated broiler house

Results and discussion

Results of TSP concentration monitoring

The monitoring results for TSP concentration are shown in Figure 3. The results for PM10 show a similar tendency. Measured mean values for TSP from each broiler house showed similar concentrations and tendencies according to the age in weeks and seasonal changes, except in the experimental situations with broiler ages of 2 and 4 weeks in the cold season. On the other hand, the mean TSP concentrations measured in the NV broiler house during the summer were generally higher than those in the MV broiler house (92~176%). The reasons for these differences in dust concentration could be: i) unfavourable air exchange through winch curtain openings due to the relationship between wind direction and building arrangement, ii) increase in broiler activities where a brighter light environment could be created due to the broad winch curtain openings and incoming sunlight (Hessel & Van den Weghe, 2007) and iii) dehumidification effects of incoming sunlight on bedding materials in the NV broiler house; when winch curtain openings were used, the water content of the bedding materials was lower than in the MV broiler house (62~99%).

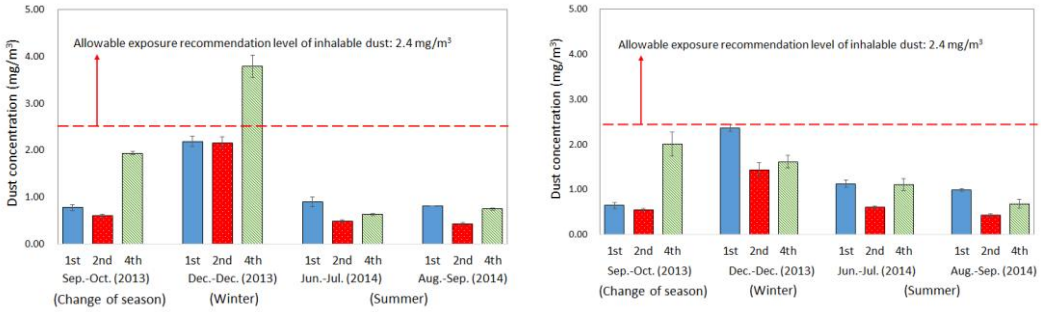


Figure 3: Monitoring results for TSP concentration in a mechanically ventilated broiler house (left) and naturally ventilated broiler house (right)

Result of inhalable dust concentration monitoring

Figure 4 shows the inhalable dust concentration measured at broiler height in the MV and NV broiler house, respectively. As shown in Figure 4, relatively higher concentrations of inhalable dust were found in the NV broiler house than in the MV broiler house. These observations could be explained by the following facts: i) a higher rearing density (113%) than in the MV broiler house, ii) dehumidification effects of bedding materials due to excessive heating in the cold season. In interviews with farmers, the heating cost for the NV broiler house was generally 1.5~2.0 times higher than for the MV broiler house to compensate for heat loss from leakage through the winch curtain opening. iii) effects of

incoming sunlight in summer and the change of season. When winch curtain openings were used, sunlight coming through openings could desiccate the surface of the bedding materials, therefore increased dust potential could be expected as mentioned above. An increase in animal activity was also identified in a brighter environment, as reported in previous studies (Hessel & Van den Weghe, 2007); the increase in animal activity is strongly related to high concentrations of pollutants inside the facility.

Like the results for TSP, some results for inhalable dust in both experimental broiler houses decreased temporarily as the broiler age increased from 1 to 2 weeks, and relatively higher dust concentrations were observed at 4 weeks old; these tendencies were not found in the summer, especially in NV broiler house where natural ventilation was prominent. These observations could be explained by the unbalanced relationship between the dust emission rate and the decontamination rate of the ventilation system according to the rearing stage, as mentioned earlier. In other words, irregular dust concentration tendencies measured at the age of 2 weeks during the summer might be inferred from the following facts; i) ineffective air exchange rate through winch curtain openings during the summer and ii) increase in broiler activity due to incoming sunlight. Some results for inhalable dust concentration, usually measured during the change of season and winter, exceeded the recommended level for animals of 3.7 mg/m3 (CIGR, 1994). In particular, a 148 and 214% excess was observed at the age of 4 weeks during the winter season in the MV and NV broiler house, respectively.

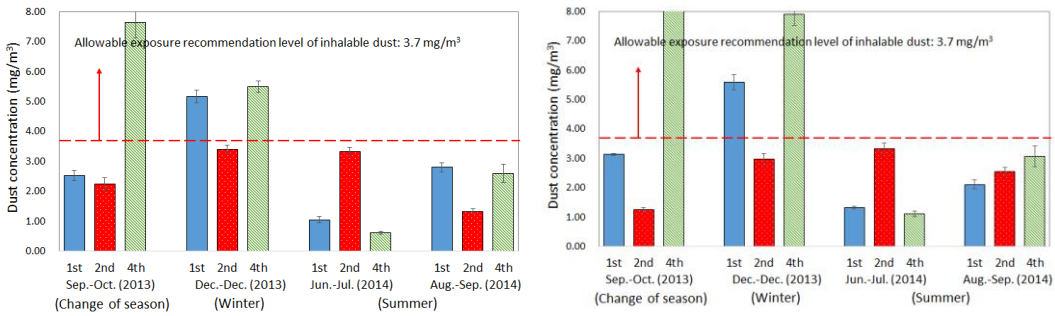


Figure 3: Monitoring result for inhalable dust concentration in a mechanically ventilated broiler house (left) and naturally ventilated broiler house at broiler height

<u>Multiple regression analysis of measured occupational dust</u>

Multiple regression analyses were conducted on the basis of the measured inhalable ($C_{Inhalable}$; mg/m³) and respirable dust concentration ($C_{Respirable}$; mg/m³) at broiler height and environmental conditions. To ensure the

independence of the experimental variables, correlation tests and multi-collinearity tests were carried out. From the result, the independent variables selected were broiler age (Age; days), CFD computed ventilation rate (VR; AER/min), outdoor absolute humidity level (AH_o; kg/kg-da), indoor air temperature (T_i; °C), indoor absolute humidity level (AH_i; kg/kg-da), water content of bedding materials (WC; %), and activity status of broilers (Ac). The activity status was a nominal factor, which reflects the effect of broiler status in relation to the entry of workers and work activities. Additionally, a backward elimination process was applied to select predictive variables for each regression model. Following a normality test using the Shapiro-Wilk test, some of the residuals of the regression models were found to be unsatisfactory as a prerequisite for normal distribution. Therefore, log transformation was carried out for the dependent variable of the models.
The linear regression equations for occupational dust at broiler height are presented below.

$$\mathbf{C_{Inhalable}\ in\ MV = -62.304 + 0.960 \cdot Age - 3.565 \cdot VR - 561.317 \cdot AH_o + 2.437 \cdot T_i - 851.148 \cdot AH_i + 10.760 \cdot Ac} \quad (1)$$

$$\mathbf{C_{Respirable}\ in\ MV = -3.812 + 0.061 \cdot Age - 0.362 \cdot VR - 75.671 \cdot AH_o + 0.131 \cdot T_i + 0.008 \cdot WC + 0.628 \cdot Ac} \quad (2)$$

$$\mathbf{C_{Inhalable}\ in\ NV = 12.552 + 0.219 \cdot Age - 986.194 \cdot AH_i + 0.091 \cdot WC + 11.096 \cdot Ac} \quad (3)$$

$$\mathbf{\log(C_{Respirable})\ in\ NV = 4.706 - 63.707 \cdot AH_o - 0.126 \cdot T_i - 72.217 \cdot AH_i} \quad (4)$$

The linear regression equations for occupational dust at worker respiration height are presented below.

$$\mathbf{\log(C_{Inhalable})\ in\ MV = 0.595 + 0.047 \cdot Age - 1.021 \cdot VR + 0.069 \cdot T_i - 156.645 \cdot AH_i + 0.873 \cdot Ac} \quad (5)$$

$$\mathbf{\log(C_{Respirable})\ in\ MV = -5.597 + 0.083 \cdot Age - 0.972 \cdot VR - 117.939 \cdot AH_o + 0.154 \cdot T_i + 0.668 \cdot Ac} \quad (6)$$

$$\mathbf{C_{Inhalable}\ in\ NV = 6.568 + 0.318 \cdot Age - 5.216 \cdot VR - 598.522 \cdot AH_i + 0.082 \cdot WC + 3.348 \cdot Ac} \quad (7)$$

$$\log(C_{Respirable}) \text{ in NV} = 4.585 - 67.609 \cdot AH_o - 0.174 \cdot T_i \quad (8)$$

Age and activity status of the broilers, ventilation rate and indoor absolute humidity level were significant variables in several regression models. Considering that the broiler's age and activity status as the farmer enters are uncontrollable factors, temporal management of the ventilation rate and humidity level of the facility can be helpful to reduce the dust concentration in broiler houses. The ventilation rate range that can be applied in livestock production facilities is limited, and an inappropriate increase in the ventilation rate could cause unfavourable thermal and humidity conditions in the animal zone. In terms of applicability, control of the humidity level can be a significant factor in reducing occupational dust in broiler houses. However, increased humidity could cause proliferation of micro-organisms and loss of productivity. Therefore, additional research to derive optimal indoor humidity levels, taking account of both biological safety and dust environment, is needed.

Conclusions

In this study the concentration of TSP, PM10, inhalable dust, and respirable dust in different environmental condition was regularly monitored in mechanically and naturally ventilated broiler houses. Relatively high dust concentrations were measured in the naturally ventilated broiler house. It was found that dehumidification and increased broiler activity due to sunlight entering through the winch curtain, and a relatively high rearing density were the cause of this phenomenon. Multiple linear regression analysis was conducted to derive the relationship between occupational dust concentration and environmental factors including ventilation rate calculated using CFD simulation. As a result, it was found that the activity status of broilers, ventilation rate and the humidity level of the facility were major factors in occupational dust generation. In terms of practical applicability, the humidity level can be the key factor for dust control in broiler houses. However, humidity inside the facility should be carefully controlled with a view to ensuring biological safety.

References

Banhazi, T. M., Seedorf, J., Rutley, D. L., & Pitchford, W. S. 2008. Identification of risk factors for sub-optimal housing conditions in Australian piggeries: Part 2. Airborne pollutants. *Journal of Agricultural Safety and Health*, 14(1), 21.

Hartung, J., & Saleh, M. 2007. Composition of dust and effects on animals. *Landbauforsch. Völk*, 308, 111-116.

Hessel, E. F., & Van den Weghe, H. F. 2007. Airborne Dust (PM 10) concentration in broiler houses as a function of fattening day, time of the day, and indoor light. In: *DustConf International Conference in Maastricht*, The Netherlands (pp. 23-24).

Hugh-Jones, M., Allan, W. H., Dark, F. A., & Harper, G. J. (1973). The evidence for the airborne spread of Newcastle disease. *Journal of hygiene*, 71(02), 325-339.

Pedersen, S., & Robertson, J. 1994. Aerial environment in animal housing-concentrations in and emissions from farm buildings. *CIGR*, 1.

Power, C. A. (2005). An investigation into the potential role of aerosol dispersion of dust from poultry barns as a mode of disease transmission during an outbreak of avian influenza (H7: N3) in Abbotsford, BC in 2004. *BULLETIN-AQUACULTURE ASSOCIATION OF CANADA*, 105(1), 7.

Rosentrater, K. A. (2004). Laboratory analysis of an electrostatic dust collection system. *CICR Journal of Scientific Research and Development*.

Tucker, W. G. (2000). An overview of PM 2.5 sources and control strategies. *Fuel Processing Technology*, 65, 379-392.

Can the dust concentration in broiler houses be modelled on the basis of ventilation rate and broiler activity?

T. G. M. Demmers[1], Q. Tong[1], A. Youssef[2], A. Peña Fernández[2], E. Vranken[3], D. Berckmans[2]
[1]*RVC Animal Welfare Science and Ethics, Royal Veterinary College, Hawkshead Lane, North Mymms, AL9 7TA, United Kingdom*
[2]*KU Leuven, M3-BIORES , Kasteelpark Arenberg 30, BE-3001 Heverlee, Belgium*
[3]*Fancom BV, Industrieterrein 34, 5981 NK Panningen, The Netherlands*
TDemmers@rvc.ac.uk

Abstract

Potentially, the bio-aerosol emission can be reduced using adaptive control of ventilation rate governed by the measured animal activity which acts as a proxy for dust concentration. A data set comprising continuous measurements of particulate concentrations, ventilation rate, broiler activity, mortality and weight over 14 batches at a modern broiler farm was used to test the hypothesis.
Typically dust concentration increased with increasing activity, with peak values in activity and dust concentration due to dawn or feed events coinciding. A good correlation between particulate matter and activity was found for any 24hr period (0.6), but the correlation for a full crop was substantially lower at 0.39.
Modelling the relationship between dust concentration and bird activity, required for adaptive control of ventilation rate, proved difficult. Transfer function models, often used for control purposes, were not suitable as the order of the model, as well as the values of the model parameters changed from day to day. A dynamic linear model approach functioned better with a mean relative prediction error of 10% for a prediction horizon of 2 minutes, based upon a time window of 30 minutes. However, both models required regular real time measurement of the aerosol concentration, to re-estimate the model parameters, thus to avoid deviation from the true value. Potentially, generalised linear or generalised non-linear models will be more suitable to this relationship but have not yet been applied to this dataset.

Keywords: dust, activity, broiler, model, transfer function, emission

Introduction

Poultry production in the UK stands at 1.42 million tons per annum (National Statistics, 2016) and is projected to become the biggest source of meat in the

near future at 134 million tons produced worldwide in 2023 (OECD and FAO, 2014). Poultry production produces roughly half of the total UK emission of bio-aerosols and/or particulate matter (PM) from housed livestock (Klimont and Amann, 2002; Winkel et al., 2015) often associated with negative effects upon the health and welfare of poultry and humans (Donham et al., 2002; Cambra-Lopez et al., 2010; Guillam et al., 2013; Basinas et al., 2015; Radon et al., 2017). Indoor concentrations regularly exceed the recommended maximum concentrations of 3.4 and 1.7 $mg.m^{-3}$ for inhalable and respirable particulate matter, respectively (CIGR, 1992; Takai et al., 1998). The most recent emission factors for PM2.5 and PM10 measured in the UK were 5.1 and 31.6 mg $animal^{-1}$ day^{-1} (Demmers et al., 2010), well within the published range of values (Oenema et al., 2012; Wathes et al. 1997; Cambra-Lopez et al., 2015). Most UK poultry operations are subject to environmental legislation and obliged to demonstrate dust management measures, i.e. simple control-at-source measures such as using pelleted rather than meal feed or simple end of pipe control methods. More complex and expensive dust abatement systems are rarely used in the UK, but more so elsewhere in Europe.

Particulate matter concentration is known to vary with animal activity [1-3], whilst Demmers et al (2011) showed animal activity, and particularly broiler activity, can be managed by modifying the lighting regimes over the day, with high activity associated with increased particulate matter concentrations. Ventilation rate has been proven to play a major role in particulate matter concentration as well (Calvet et al., 2010).Thus potentially, EyeNamic a commercial Precision Livestock Farming (PLF) system designed to provide broiler farmers with activity and distribution data of the flock could be used as an estimate of particulate matter concentration and therefore used to guide the buildings climate control system to minimise the emissions to the environment.

Data based or “black box” models such as transfer function (TF) and Dynamic linear regression (DLR) models have been used successfully to model biological processes (Aerts, 2003; Aerts 2008). The aim of this work is to use these modelling approaches to accurate predict the dust concentration based on the main drivers, activity and ventilation rate.

Material and methods

The experiments were carried out on a commercial broiler farm in a newly build mechanically ventilated broiler house (110m*20m; capacity 55.000birds). The building was indirectly heated using a central heating system and heat exchangers placed below the ridge line of the building (CUBO, Chore-time). Water was provided using nipple drinkers and dry pelleted feed was supplied to standard poultry feeders using augers.

Bio-aerosol concentration was measured below two fan shafts (ventilation stage 1 and 2 respectively) using two DustTrak DRX 8533 analysers (TSI Ltd) fitted with a PM10 inlet, providing simultaneous data for PM1, PM2.5, Respirable, PM10 and Total inhalable dust at 2 minute intervals. Due to the variable fan speed, some non-isokinetic sampling was to be expected. The background PM concentrations were measured on over two dates and found to be consistent with those measured at the nearest Automatic Urban and Rural Network (AURN) sites. The later were used to correct the PM emission data. The DustTrak instruments were factory calibrated to the respirable fraction of standard ISO 12103-1, A1 test dust. The inlet and PM10 impactor of the DustTrak instruments were serviced and cleaned prior to use in each batch and the instruments returned to the factory for internal cleaning of the optics and calibration after on average 1600 hrs of use. A correction factor of 1.29 for poultry dust was obtained using the internal gravimetric filter of the DustTrak as the reference sampler (n=8), which was lower than the factor obtained against European reference samplers of 1.58 by Winkel et al. (2015). Ventilation rate was measured using three full size measuring fans (Fancom BV, Netherlands) fitted below fans of ventilation stage 1, 2 and 3 (out of 6), as well as the duration each fan and ventilation stage was operational at any one time. The total flowrate calculated from these data was deemed to be an accurate measure of the overall ventilation rate. Activity was estimated using eYeNamic™, a camera system that captures two images of the floor area per minute. Buildin image analysis software translates the acquired images into indexes of activity and distribution. Data were collected from a total of 14 batches over a period of 2.5 years. The EyeNamic data were logged separately from the fourth batch onwards following a software modification. All other data were logged using Labview Virtual Instrument routines running on a local PC.

The multi-input, single output TF approach (Young, 1984) with broiler activity and ventilation rate and PM concentration as the input and output of the model respectively, was used to study the relationship in more detail. The models equations (Young, 1984; Aerts, 2003) were solved using Matlab identifying the structure of the model and estimating the value of the parameters.

The dynamic linear regression (DLR) approach is a state space model using time-variant parameters (Pedegral et al, 2007) rather than fixed parameters and thus is more able to account for external factors not directly accounted for in the model such as broiler age or other environmental factors. Matlab was used to identify the parameters for each time period.

Results and discussion

As was to be expected for data collection on a commercial farm each data set had one or more data points missing due to problems with the equipment, ranging from power supply issues to pollution of the internal parts of the dust samplers and management decisions by the farm staff.
The expected primary relationship between dust concentration and activity as measured with EyeNamic was clear, especially around the changes from dark to light (Figure 1) with the concentration of all size fractions (PM1 to PM10) falling at the start of the dark period, with the sharpest fall for the larger particles. Eventually, towards the end of the dark period, the dust concentration slowly dropped to a base level of approximately 0.02 mg m^{-3} for PM1. The activity during the dark period is arbitrarily set to zero although there might be some bird movement which cannot be registered by the eYeNamic system. After the dark period a large peak in animal activity was observed which tended to be the highest activity in any 24hr period. The remaining peaks are potentially associated with the feed system running (verbal communication farm manager).

Although figure 1 suggests a high correlation between dust concentration and activity the correlation was highly variable over the length of the growing period (figure 2) with a mean value of just 0.28.

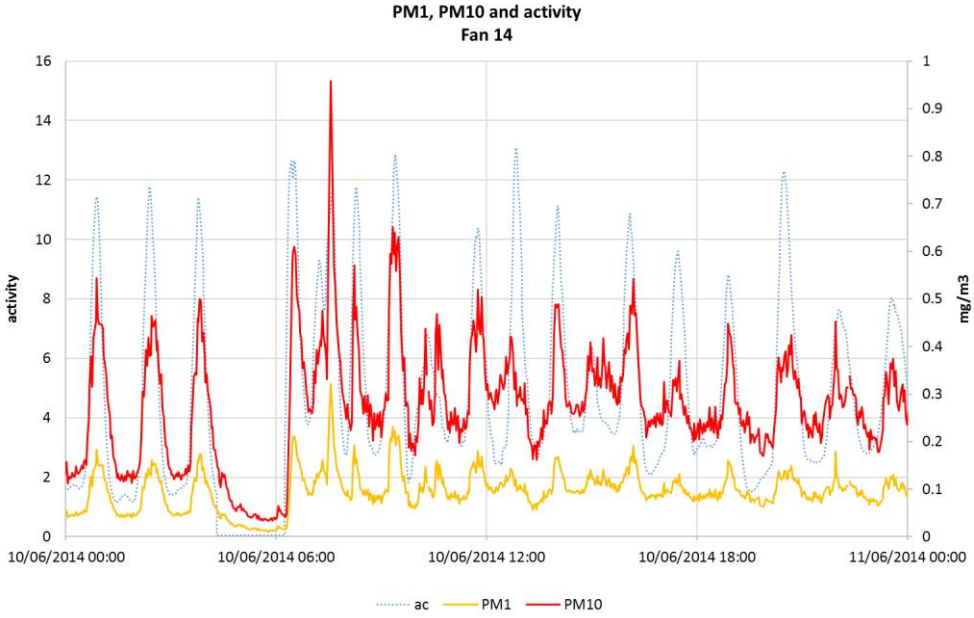


Figure 1 The PM1, PM10 and broiler activity measured on day 11 of the growing cycle under fan 14 (fan stage 2) in a commercial UK broiler house.

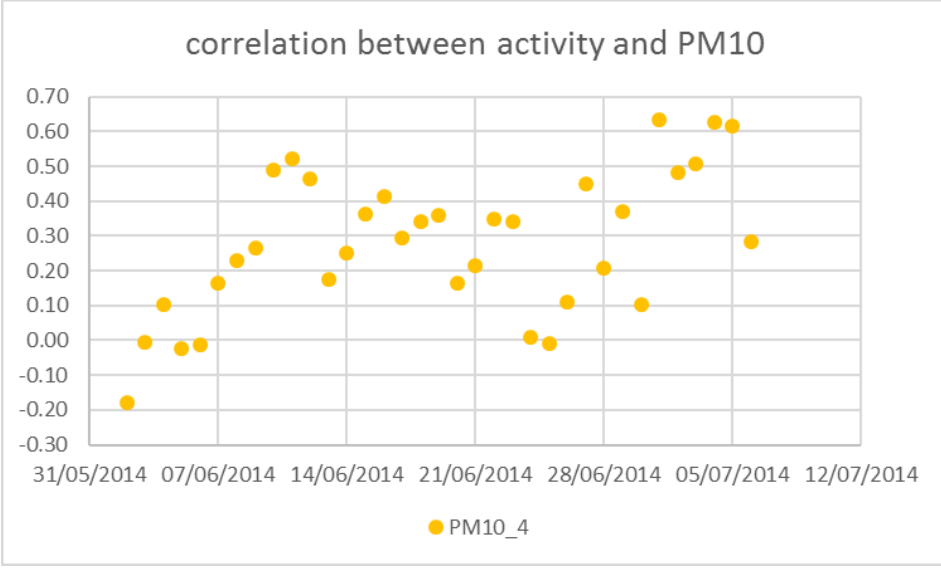


Figure 2: Correlation between broiler activity and PM10 during the growing cycle in a commercial UK broiler house.

Despite the low overall correlation between broiler activity and PM, the TF approach for modelling the relationship was pursued as this does also take ventilation rate into account. The system identification process, applied to individual data for each day in the growing cycle, yielded a first order model with a second order B-polynomial multiplying broiler activity, without any delay, and a first order B-polynomial with varying delay multiplying ventilation rate. Hence, broiler activity drives short term dynamics and ventilation rate the longer term dynamics all be it with a delay of the particulate matter concentration, respectively. However, the model performance was average with a fitting agreement (R^2) of just 50% for 70% of the growing cycle. Especially, the model lacks the ability to fully mimic the fast variation in PM concentration due to the broiler activity (figure 3).

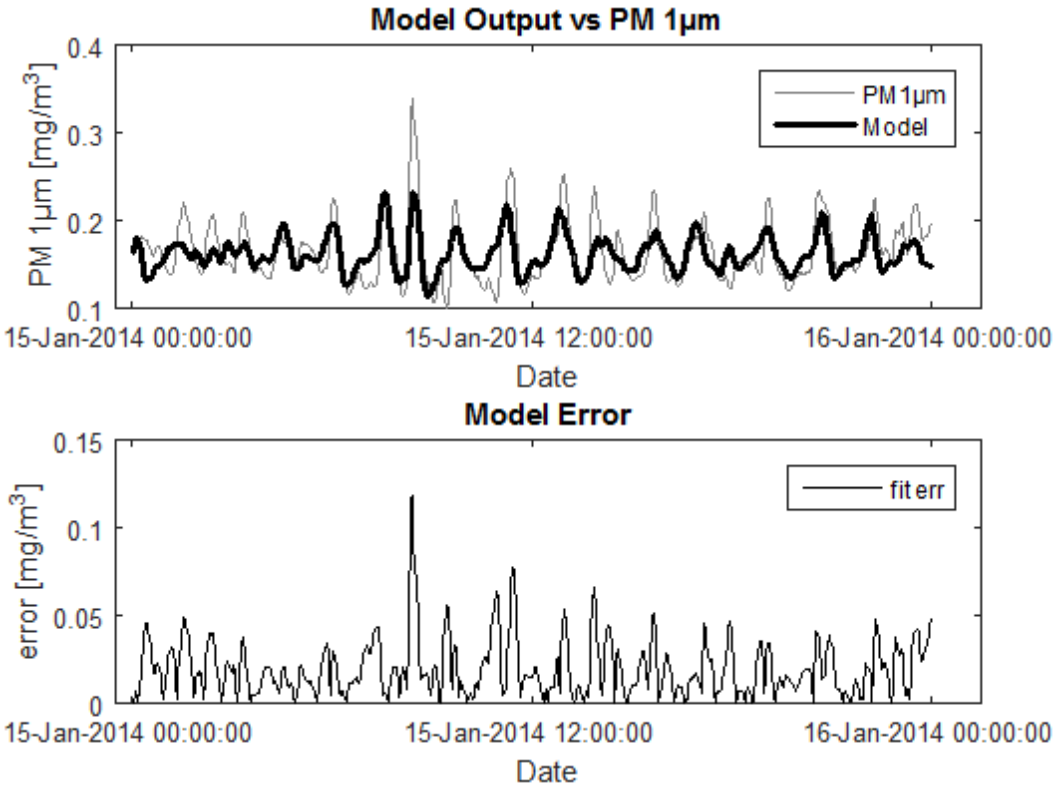


Figure 3: Example of the MISO TF model output (thick line) using the raw data for one day of the growing cycle for the inputs (broiler activity and ventilation rate) and the output (particulate matter 1um size concentration) (upper graph). In the lower graph the fitting error is shown for each sample.

The parameters of the model were however highly variable over the duration of the growing. Moreover, the parameters of the MISO model were different for each size fraction lowering the accuracy of a unique model for predicting the PM concentration over the whole period using average parameter values further, rendering the model unsuitable for this purpose.

The DLR modelling approach using variable parameters over time, does potentially take into account the effect of unknown variables affecting broiler activity or ventilation rate and hence PM concentration, without explicitly using these variables in the model. This significantly reduces the model complexity. The results showed that the DLR modelling approach was much better than the MISO approach at modelling both the short term daily variation in PM concentration due to broiler activity as well as the longer term variation due to ventilation. After evaluating a range of time windows and prediction horizon

sizes, a sample window size of 17, e.g. 34 minutes was found to be sufficient to predict the PM concentration 1 sample, e.g. 2 minutes ahead with a mean relative prediction error up to 1.7%.
These results of the modelling approaches clearly show the relationship between PM concentrations on the one hand and broiler activity and ventilation rate is more complex than expected. The DLR model is potentially suitable for simulation of the effect management changes in light/dark regime and ventilation rate might have on the PM concentration. However, the need for recent, at least daily, data of PM concentration to ensure the model result does not drift too far from the actual PM concentration precludes this model from being used in practical applications as there are, to date, no suitable PM samplers available for long term commercial use on livestock farms.

Conclusions

The results clearly show the relationship between PM concentration and broiler activity and ventilation rate, but highlight the high variability of this relationship over the course of the growing cycle.
The transfer function MISO modelling approach tested, was not able to capture both the short term and long term response of PM concentration to broiler activity and ventilation rate convincingly, due to the use of fixed parameters in the model.
The dynamic linear regression model performed much better due to the use of time-variant model parameters and best results forecasting the PM concentration as a function of the broiler activity and ventilation rate were obtained using a sample window of 17 samples to predict the PM concentration 1 sample ahead with a high accuracy (MRPE 1.7%).
The dynamic linear regression model could potentially be used for a future control system to actively manage the PM concentration by varying the broiler concentration and ventilation rate as required.
However, the continued requirement for regular PM concentration data all be it at long intervals makes use of the DLR model unsuitable for implementation on farm at the current time.

Acknowledgements

This project has received funding from the European Union’s Seventh Framework Programme for research, technological development and demonstration under grant agreement n° 311825.
DISCLAIMER: The views expressed in this publication are the sole responsibility of the author(s) and do not necessarily reflect the views of the

European Commission. Neither the European Commission nor any person acting on behalf of the Commission is responsible for potential uses of this information. The information in this document is provided with no guarantee or warranty that the information is fit for any particular purpose. The user thereof uses the information at his or her sole risk and liability.

References

Aerts, J. M., Wathes, C. M., and Berckmans, D. 2003. Dynamic data-based modelling of heat production and growth of broiler chickens: Development of an integrated management system. *Biosystems Engineering* ***84***(3), 257–266.

Aerts, J. M., Vranken, E., Berckmans, D., & Guarino, M. 2008. Modelling Dust Emission from Fattening Pig Houses. *Automatika* ***49***(3–4**)**, 119–125.

Basinas, I., Sigsgaard, T., Kromhout, H., Heederik, D., Wouters, I. M., and Schlü Nssen, V. 2015. A comprehensive review of levels and determinants of personal exposure to dust and endotoxin in livestock farming. *Journal of Exposure Science and Environmental Epidemiology* **2583**(10), 123–137.

Calvet, S., H. Van den Weghe, R. Kosch, and F. Estelles. 2009. The influence of the lighting program on broiler activity and dust production. *Poultry Science* **88,** 2504-2511.

Calvet, S., Cambra-López, M., Blanes-Vidal, V., Estellés, F., and Torres, A. G. 2010. Ventilation rates in mechanically-ventilated commercial poultry buildings in Southern Europe: Measurement system development and uncertainty analysis. *Biosystems Engineering* **106**(4), 423–432.

Cambra-López, M., Aarnink, A. J. A., Zhao, Y., Calvet, S., and Torres, A. G. 2010. Airborne particulate matter from livestock production systems: A review of an air pollution problem. *Environmental Pollution* **158**(1), 1–17.

Cambra-López, M., Winkel, A., Mosquera, J., Ogink, N. W. M., and Aarnink, A. J. A. (2015). Comparison between light scattering and gravimetric samplers for PM 10 mass concentration in poultry and pig houses. *Atmospheric Environment* **111**, 20–27.

CIGR. 1992. Climatization of animal houses, Commission International du Genie Rural, Ghent, Belgium.

Costa, A., and Guarino, M. 2009. Definition of yearly emission factor of dust and greenhouse gases through continuous measurements in swine husbandry. *Atmospheric Environment* **43**(8), 1548–1556.

Demmers, T. G. M., Cao, I., Parsons, D., Gauss, S and Wathes, C.M. 2011. Modelling and control of broiler activity. In: J. Kofer and H. Schobesberger (eds.) *Proc. XVth ISAH Congress No. III.* 243-246. Tribun EU s.r.o., Viena.

Demmers, T. G. M., Saponja, A., Thomas, R., Phillips, G. Mcdonald, A., Stagg, S., Bowry, A. and Nemitz E. 2010. Dust and ammonia emissions from UK poultry houses. In: *Proc. CIGR XVIIth World Congress No. CSBE10942*. 10pp, Québec City, Canada.

Donham, K. J., D. Cumro, and S. Reynolds. 2002. Synergistic effects of dust and ammonia on the occupational health effects of poultry production workers. *Journal of agromedicine* **8**, 57-76.

Guillam, M. T., Pédrono, G., Le Bouquin, S., Huneau, A., Gaudon, J., Leborgne, R., Ségala, C. 2013. Chronic respiratory symptoms of poultry farmers and model-based estimates of long-term dust exposure. *Annals of Agricultural and Environmental Medicine* **20**(2), 307–311.

Klimont, Z., and M. Amann. 2002. European control strategy for fine particles: the potential role of agriculture. *Landbauforschung Völkenrode Special issue* **235**, 29-35.

OECD, and FAO. 2014. *OECD-FAO Agricultural Outlook 2014*. OECD Publishing, Paris.

Oenema, O., Velthof, G., Amann, M., Klimont, Z., and Winiwarter, W. 2012. *Emissions from agriculture and their control potentials*. TSAP Report #3, Version 1.0, DG-Environment of the European Commission, (June), 34. http://webarchive.iiasa.ac.at/Admin/PUB/Documents/XO-12-013.pdf

Pedersen, S., Nonnenmann, M., Rautiainen, R., Demmers, T. G., Banhazi, T., and Lyngbye. M. 2000. Dust in pig buildings. *Journal Agricultural Safety and Health* **6**, 261-274.

Pedregal, P., and Tiago. J. 2007. New existence result for autonomous one-dimensional optimal control problems. *Journal of Optimization Theory and Applications* **134**, 241-255

Radon, K., Weber, C., Iversen, M., Danuser, B., Pedersen, S., Nowak, D. 2001. Exposure assessment and lung function in pig and poultry farmers Exposure assessment and lung function in pig and poultry farmers. *Occupational and Environmental Medicine*, **58**, 405–410.

Takai, H., Pedersen, S,. Johnsen, J. O., Metz, J. H. M., Groot Koerkamp, P. W. G., Uenk, G. H., Phillips, V. R., Holden, M. R., Sneath, R. W., Short, J. L., White, R. P., Hartung, J., Seedorf, J., Schröder M., Linkert, K. H., and Wathes, C. M. 1998. Concentrations and Emissions of Airborne Dust in Livestock Buildings in Northern Europe. *Journal of Agricultural Engineering Research* **70**, 59-77

Wathes, C. M., Holden, M. R., Sneath, R. W., White, R. P., & Phillips, V. R. (1997). Concentrations and emission rates of aerial ammonia, nitrous oxide, methane, carbon dioxide, dust and endotoxin in UK broiler and layer houses. *British Poultry Science*, **38**(1), 14–28

Winkel, A., Llorens Rubio, J., Huis in′t Veld, J. W. H., Vonk, J. and Ogink' N. W. M. 2015. Equivalence testing of filter-based, beta-attenuation, TEOM, and light-scattering devices for measurement of PM10 concentration in animal houses. *Journal of Aerosol Science* **80**, 11-26.

Winkel, A., Mosquera, J., Groot Koerkamp, P. W. G., Ogink, N. W. M. and Aarnink, A. J. A. 2015. Emissions of particulate matter from animal houses in the Netherlands. *Atmospheric Environment*, **111**, 202–212.

Young, P. C. 1984. *Recursive estimation and time-series analysis*. Springer-Verlag Berlin

Development of a VR simulator for educating swine farmers using open-source CFD

J. Kim, R. Kim, I-B. Lee
Department of Rural Systems Engineering, Research Institute of Agriculture and Life Science, College of Agriculture and Life Sciences, Seoul National University, 599, Gwanak-ro, Gwanak-gu, Seoul, 151-921, Republic of Korea
kjkkjk9410@snu.ac.kr

Abstract

Although the livestock industry in Korea has developed greatly in recent years, many problems have occurred in terms of maintaining an optimum micro-climate in livestock buildings. In particular, many consultants and farmers have easily misunderstood the ventilation efficiency and internal airflow distribution and wrong judgments have therefore been made. The air flow is the main mechanism of internal environmental distribution for gas, temperature, humidity and dusts; however, as is well known, the airflow is invisible and difficult to predict and measure. Therefore, it is essential to develop training materials to enable farmers to recognize the micro-climate visually. In this study, an aerodynamic approach was adopted using CFD (computational fluid dynamics) in combination with VR (virtual reality) technology. First, a number of research papers, reports, journals and publications on the livestock industry were reviewed to find representative problems in swine houses during the hot and cold seasons in Korea. Open-source CFD, non-commercial software, was then used to compute selected problems and their solutions. The design of the livestock house models was based on the 2009 Korean Standard for swine houses. These CFD computed results, such as air flow, temperature, humidity and gas, were applied to a VR simulator for educating swine farmers.

Keywords: virtual reality (VR), livestock, CFD, micro-climate

Introduction

Livestock facilities in South Korea have become larger and more automated in order to increase meat production. However, it is difficult to maintain a suitable and uniform micro-climate in large facilities because most swine facilities are managed with limited resources. It is common for livestock facilities to experience many problems in terms of maintaining an optimum micro-climate. For example, animals often suffer from various stresses in poor environment. These stresses could weaken the immune system of animals (Myer & Bucklin, 2007).

Various studies based on field experiments have been conducted with a view to maintaining an optimum micro-climate in swine houses because field experiments are one of the most reliable methods (Myer & Bucklin, 2007; Wang, Zhang, Riskowski, & Ellis, 2002). However, field experiments also have limitations: 1) time and labour requirement problems, 2) various changes in environmental conditions, 3) representation of measured values. Because of these limitations, it is difficult to obtain results from field experiments. Recently, computational fluid dynamics (CFD) has been widely used to analyse air flow, temperature, humidity, gas and dust concentration under various environmental conditions (Bartzanas, Kittas, Sapounas, & Nikita- Martzopoulou, 2007; Bjerg, Lee et al., 2002, 2004, 2009; Seo, Lee, Kwon, et al., 2009). However, livestock farmers and consultants do not find it easy to understand these computed results. Therefore, educational technology which can effectively display the aerodynamic results is necessary to help maintain an optimum micro-climate in livestock facilities.

Virtual reality (VR) technology which can offer a virtual experience of invisible things has been developed and used in various fields. It has developed significantly, and has recently become a major industry. The VR industry has a variety of applications. It helps users to make clear decisions and visualisations so that they can easily understand the environment in the facilities.

In this study, an aerodynamic approach was adopted using CFD (computational fluid dynamics) in combination with VR (virtual reality) technology and educational materials were developed for general commercialisation.

Materials and methods

Experimental swine house

In South Korea, most nursery swine houses are mechanically ventilated, although many fattening swine houses are naturally ventilated via winch curtain openings. Many mechanically ventilated facilities are built to the 2009 Korean Standard for swine houses (Korea Pork Producers Association, 2009). Many problems have occurred in swine houses during the hot and cold seasons as there are four distinctively different seasons. Therefore, it is a laborious task for farmers to maintain an optimum micro-climate in swine houses with facilities built to the 2009 Korean Standard. In this study, one nursery swine room based on this standard was chosen as the experimental room to develop a simulation model and analyse the micro-climate. The experimental room was 5.5 m wide, 9.0 m long and 2.4 m high, as shown in Figure 1.

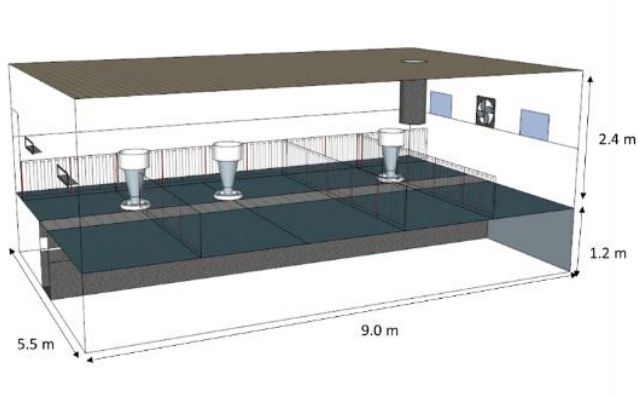


Figure 1: Schematic diagram of the experimental nursery swine house.

Computational fluid dynamics (CFD)

CFD is a numerical method for computing the behaviour of fluids by solving a nonlinear partial differential equation, such as the Navier-Stokes equation, based on the principles of mass conservation, Newton's second law, and the first law of thermodynamics. CFD has proved a powerful tool in the field of agriculture for micro-climatic analyses of livestock houses, as well as in studies on the dispersion of livestock odour and aerosols (Launder and Spalding, 1974). CFD analysis is a technique that numerically solves equations based on the finite volume method (FVM), which consists of three design stages. In the pre-processing stage, the physical shape of the target area is designed and used to generate a grid mesh. In the main processing stage, each governing equation for the physical phenomena is discretised and solved. A qualitative and quantitative analysis of computation results is conducted in the post-processing stage. Software discretises and solves the Navier-Stokes equations for the conservation of mass, energy and momentum regarding the transport of fluid and energy, where the equations for the conservations

Virtual Reality (VR)

Virtual reality (VR) typically refers to computer technologies which use virtual reality headsets to generate realistic images, sounds and other sensations that replicate a real environment or create an imaginary setting. Recently, research focused on practical application and industrialisation based on ICT has been conducted. It is particularly important to create a micro-climate in livestock facilities which maintains a suitable environment. The invisible air and heat flow can be visualised through VR. It is useful to develop training materials for farmers so that they can recognise the micro-climate visually. Because of these advantages, in this study, VR technology was used to develop training materials, as shown Figure 2.

Figure 2: Virtual reality simulation equipment (Usman, 2016).

Development of a CFD simulation model

Design-modeler (Release 16.1, ANSYS Inc, U.S.A) was used to design the 3-D computational domain with meshes, including the specific configurations of the different components of the experimental swine house. The designed mesh domain, as shown in Figure 3, was exported to OpenFOAM (version 2.1.1), the main solver for the numerical calculation which uses the CFD technique that solves the Navier-Stokes equations with Reynolds theory for all meshes in the computational domain. A validated model, based on previous research, was used in this study (Seo et al., 2009; Kwon et al., 2016). Therefore, the turbulence model was determined as RNG k-ε and the grid size was determined as 0.1 m based on grid independence tests.

Figure 3: Computational domain and mesh design for the nursery swine house.

Table 1: Data for mesh and environment condition.

Contents	Values
Model size	5.5 m width × 9.0 m length × 2.5 m height
Shapes of mesh	Tetra, Multi-zone
Number of meshes	6,107,109
Orthogonal quality	Min 0.219 > 0.01
Skewness	Max 0.850 < 0.95
Outdoor temperature	264 K (cold season), 304 K (hot season)
Velocity outlet (total)	0.9 m/s (cold season), 15.5 m/s (hot season)
Pig surface temperature	313 K

Investigating the main problems

To investigate the main problems of swine houses, a number of research papers, reports, journals and publications on livestock industry were reviewed in order to identify representative problems at swine houses during the hot and cold seasons in South Korea. The 63 papers and 14 journals investigated were summarised for the simulation environment conditions. The major problems of swine houses were divided into two categories. During the cold season, the problems include cold stress, internal non-uniformity, insufficiency of ventilation rate, high gas and odour concentration, etc. In particular, failing to maintain an appropriate micro-climate during the cold season causes the swine to lose their immunity. Also, in order to maintain an appropriate micro-climate, ventilation should take account of environmental changes. Since many farmers do not fully understand the air flow, appropriate improvements in the ventilation system are needed. Similarly, during the hot season, major problems of swine houses are heat stress, internal non-uniformity, excessive flow rate, rearing density, etc. Although gas and odour problems are insignificant during the hot season because of maximum ventilation, excessive air flow has a negative influence on swine. In order to solve these problems, aerodynamic approaches should be considered to control the micro-climate in swine houses.

Combination of CFD simulation and virtual reality

CFD calculation was performed based on the major problems mentioned. These results show air flow, gas concentration and temperature distribution in the swine house. However, farmers may find it difficult to understand these results. Therefore, it is necessary to develop visualisation materials based on the computed results. Since the exported data have a lot of grids, they could be overloaded in a virtual reality simulation. A point has data such as temperature, x-velocity, y-velocity, z-velocity, vector, humidity and NH3 concentration in each grid. The points in the CFD domain are located at intervals of 10 cm. The position of points will be modified for use in the virtual reality program. Each point will be streamlined to visualise the air flow. VR equipment shows satisfactory simulation of the micro-climate in the virtual reality simulation.

Results and Discussion

CFD simulation results

During the cold season with ventilation through the side slots in the swine house, cold air might come into direct contact with the swine and could cause serious problems in nursery swine. Figure 3(a) shows the temperature and direction of inflow air through the side slots. However, it is difficult to measure the temperature distribution accurately using several thermometers because of the

non-uniformity of the indoor air temperature. The average temperature near the slots was about 274 K, while the average temperature in the centre of the house was about 301 K. This temperature is far lower than the appropriate temperature for nursery swine. Also, as shown in Figure 3(a), ammonia gas accumulated increasingly as the distance from the side slots increased. This means that the fresh air could not reach the end of the facility. In order to solve these problems, there is a method of adjusting the inlet angle. When the inlet angle is adjusted to 45 degrees at the side slot, the inflow air rises up to the top and falls down onto the nursery swine, as shown in Figure 3(b). Since the risen air mixes better with warm air at higher levels, the difference between inflow air temperature and indoor temperature could be reduced by about 2-3 K. During the cold season, however, the ventilation rate is low, so the inflow air does not stay on top for long. The air temperature is still non-uniform and unsuitable for nursery swine. Also, this modified structure cannot remove ammonia gas sufficiently. An alternative solution is to make holes in the ceiling to avoid inflowing cold air and improve internal uniformity (Figure 3(b)). The cold air remains at ceiling level to warm up and slowly flows into the house through small holes. During the hot season, the air temperature in the ceiling is lower than outside. This could help to prevent the direct inflow of hot air from outside.

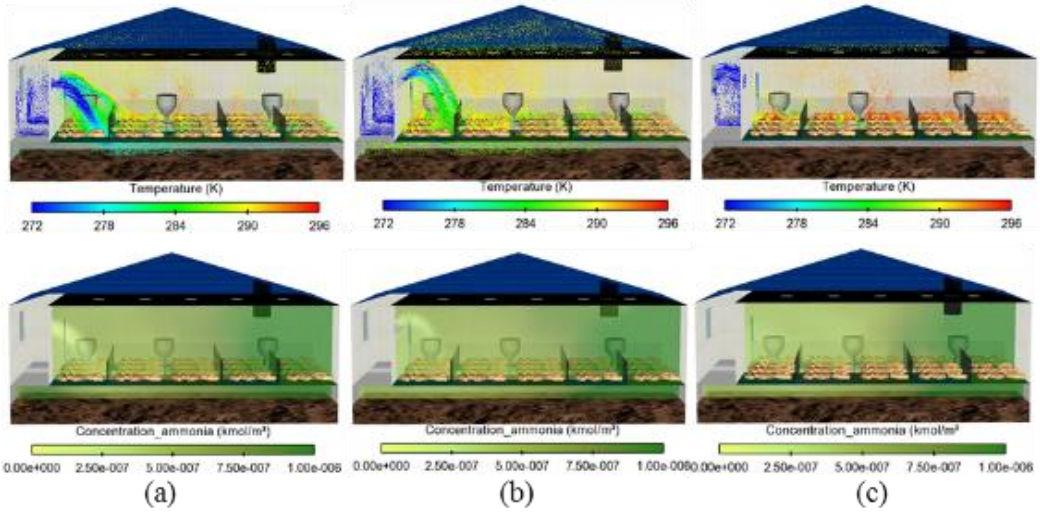


Figure 3: Temperature (top row) and concentration of ammonia (bottom row) using side slots (left column), modified side slots (middle column) and ceiling holes (right column)

Design of the simulation model

It is important to make real swine models for virtual reality simulation. In the CFD simulation, structures and swine shapes were simplified for efficient computation.

However, in virtual reality, these models must be realistic. This depends on a number of polygons which are closely related to the resolution of the model geometry. If the model has too many polygons, the virtual reality equipment cannot run the difficult simulation. Sometimes it would make the user dizzy. On the other hand, a model with too few polygons looks too simple and unrealistic. As shown in Figure 4, to determine the optimal number of polygons, the appropriate quality for smooth operation was identified. Consequently, the middle polygon model was chosen as the VR simulation model for the VR simulator.

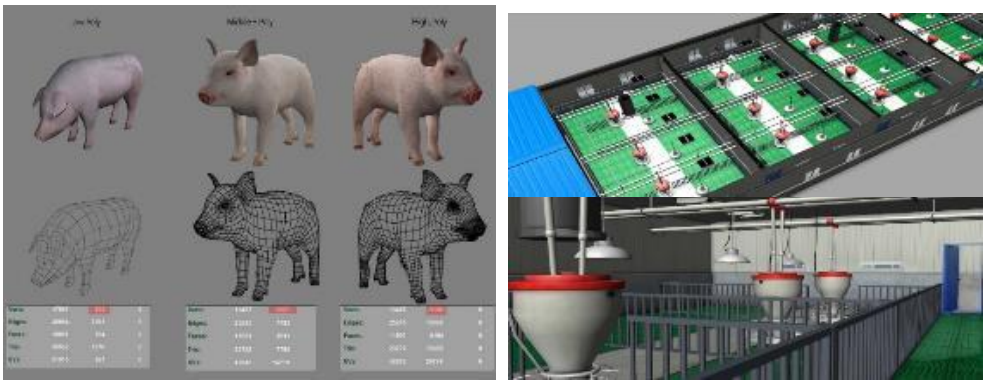


Figure 4: The comparative pig model quality data (left) and the views of the nursery house in the virtual reality simulation (right)

Development of the VR simulator

To combine the CFD simulation data and the virtual reality simulator, it is necessary to determine the same data point to display the same contour or vector field in virtual reality simulation. In the CFD simulation results, there are as many points as the number of grids. However, virtual reality hardware performance is not sufficient to handle such huge amounts of data. If there is too much data, a lot of frames will be needed for the simulation. Eventually this causes motion sickness in the user. Therefore, the distance between points should be modified to reduce the total number of points. To find the optimal distance, 0.05 m, 0.1 m, 0.15 m, and 0.2 m were used in the test. The distance between points selected was 0.1 m based on the test. Each point has its own data such as temperature, velocity, direction, gas concentration, etc. In the virtual reality simulation, visualised air flow streamlining, temperature and gas concentration with colours will be inserted with the contour and vector field.

In the next step, a virtual reality simulator which provides micro-climate information for educating farmers will be developed with various cases. In order to obtain sufficient data, various cases must be computed by CFD. Each case has a different structure, environmental conditions and ventilation system. Because each case takes up considerable computation time, computation should be carried out with the most typical problems.

Figure 5: Various example applications of virtual reality technology on fluids (Hynek et al., 2005; Kelly, 2016).

Conclusion

In this study, an aerodynamic approach was adopted using CFD (computational fluid dynamics) for combination with VR (virtual reality) technology and educational materials were developed for general commercialisation. Many documents were reviewed to investigate representative problems in swine houses. CFD modelling was carried out based on the cases identified. Only one case relating to ventilation during the cold season was investigated. The results show the problems of side slot ventilation in the swine house. An inflow method through ceiling holes was proposed as an appropriate way to solve cold stress and non-uniformity. In order to develop a virtual reality simulator, the data points including computed results should be converted for high quality resolution. Also, to avoid overloading the VR simulation, the number of polygons should be reduced while maintaining sufficiently high quality.

In a future study to develop a higher-resolution simulator, the computed results must be optimised. The results have many data points including micro-climate information. The distance between the points must be modified for stable virtual reality simulation. With improved computer resources, higher-quality models and structural configurations including detailed resolution could be considered. Also, more cases should be computed by CFD for various training situations.

Acknowledgements

This work was carried out with the support if the “Development of virtual reality based aerodynamic simulator for environmental management of smart farm (Project No. PJ012038)”, Rural Development Administration, Republic of Korea.

References

Bartzanas, T., Kittas, C., Sapounas, A. A., & Nikita- Martzopoulou, Ch. 2007. Analysis of airflow through experimental rural buildings: sensitivity to turbulence models. *Biosystems Engineering*, 97, 229-239.

Bitog, J. P., Lee, I. B., Hwang, H. S., Shin, M. H., Hong, S. W., Seo, I. H., et al. 2012. Numerical simulation study of a tree windbreak. *Biosystems Engineering*, 111(1), 40-48.

Bjerg, B., Svidt, K., Zhang, G., Morsing, S., & Johnsen, J. O. 2002. Modeling of air inlets in CFD prediction of airflow in ventilated animal houses. *Computers and Electronics in Agriculture*, 34, 223-235.

Hynek,, Bryden, Richard. 2005. Potential applications of virtual engineering to swine production systems. *American Society of Agricultural Engineers.* 701P0205

Kelly Maes. 2016. Zorgt Virtual Reality voor een transformative binnen de verzekeringswereld. Linked in journal.

Korea Pork Producer Association. 2009. 2009 Korean Standard of swine

Kwon, K., Lee, I., Zhang, G. Q., & Ha, T. 2015. Computational fluid dynamics analysis of the thermal distribution of animal occupied zones using the jet-drop-distance concept in a mechanically ventilated broiler house. *Biosystems Engineering*, 136, 51-68.

Kwon, K,. Lee, I., Ha, T. 2016. Identification of key factors for dust generation in a nursery pig house and evaluation of dust reduction efficiency using a CFD technique. *Biosystems Engineering*, 151, 28-52

Launder, B., & Spalding, D. 1974. The numerical computation of turbulent flows. *Computer Methods in Applied Mechanics and Engineering*, 3(2), 269-289.

Lee, I., Park, W., Yu, B., Yun, J., Chun, J., Kim, K., Cho, H. 2002. Optimum design of forced ventilation system of piglet house using computer simulation. *2002 ASAE Annual International Meeting/CIGR XVth World Congress*. Paper number 024109.

Lee, I.-B., Sase, S., Han, H.-T., Hong, H.-K., Sung, S.-H., Hwang, H.- S., et al. 2009. Ventilation design for a chick incubator using computational fluid dynamics. *JARQ*, 43(3), 227-237.

Lee, I.-B., You, B.-K., Kang, C.-H., Jeun, J.-G., Kim, G.-W., Sung, S.- H., et al. 2004. Study on forced ventilation system of a piglet house. JARQ, 38(2), 81-90.

Myer, R. O., & Bucklin, R. A. 2007. Influence of rearing environment and season on growth performance of growingfinishing pigs. *Transactions of the ASABE*, 50(2), 615-620.

Seo, I.-H., Lee, I.-B., Kwon, S.-H., Hwang, H.-S., Hong, S.-W., Bitog, J. P., et al. 2009a. Numerical investigation of the pig house to prevent pig respiratory disease according to ventilation system. *In The 2009 CIGR international symposium of the Australian society for engineering in agriculture*. Brisbane, Queensland, Australia: The Chifley at Lennons.

Usman Prizada. 2016. AMD reveals list of qualified FX series processors for an Oculus Rift 'VR-Ready' PC build. WWFTECH journal.

Wang, X., Zhang, Y., Riskowski, G. L., & Ellis, M. 2002. Measurement and analysis of dust spatial distribution in a mechanically ventilated pig building. *Biosystems Engineering*, 81(2), 225-236.

Achievements of CFD to investigate internal climate and air quality of poultry houses

F. Rojano[1], P-E. Bournet[1], M. Hassouna[2], P. Robin[2], M. Kacira[3], C. Y Choi[4]
[1]*EPHor, Environmental Physics and Horticulture Research Unit, AGROCAMPUS OUEST, Centre d'Angers, 2, rue Le Nôtre, 49045 Angers, France.*
[2]*SAS Lab. INRA 65 Rue de Saint-Brieuc 35042 Rennes, France.*
[3]*Agricultural and Biosystems Engineering, The University of Arizona. Tucson, AZ 85721 USA.*
[4]*Biological Systems Engineering, University of Wisconsin. Madison, WI 53706 USA.*
Pierre-Emmanuel.Bournet@agrocampus-ouest.fr

Abstract

Poultry production buildings must promote growth while maintaining animal welfare. The specific design of the building and the equipment used determine the operating conditions that will provide the internal environment required by the animals. The present work summarises a series of computational fluid dynamics (CFD) studies under transient conditions which investigate each of the main elements that modify the internal climate and air quality of a naturally ventilated poultry house. Interactions between the interior and exterior were modelled, taking account of radiative, convective and conductive heat transfer. Furthermore, the investigation included contributions (e.g. heat and water vapour) pertaining to the animals and the rearing system (e.g. accumulated litter) in the animal occupied zone. Thus, internal climate was described by means of internal temperature and absolute humidity, which also served to quantify sensible and latent heat. Validation was undertaken on the basis of the distributed temperature and humidity patterns. Gas exchanges were studied by analysing water vapour concentrations and estimating ventilation rates. A derived study was also undertaken to assess the impact of wind direction on the internal climate and consequently on the predictions of gas discharge, together with the capacity of the building to renew air. The overall investigation serves to enhance predictions related to climate and air quality. These contributions may also serve as a reference for strategic further research on internal climate and gas exchanges occurring in livestock buildings.

Keywords: natural ventilation, microclimate modelling, livestock buildings, water vapour

Introduction

Successful animal production means meeting the necessary requirements in relation to housing. The climate and air quality of a building should be investigated together in order to propose solutions which satisfy the climate requirements of the animals and optimise management of the building. Poultry house management relies primarily on heating and ventilation. Heating covers the climate requirements while ventilation renews air and may also increase or decrease internal temperature and humidity, and affect air quality. Various advances with regard to the climate and emissions in poultry houses have proved the accuracy of modelling natural ventilation (Lee *et al*., 2007), emissions from livestock buildings (Bjerg *et al*., 2013) and analysing the effects of different vent configurations in livestock buildings (Norton *et al*., 2010). Thus, this work contributes to the current state of the art by means of a series of studies related to housing needs for hen production. Internal climate dynamics were investigated by integrating the external and internal climate, the characteristics of the building, the equipment, the animals and the rearing system. A computational fluid dynamics (CFD) model was developed, integrating all the different sinks and sources, where climate conditions were described through variables associated with the air: temperature, humidity, pressure and velocity. Complementary information about air quality was obtained using water vapour gradients. Experimental data were used to validate the internal climate dynamics of the CFD model and predictions obtained from the CFD model were used to investigate gas dispersion downwind of the building.

Materials and methods

Experimental rig

A building (Figure 1) located in western France (46.15 N, -0.69 W) at the INRA experimental station “Le Magneraud” was used in the experimental phase. It was designed for organic hen production. Specifications of the building are provided in Figure 1 and Table 1. To collect outside climate data, a meteorological station (AWS310, Vaisala, France) located 30 m away from the building was used. The station logged data relating to wind velocity and direction, solar radiation, air temperature and relative humidity. Inside the building, temperature (±0.1 °C) and relative humidity (±3 %) measurements were taken using 15 portable sensors (DL-101T USB, Voltcraft, France) distributed in a vertical (sensors 4 to 12) and a horizontal plane (sensors 1, 2, 3, 13, 14 & 15) as shown in Figure 1.

CFD modelling

A three-dimensional representation of the building was meshed by means of ICEM software from Ansys, 2015 using a hexahedral-cell-type (Figure 2). Outer dimensions were in accordance with recommendations based on previous studies (Bournet & Boulard, 2010). A dimension H (equal to 2.6 m) was chosen to represent the distances associated with the outer surfaces of the building. The domain used the grid convergence index (GCI) to select the appropriate mesh, after evaluating three mesh densities. Further information can be found in Rojano *et al.* (2016).

Table 1 Material specifications.

Material	Density ($kg\ m^{-3}$)	Specific heat ($J\ kg^{-1}\ C^{-1}$)	Thermal conductivity ($W\ m^{-1}\ C^{-1}$)	Thickness (mm)
Wall (polystyrene)	50	1300	0.05	40
Wall (curtain)	920	2100	0.33	0.5
Roof (metal sheet)	6700	490	43	0.5

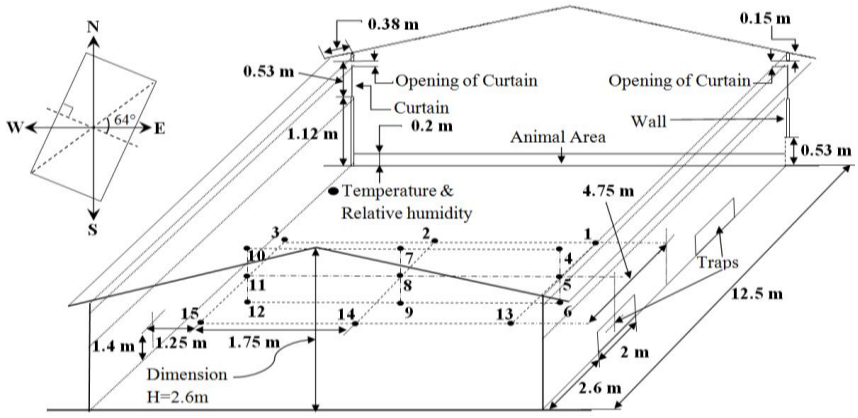


Figure 1: Poultry house dimensions and locations of the sensors used to collect climate data.

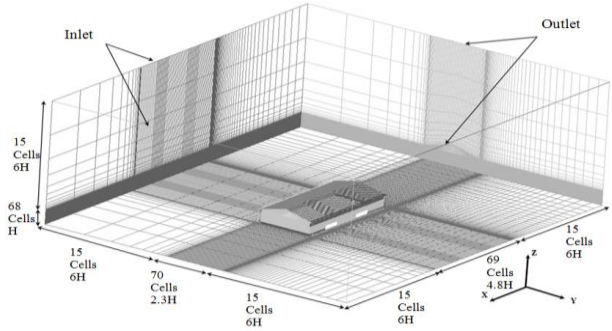


Figure 2: Three dimensional domain of a naturally ventilated poultry house.

Governing equations

The Navier-Stokes equations were used for the modelling stage based on a finite-volume approach and following the Reynolds-average method. Turbulence effects were included by adding two complementary equations which computed the kinetic energy k and dissipation rate ε within the k-ε model (Mohammadi & Pironneau, 1994). Enhanced predictions required the radiative transfer equation, considering the effects of two bands: solar radiation (with wavelengths from 0.1μm to 3μm) and thermal radiative energy (with wavelengths from 3μm to 100μm). The discrete ordinate method was used in a similar way to the work presented by Bournet *et al.* (2007). A full description of this equation applied to a poultry house may be found in Rojano *et al.* (2015a). Animal and litter heat generated was computed according to the equations recommended by CIGR (2002). Additional input data required for simulations is provided in Rojano *et al*. (2016).

Animal impact in the internal climate

Animals were included only as heat and mass sources within a space denoted as the animal occupied zone, measuring 0.2 m (height) × 6 m (width) × 12.5 m (length). This space corresponded to less than 10% of the internal volume of the building, where ventilation rates had not been significantly modified (Rojano *et al.*, 2014). This study had an animal density of 10 hens m^{-2} and average weight of 2.2 kg (for the 55th day of production), giving an approximate total heat of 19 W hen^{-1} from CIGR (2002).

Initial and boundary conditions

Initial conditions for the domain were obtained under steady state conditions with Fluent from Ansys, 2015 and using the input data presented in Figure 3. Shortwave radiation data was set according to experimental measurements, and longwave radiation was computed based on the procedure described in Rojano *et al.* (2015b). The boundary conditions are provided in Table 2. The domain's atmospheric pressure (p_o) was 100.4 kPa (i.e. 80 m above sea level), assuming air to be an incompressible ideal gas subjected to the effects of gravitational forces. Specifications for the operating conditions of the poultry house were set as described in Table 3.

Table 2 Boundary conditions.

Boundary	Value	Reference
Inlet	Wind velocity, $u_o(x) = \frac{u_*}{K} ln\left(\frac{z+z_o}{z_o}\right)$	(Richards & Hoxey, 1993)
	Turbulence kinetic energy, $k_z = \frac{u_*^2}{\sqrt{C_\mu}}$	(Richards and Hoxey, 1993)
	Turbulence energy dissipation, $\varepsilon_z = \frac{u_*^2}{K(z+z_o)}$	(Richards and Hoxey, 1993)
	Outdoor temperature, T_o	Experimental data
	Outdoor absolute humidity, h_o	Experimental data
Outlet	Atmospheric pressure, p_o	Experimental data
Top	Shortwave radiation, S_R and longwave radiation, q	Experimental data
Floor	Indoor floor temperature, T_{fi}	Experimental data

$u_* = KU/ln\left(\frac{h+z_o}{z_o}\right)$; Karman's constant K=0.42; $C_\mu = 0.013$; roughness length for grass is $z_o = 0.1m$ and velocity measurements of wind velocity U at reference height h_o= 4.5m

Table 3. Information used in CFD simulations.

Traps	Open
Curtain opening, m	0.1
Indoor floor temperature, $\mathbf{T_{fi}}$, °C	22 (± 0.5)
Longwave radiation, **q**, W m^{-2}	225 (± 5)
Solar position (elevation, azimuth), rad	(0.34, 1.33)

The domain shown in Figure 2 had two sides as the velocity inlet and two sides as the pressure outlet. In the velocity inlet, the measurements of wind velocity, temperature and absolute humidity shown in Figure 3 were included. The top boundary was set as a slip wall with wind direction and velocity equal to field observations; additionally, in this study, boundary radiative energy was imposed for short- and long-wave based on experimental data. Bottom ground was set as adiabatic outside the poultry house, and floor temperature inside the building was set according to experimental data. Enhanced wall treatment was applied to all the walls of the building.

Results and discussion

Experimental data

Experimental data was used to validate the CFD model. Only short time intervals could satisfy the requirements for CFD modelling; i.e. with a stable wind direction. Orientation of the building (21° North-East), wind velocity and direction became the main variables impacting the capability of the building to renew air. A period of 4h on 15 June 2014, with a prevailing wind direction of 57° (wind vane North-East), was chosen for evaluation of the CFD model. Initial conditions used input data corresponding to time step 1 of Figure 3; then, unsteady state conditions were examined using input data from time step 2 to 7 from the same figure. Experimental data was collected every 10 minutes, and a moving average filter was implemented to obtain a 30 min-time step. Additional information about data treatment to set an adequate time step can be found in Rojano *et al.* (2016).

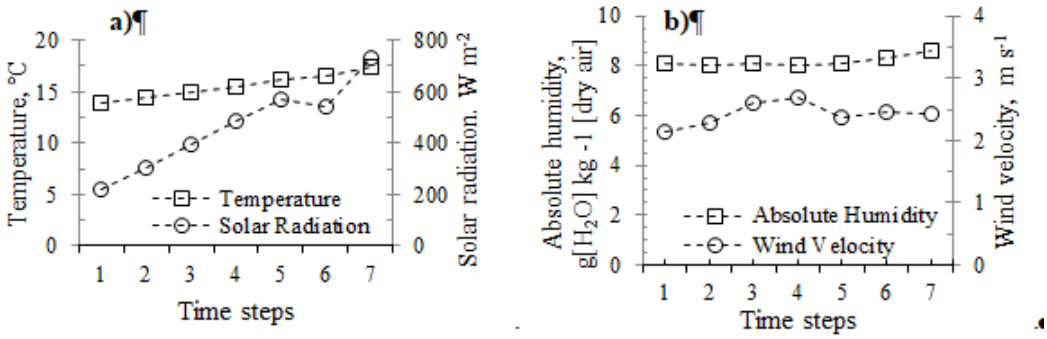


Figure 3: Input data for a) external temperature, solar radiation, b) absolute humidity and wind velocity.

CFD validation of the internal climate dynamics

A numerical solution was obtained using the SIMPLE method with a second-order upwind discretisation scheme. The iteration process reached a convergence with residuals $<10^{-6}$ for continuity, x, y and z velocity, kinetic energy and turbulence energy dissipation; and with residuals $<10^{-10}$ for water vapour, discrete ordinates and energy. The CFD model accuracy was computed through the RMSE which had 1.2°C and 0.6 g [H_2O] kg $^{-1}$[dry air] for internal temperature and absolute humidity. The maximum, minimum and standard deviation for experimental and simulated data are shown in Figure 4. During the analysis period, outside temperature and absolute humidity were 15.5±1.2°C and 8.2±0.21 g [H_2O] kg^{-1}[dry air], respectively. Based on 90 values inside the building, experimental data showed 20.2±1.4°C and 9.5±0.4 g [H_2O] kg^{-1}[dry air] for temperature and absolute humidity, respectively; whereas the CFD model

predicted 20.1±1.2°C and 9.4±0.5 g [H_2O] kg^{-1}[dry air] for temperature and absolute humidity, respectively

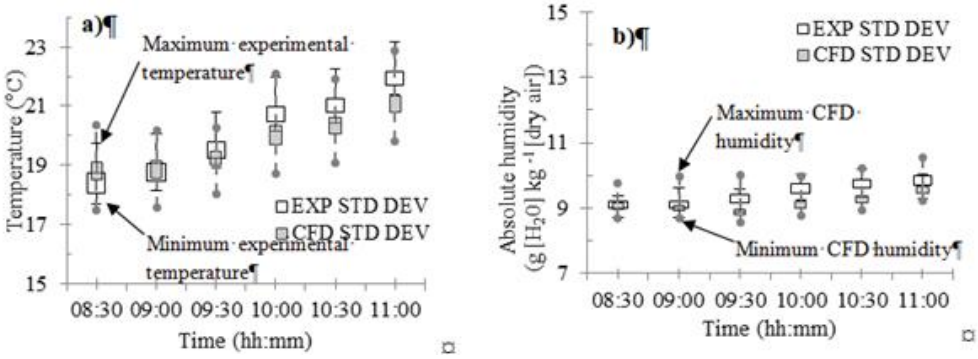


Figure 4: Internal temperature (a) and absolute humidity (b) dynamics.

Estimation of the ventilation rates and heat losses

Air changes per hour (ACPH) for livestock buildings are computed by means of three quantities: area of vents (Av), average wind velocity (V), and volume of the building (Vol) using the equation $\mathrm{ACPH_b} = \frac{3600\ \mathrm{Av*V}}{\mathrm{Vol}}$. It is assumed in $\mathrm{ACPH_b}$ that air entering the building will remove the internal air, neglecting the short-circuit air paths between vents as inlets and outlets, and air mixing. Rojano *et al.* (2016) investigated the impact of short-circuit air paths and air mixing by means of air residence time. The procedure consisted of injecting a virtual tracer gas into the numerical solutions following the method presented in Kwon *et al.* (2011) to estimate ACPH. Figure 5a compares ACPH and $\mathrm{ACPH_b}$, indicating that short-circuit air paths and air mixing caused an $\mathrm{ACPH_b}$ overestimation of approximately 60%, based on this study. The ACPH and the average values for internal temperature and absolute humidity were used to calculate sensible and latent heat losses by convection using equations cited in Rojano *et al.* (2016). Figure 5b shows sensible and latent heat losses and their corresponding standard deviations obtained from 15 sensor locations. This study found that sensible heat loss was predominant, since it represented 68% and 79.5% in the experimental and simulated data, respectively. Conductive and radiative heat transfer were not analysed due to difficulties in verifying them experimentally.

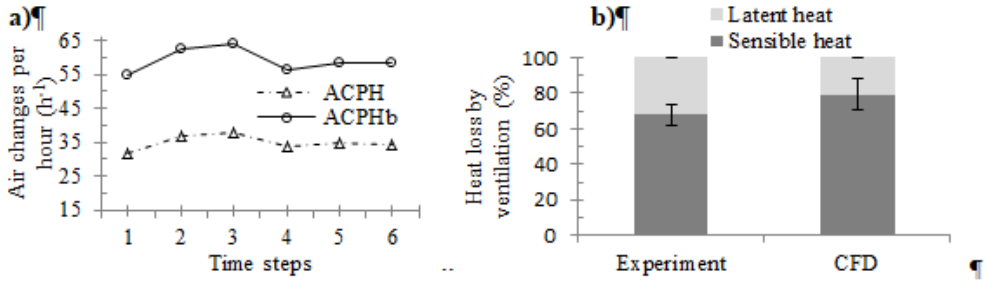


Figure 5: CFD estimations of a) ventilation rates and b) heat loss by ventilation.

Gas discharge analysis

The period under analysis had a wind vane direction of 57° (relatively to the North), and the building had an orientation of 21°; air therefore blew at an angle of 36° (to the building). This condition was maintained during the simulation period. The CFD predictions corresponding to the third time step were retrieved in order to analyse the discharge of water vapour from the building; and how it spreads downstream from the building. The wind direction with an angle of 36° distorted the discharge from vent outlets, differing from the typical spread as a plume which follows a normal distribution shown in previous studies (Venkatram *et al.*, 2004; Rojano *et al.*, 2015a). The corresponding expected plume development is shown in Figure 6.

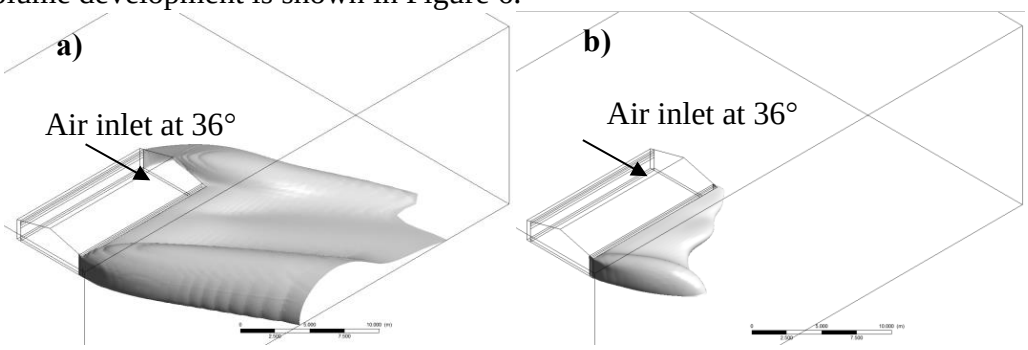


Figure 6: Plume contour represented by a threshold of a) 1% and b) 10% of the relative increment of water vapour RIWV=$100 * \left(\frac{h_o - h_{o,\ in}}{h_{o,\ out} - h_{o,\ in}}\right)$; where h_o is outside absolute humidity; $h_{o,\ in}$ and $h_{o,\ out}$ are the absolute humidity at the vent inlet and outlet, respectively.

Conclusions

Modelling internal climate dynamics of a naturally ventilated poultry house using a 3D CFD model found a RMSE of 1.2 °C and 0.6 g [H_2O] kg^{-1} [dry air]

and 0.9 g [H_2O] kg^{-1} [dry air] for internal temperature and absolute humidity, respectively. The ability to reproduce internal climate was considered adequate for relying on predictions from the same CFD model to estimate ventilation rates by means of the ACPH. Together, the ACPH and water vapour discharge could be used to compute sensible and latent heat losses by natural ventilation. Analysis of the discharge of water vapour by means of absolute humidity helped to define an expected area downstream of the building, which can be studied as a plume. The particular specifications of the water vapour discharge from a naturally ventilated poultry house in the downstream area of the building and the external wind velocity and direction were adequately represented in the CFD model to characterise the plume rise when air blew with a wind vane direction of 57° (North-East).

References

ANSYS. (2015). *Ansys User's Guide*. (2015). Canonsburg, Pa.: ANSYS, Inc.

Bjerg, B., Norton, T., Banhazi, T., Zhang, G., Bartzanas, T., Liberati, P., … Marucci, A. (2013). Modelling of ammonia emissions from naturally ventilated livestock buildings. Part 1: Ammonia release modelling. *Biosystems Eng*, *116*(3), 232–245.

Bournet, P., & Boulard, T. (2010). Effect of ventilator configuration on the distributed climate of greenhouses: A review of experimental and CFD studies. *Computers and Electronics in Agriculture*.

Bournet, P. E., Ould Khaoua, S. A., & Boulard, T. (2007). Numerical prediction of the effect of vent arrangements on the ventilation and energy transfer in a multi-span glasshouse using a bi-band radiation model. *Biosystems Engineering*, *98*(2), 224–234.

CIGR. (2002). *Climatization of animal houses* (4th Report). (S. Pedersen & K. Sallvik, Eds.). International Commission of Agricultural Engineering.

Kwon, K.-S., Lee, I.-B., Han, H.-T., Shin, C.-Y., Hwang, H.-S., Hong, S.-W., … Han, C.-P. (2011). Analysing ventilation efficiency in a test chamber using age-of-air concept and CFD technology. *Biosystems Engineering*, *110*(4), 421–433.

Lee, I., Sase, S., & Sung, S. (2007). Evaluation of CFD Accuracy for the Ventilation Study of a Naturally Ventilated Broiler House. *JARQ*, *41*(1), 53–64.

Mohammadi, B., & Pironneau, O. (1994). *Analysis of the k-epsilon turbulence model*. Paris: Wiley.

Norton, T., Grant, J., Fallon, R., & Sun, D.-W. (2010). Optimising the ventilation configuration of naturally ventilated livestock buildings for improved indoor environmental homogeneity. *Building and Environment*, *45*(4), 983–995.

Richards, P. J., & Hoxey, R. P. (1993). Appropriate boundary conditions for computational wind engineering models using the k-E turbulence model. *J of Wind Eng and Industrial Aerodynamics*, *47*, 145–153.

Rojano, F., Bournet, P. E., Hassouna, M., Robin, P., Kacira, M., & Choi, C. Y. (2015a). Investigation of gas emissions and spreading inside and outside of a naturally ventilated poultry house using a 3D CFD model. In *12 th International Conference on Construction, Technology and Environment in Farm Animal Husbandry, Sept. 8-10*.

Rojano, F., Bournet, P. E., Hassouna, M., Robin, P., Kacira, M., & Choi, C. Y. (2016). Computational modelling of thermal and humidity gradients for a naturally ventilated poultry house. *Biosystems Engineering*, *151*, 273–285.

Rojano, F., Bournet, P.-E., Hassouna, M., Robin, P., Kacira, M., & Choi, C. Y. (2015b). Modelling heat and mass transfer of a broiler house using computational fluid dynamics. *Biosystems Engineering*, *136*, 25–38.

Rojano, F., Bournet, P.-E., Robin, P., Hassouna, M., Choi, C. Y., & Murat, K. (2014). Test of two different schemes through CFD to include heat and mass transfer induced by animals inside a broiler. In *International Conference of Agricultural Engineering, Zurich, Switzertland July 6-10*.

Schulman, L. L., Strimaitis, D. G., & Scire, J. S. (2000). Development and Evaluation of the PRIME Plume Rise and Building Downwash Model. *Journal of the Air & Waste Management Association*, *50*(3), 378–390.

Venkatram, A., Isakov, V., Yuan, J., & Pankratz, D. (2004). Modeling dispersion at distances of meters from urban sources. *Atmospheric Environment*, *38*(28), 4633–4641.

Session 9

PLF and economics

An ex ante analysis of the economic profitability of automatic oestrus detection devices in different dairy farming systems in France

M. A. Bekara[1], N. Bareille[1], F. Bidan[2], C. Allain[3], C. Disenhaus[4].
[1]*BIOEPAR, INRA, Oniris, La chantrerie, 44307, Nantes, France*
[2] *Institut de l'Elevage, La chantrerie, 44307, Nantes, France*
[3]*Institut de l'élevage, Monvoisin, 35650, Le Rheu, France*
[4]*PEGASE, INRA, Agrocampus Ouest,* 65 *rue de Saint-Brieuc, 35042, Rennes, France*
nathalie.bareille@oniris-nantes.fr

Abstract

The reproductive performance of dairy herds is mainly influenced by the physiological reproductive status of the cows and by herd management. The objective of this work was to evaluate the economic benefits of investment in a sensor system for oestrus detection (pedometer or activity meter) in different dairy farming systems in France.
A stochastic dynamic model was used to simulate all the physiological and management processes occurring in a dairy operation. Seven French dairy farms with different breeds (Holstein, Montbéliarde and Normande), size (30 to 119 cows), milk price (conventional or protected designation of origin) and calving strategies (grouped or continuous calving) were simulated. Six scenarios with different oestrus detection rates (50% before and 90% after use of the equipment) and percentage of cows equipped (40%-80%-100%) were applied to each farm. The internal rate of return was used to evaluate the economic benefits of the investment. It was estimated that the system for transmitting and analysing data from pedometer and activity meter systems would cost €6,498 and €4,430 respectively.
The use of an automatic oestrus detection device reduced the calving interval by between 7d (herds with Normande cows) and 23d (herds with Holstein cows) and increased the annual gross margin per cow by between €8 (small herd with Normande cows) and €92 (herd with Montbéliarde cows). The investment appeared profitable in two-thirds of the situations, characterised by high milk prices, large herd size or low percentage of cows equipped.
These results suggest that the return on investment should be estimated at each farm level.

Keywords: dairy farming systems, reproductive performance, economic profitability, automated oestrus detection, model.

Introduction

The negative impact of poor reproductive performance on the economic profitability of dairy farms has been demonstrated in several studies carried out on simulated data using mathematical models (Cabrera, 2014; Inchaisri et al, 2010). Factors influencing the reproductive performance of dairy herds are related, on the one hand, to the intrinsic characteristics of cows (genetic value, age, reproductive function, disorders and health problems) and, on the other hand, to herd management practices (production and feeding strategy, heat detection and culling strategy) (Hudson et al, 2012; Lucy, 2001). Better heat detection by the farmer has a significant impact on reproductive performance; it has been proven in many studies that increasing the sensitivity (Se) of heat detection improves the techno-economic performance of dairy cattle farms (Inchaisri et al, 2010). However, improving the Se of heat detection by the farmer without increasing the labour time requires an investment in equipment such as an automatic oestrus detection device.

Rutten et al, 2014 showed that investment in activity meters is economically profitable, depending on the culling rate and the initial Se of visual heat detection by the farmer. However, in their study, the impact of dairy farming systems was not taken into account. In France, there is great heterogeneity between the different dairy farming systems in terms of reproduction management (grouped or continuous calving), culling strategy, cattle breeds and milk yield. To take all these elements into account, the objective of this work was to evaluate the economic benefits of investment in a sensor system for oestrus detection (pedometer or activity meter) in different dairy farming systems in France.

Materials and methods

Model simulation

A dynamic individual-based stochastic model, operating in discrete time, was developed to simulate the life of a cow, from its entry into the herd (birth or purchase) until its exit (culling or death). The time step used is the day. The model was created using Access software (Microsoft Corporation, Redmond, WA, USA). All discrete events at the animal level (such as ovulation, heat detection, conception, foetal sex, health and reproductive disorders) are generated stochastically by random draw from the appropriate probability distribution.

The model simulates the biological processes (genetic value, reproductive cycle, lactation function and health problems), the herd management practices (feeding,

renewal, sale, culling, purchase and reproduction management) and the interaction between the biological processes and the herd management practices.

Simulated herds

Seven dairy herds corresponding to 7 different dairy farming systems in France were simulated with the model (Table 1). These herds differ in terms of dairy breed (Holstein, Normande and Montbéliarde), herd size (from 30 to 119 cows), average milk yield per cow per year (from 5200 l to 8450 l), location (plains vs. mountains), and type of milk produced (conventional vs. PDO). Thus, these herds have different breeding practices (compact: grouped calving over 5 months vs. continuous: calving over the whole year). The data for these 7 herds were obtained from the INOSYS breeding networks of the Institut de l'Elevage France.

Table 1: The main characteristics of the seven simulated farms

Farm identification	Breed type	Herd size	Milk yield (l)/cow/year	Calving management	Milk price
1	Holstein	50	5,755	Grouped	Conventional
2	Normande	56	6,350	Grouped	PDO*
3	Normande	68	6,322	Grouped	PDO*
4	Holstein	119	8,450	Continuous	Conventional
5	Montbéliarde	30	5,200	Continuous	Conventional
6	Montbéliarde	77	7,003	Continuous	Conventional
7	Holstein	38	7,021	Continuous	Conventional

* *PDO: Protected Designation of Origin*

Simulated scenarios

For each farm, six scenarios were simulated. These scenarios were obtained by combining:

- Two values of Se for heat detection: 50% (sensitivity of heat detection before use of automatic oestrus detection devices) and 90% (sensitivity of detection of heat with automatic oestrus detection devices). The specificity was kept at 95%.
- Three equipment rates (cows with collars): 40%, 80% and 100%. The 40% rate was not used in herds with grouped calving.

For each simulated scenario, 10 years were fitted, with 250 repetitions. Data from the first 5 years of simulation were not used in our study because they were used to calibrate the simulations. Consequently, the average of simulation results over the last 5 years was used to calculate the return on investment in a sensor system for oestrus detection.
The economic data (selling prices for milk and animals and purchase prices for concentrates) used to simulate each herd were obtained from the 2014 French economic context.

Estimation of economic profitability of a sensor system for oestrus detection
The difference in the annual gross margin (ΔAGM) before and after the use of a sensor system for oestrus detection was used to estimate the economic profitability of such an investment. Two types of automated heat detector were tested (activity meter and pedometer) with lifetime and investment costs specific to each type (Table 2). The annual maintenance and replacement costs for broken sensors were disregarded because of a guarantee. Two indicators of economic profitability were calculated: the net present value (NPV) and the internal rate of return (IRR).
The NPV is the difference between the sum of the ΔAGM updated during the detector lifetime and the initial investment cost (IIC):

$$NPV = \sum_{n=1}^{n=p} \frac{\Delta GM}{(1+DR)^n} - IIC \quad (1)$$

where n is the technical lifetime of automatic heat detectors, and DR is the discount rate. The value used in our study (2.1%) was set according to data from the Organization for Economic Co-operation and Development (OECD).
An investment is considered profitable if the NPV is greater than zero. The second indicator (IRR) corresponds to the discount rate value that nullifies the NPV. If the IRR is higher than the chosen DR (2.1%), this means that the investment is profitable.
Table 2: Economic input of two simulated sensor system for oestrus detection (activity meter and pedometer) obtained from technology providers in France

	Pedometer	Activity meter
Technical lifetime (years)	10	5
Cost of sensor system		
Data transmission system and software	6,498	4,430
Collar (€/cow)	107	120

Results and discussion

Table 3 shows that the use of an automatic oestrus detection device decreases the calving interval by between 7d (herds with Normande cows) and 23d (herds with Holstein cows). These results are in agreement with the reproductive performances observed in the study by Delaby et al, 2013, which was carried out on an experimental farm in France: the success rates for first AI and cumulative AIs were higher in the Normande then in Holstein cows.
The increase in the Se of heat detection due to the use of an automated heat detection system had a significant effect on calving interval in herds with continuous calving (reduction of between 10 and 23 days) compared to herds with grouped (reduction of between 6 and 11 days) (Table 3). This result is explained by the higher culling rate of cows with reproductive disorders or infertility in herds with grouped calving than in herds with continuous calving. Consequently, the improvement in the sensitivity of heat detection has a greater impact on herds with spread calving. This phenomenon is called selective survival bias.

Table 3: Variation in calving interval and in annual gross margin per cow between situation with (Se = 90%) and without (Se = 50%) use of an automatic oestrus detection device

Farm identification	Variation in calving interval (days)	Variation in annual gross margin (€/cow)
1	- 12	+ 49.5
2	- 6	+ 8.5
3	- 6	+ 38.4
4	- 23	+ 24.6
5	- 10	+ 92.5
6	- 16	+ 36.6
7	- 14	+ 31.7

In our study, the improvement in the sensitivity of heat detection achieved through use of an automated oestrus detection device had a great effect on the calving interval (reduction of between 14 and 23 days) for farms with high yields (> 7,000 l / cow / year) (Table 3, farms 4, 6&7). In fact, in several studies an increase in milk yield is associated with a decrease in the reproductive performance of dairy cows (Walsh et al, 2010). In addition, according to Plaizier et al, 1998, the impact of improved heat detection is greater when the initial herd reproductive performance is poor. Consequently, these two elements explain the important effect of an automated oestrus detection device on the calving interval in farms with high milk yields.

For the economic profitability of an investment in automatic oestrus detection device, Table 4 shows the value of IRR by type of equipment, equipment rates (cows with collars) and farms.

Table 4: Values of internal rate of return (IRR) according to type of automated oestrus detection device, equipment rate and dairy farming system

Herd identification	Pedometer			Activity meter		
	Equipment rate (%)			Equipment rate (%)		
	40%	80%	100%	40%	80%	100%
1	Not estimated	16.9%	14,3	Not estimated	3.9%	1.4%
15	Not estimated	*0.2%**	*0.1%**	Not estimated	*NF***	*NF***
27	Not estimated	16.6%	13.6%	Not estimated	6.1%	*1.1%**
35	13.1%	11.9%	8.5%	13.9%	*0.1%**	*NF***
41	26.8%	25.6%	23.4%	33.8%	22.7%	18.4%
42	18.4%	16.7%	13.5%	21%	5.6%	*0.05%**
46	2.7%	*1.5%**	*0.8%**	*0.04%**	*NF***	*NF***

** Investment not profitable*

***NF:* internal rate of return not found (*Investment not profitable)*

The investment appeared profitable in two-thirds of the situations, which were characterised by high milk prices, large herd size or low percentage of cows equipped. The effect of herd size corresponds to a reduction in the purchase price of a data transmission system and software, which is fixed whatever the size of herd. Similarly, the lower the equipment rate, the lower the investment cost. However, our study did not simulate the interaction between the equipment rate and the sensitivity of the automatic oestrus detection device. For the milk price effect, the main source of income for dairy farms is the sale of milk. The improvement in the sensitivity of heat detection increases the quantity of milk produced per cow (Rutten et al, 2014). Therefore, in farms where the price of milk is high (protected designation of origin), the benefits of improving the sensitivity of heat detection are more likely to cover the cost of investment. Additionally, greater benefits could be obtained if the farmer saves labour time while using the automatic oestrus detection device. Indeed, we chose not to include labour time in the estimation of the economic profitability because a previous study showed that only half of farmers considered that they saved on labour time (Allain et al, 2016).

Conclusions

The results of our study suggest that the return on investment should be estimated at each farm level, to take account of the variability in dairy farming systems.

Acknowledgements

We thank the “INOSYS” breeding networks of the Institut de l’Elevage for the quality of the data that has been made available to us. Similarly, we thank the members of the MARIAGE project for their participation in this work.

References

Allain C., Chanvallon A., Courties R., Billon D., Bareille N. 2016. Technical, economic and sociological impacts of an automated estrus detection system for dairy cows. In, *Conference on Precision Dairy Farming*, Leeuwarden, The Netherlands, 2016/06/21-23, 451-456.

Cabrera, V.E. 2014. Economics of fertility in high-yielding dairy cows on confined TMR systems. *Animal*. 8 Suppl 1:211–21. doi:10.1017/S1751731114000512.

Delaby, L., Faverdin, P., Michel, M., Disenhaus, C., and J. L. Peyraud,. 2013. Effect of different feeding strategies on lactation performance of Holstein and Normande dairy cows. *Animal*. 3: 891-905. doi: 10.1017/S1751731109004212.

Hudson, C.D., A.J. Bradley, J.E. Breen, and M.J. Green. 2012. Associations between udder health and reproductive performance in United Kingdom dairy cows. *Journal of Dairy Science.* 95:3683–97. doi:10.3168/jds.2011-4629.

Lucy, M.C. 2001. Reproductive Loss in High-Producing Dairy Cattle: Where Will It End?. *Journal of Dairy Science.* 84:1277–1293. doi:10.3168/jds.S0022-0302(01)70158-0.

Plaizier, J.C.B., G.J. King, J.C.M. Dekkers, and K. Lissemore. 1998. Modeling the relationship between reproductive performance and net-revenue in dairy herds. *Agriculurtal Systems.* 56:305–322. doi:10.1016/S0308-521X(97)00044-9.

Rutten, C.J., W. Steeneveld, C. Inchaisri, and H. Hogeveen. 2014. An ex ante analysis on the use of activity meters for automated estrus detection: to invest or not to invest? .*Journal of Dairy Science.* 97:6869–87. doi:10.3168/jds.2014-7948.

Walsh, S.W., Williams, E. J., and A. C. O. Evans. 2011. A review of the causes of poor fertility in high milk producing dairy cows. *Animal Reproduction Science*. 123: 127-138. doi: 10.1016/j.anireprosci.2010.12.001

Connecting the business model's value proposition to farmer adoption of precision farming apps

C. van der Weerdt[1], G. Paradies[2] & M. Vonder[3]
1. Department of Human Behaviour and Organisational Innovation, Earth. Life and Social Sciences, TNO, Eemsgolaan 3, 9727 DW Groningen, the Netherlands
2. Department of Human Behaviour and Organisational Innovation, Earth. Life and Social Sciences, TNO, Kampweg 5, 3769 DE Soesterberg, the Netherlands
3. Department of Monitoring & Control Services, Technical Sciences, TNO, Eemsgolaan 3, 9727 DW Groningen, the Netherlands
caroline.vanderweerdt@tno.nl

Abstract

Broader than just the financial picture of the business case, the business model defines how a product or service becomes of value for a customer; what is on offer, for whom specifically, how is it distributed, with what partners, components and resources. Moreover, innovations of a profoundly impactful nature on someone's daily work processes, such as precision dairy farming, are never adopted solely on financial grounds. For a farmer, new technologies should also adhere to beliefs and perceptions of, for instance, usefulness, reliability, attractiveness, or effect on wellbeing. These factors –together with many others- constitute the so-called 'user experience'.

This is a matter of design, and is closely connected to the most important component of the business model: the value proposition. For creators of precision farming applications, for instance, it is crucial to design in such a way that farmer adoption is most likely, because it is being valued by them. In a current project on precision dairy farming (PDF), research on user experience and the optimal value proposition for PDF applications, has resulted in two guiding tools for PDF application developers: storyboards and user experience design principles. The storyboards show how an app becomes of value in the daily life of different types of farmers, whereas the design principles are a basis for the IT development of an app. In designing applications for dairy farming practices these tools are proposed to be used as a basis.

Keywords: value proposition, user experience, storyboards, design, precision dairy farming

Introduction

Digital innovations in agriculture have the potential to fundamentally change the position of farmers in the value chain, as it can empower them with information

for improved decision-making. In turn, this can for instance make them less reliant on information from others and connect more closely with consumers. Precision dairy farming (PDF) services are a means to support this empowerment of the dairy farmer, for instance through applications (apps) that turn collected data from different sources such as milking robots and weight scales into useful insights and advice. For these PDF apps to find their way onto the farm and become part of daily practice, they should be adopted in practice by the ones who are intended to use them; the farmer, or farmer advisor, feed supplier, and so on (our research focuses on the farmer). In spite of the merits a PDF app may have, this adoption is not a given (EIP-AGRI, 2015).

Adoption success or failure is often accredited to the business model of such an app which describes how a product or service becomes of value for a customer; what is on offer, for whom specifically, how is it being distributed to the customers, are there partners involved to make or deliver it, and what components and resources are needed to realise it. Even more often, adoption potential is directly linked to the business case of an app, which describes the monetary cost and revenue streams. This reasoning however discredits the influence the dynamics of daily life on the farm have for adoption of PDF apps. For instance, a research on the economics of investing in automated versus conventional milking systems, turned out that automated milking was less profitable and the return on investment considerably lower for automated milking compared to conventional milking. In spite of this, automated milking is often being preferred by farmers over conventional systems. The researchers state: “for many farmers considering investing in an AM [automated milking] system, the economic consideration is not the central motive”. The research further states that motives such as improved flexibility and more time for a social life are considered to be important drivers next to the economic drivers (O’Brien et al, 2015). A myriad of influencers are thus at play when adopting a technological innovation and apps on the dairy farm. The influencers can be direct inhibitors of usage, such as lack of proper wifi in the stable. Other factors of a more psychological nature yet just as influential, are for instance beliefs about the effectiveness of an app itself, the above-mentioned social factors, and readiness of the farmer to change in general.

Value is thus about the worth of a service or product and why it is deemed important to use in practice. In the business model, this is described by means of the value proposition, which is the focal and central part of the model. The value proposition describes the benefits, but also the costs to materialise those benefits. These costs are not necessarily monetary, but can also be effort needed to adjust to working with the app, and risks such as losing control over working processes (Thomson, 2013). In order to design PDF apps that are actually of value, it should thus be clear from the start how the value and the app come together for the

farmer. Hence, designing a PDF app can thus very much profit from involving farmers in an early stage. Early involvement of farmers is an approach that was also explicitly addressed in focus groups with farmers on the topic of precision farming, with the recommendation to "profoundly involve farmers and cooperatives in innovation and research on decision support systems and technical solutions to current problems" (EIP-AGRI, 2015). In a Dutch project on precision dairy farming, value was the guiding principle underlying the approach to design new, value-creating PDF-related apps that have the potential to be successful and broadly adopted in practice. This approach and relevant findings from the accompanying process are explained here in further depth.

Material and Methods

Value is rather abstract, especially when one is ought make value explicit of an app that does not yet exist let alone can be worked with in practice. A means to therefore ensure the incorporation of value when designing a PDF app together with farmers is the "User Experience (UX) Framework" (Kort in Bulterman, 2012). The UX framework guides the process of finding out what are important design features for an app and has a strong focus on value. The UX framework is composed of three dimensions: (1) the dimension of meaning (2) the dimension of interactics; and (3) the dimension of aesthetics. Firstly, the UX dimension of meaning addresses users' motivations such as financial security, level of ambition and the aforementioned perceived ability and willingness to change for instance how the farm is currently being run (Hassenzahl et al, 2010; Kort in Bulterman, 2012). The dimension of interactics is about getting the job done in an effective and satisfying way. These factors can come forth from analysing a daily routine in light of the new app, such as: when will it be used? And how? The third dimension, aesthetics, addresses the physical design of products and interfaces such as form, size, and the use of sound and visuals (Kort in Bulterman, 2012).

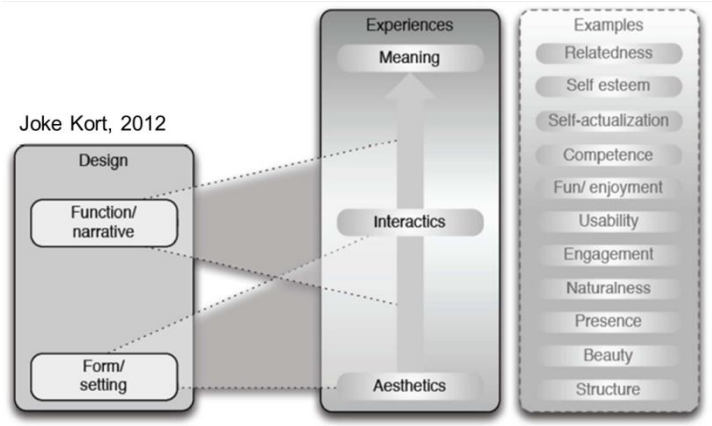


Figure 1: The User eXperience framework

In the Dutch PDF project, the UX framework was used to get insight into the most important factors on these three dimensions. These insights were retrieved from contextual inquiries (day-long interviews and observations on the farm), workshops with farmers and their advisors and desk research (Van der Weerdt & Vonder, 2013). Consequently, all the insights were comprehensibly conveyed in so-called storyboards that in turn served as the basis for app design principles for the designers and (ICT) engineers.

Storyboards and design principles: methodology

Inspired by the process of movie making, storyboards are simplified (often sketchy) representations of how users will interact with services or products; for a new app, they depict complete journeys, from how a user first hears about the app, contemplates to use it, to signing a contract. They can also depict how the user learns to use the app, is faced with problems or insecurities and eventually adopts it (or not) in daily practice. Storyboards have two main advantages: firstly, they can be easily discussed and evaluated with potential users to gather feedback on ideas and what they would find important. Secondly, they are a great way to communicate requirements to support the (ICT) engineering process because experiential journeys provide much more detail than an abstract list of requirements (Van der Weerdt, 2016).

Whereas the storyboards convey how a PDF app actually becomes of value on a farm, design requirements in turn translate these value creating (and thus adoption influencing) elements into concrete design requirements for app development. This is done by attaching functional requirements to the depictions in the storyboards. Functional requirements are descriptions of a system or elements of a system, that are used by (software) engineers to design and make the system.

Results and Discussion

Storyboards

In the Dutch PDF project, 6 different storyboards were developed. A main reason to make different storyboards is because users, in this case farmers, cannot be all regarded as one homogenous group. The different stories (all deducted from the contextual inquiries, workshops and desk research mentioned earlier) indicate that some farmers are more keen to adopt new technology on the farm, and some still are rather unsure about whether to embrace these new PDF possibilities. In the consequent design of PDF apps, designers can choose to focus on one type of farmer, or address different types of farmers e.g. by differing in range, form and complexity of features.

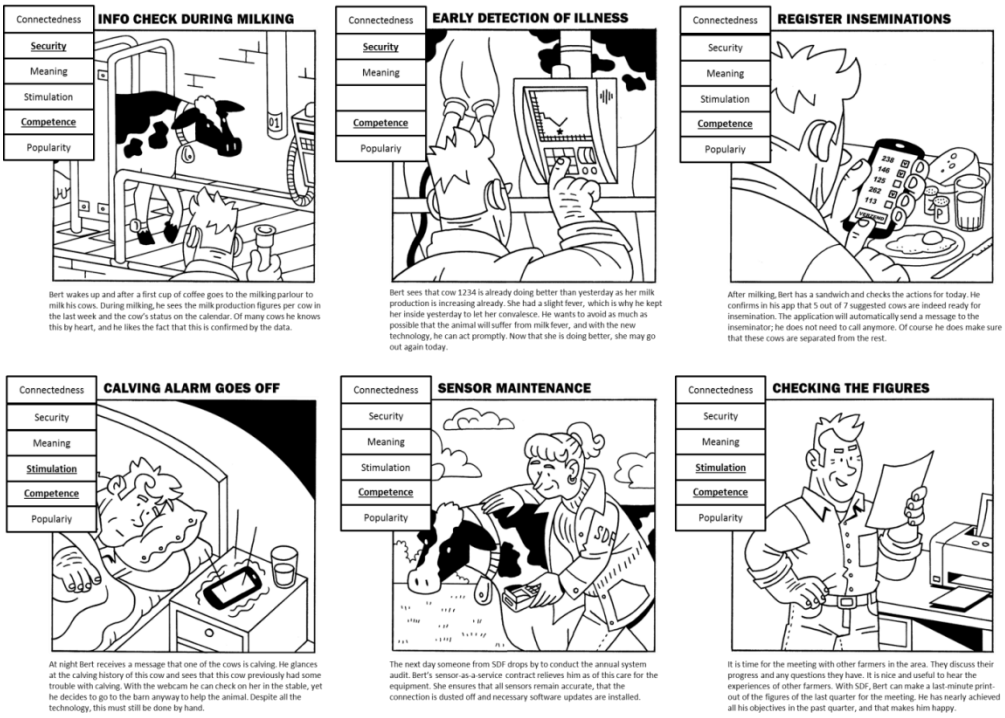


Figure 2: Example of a storyboard for the design of a PDF app

Design requirements and principles

The design requirements are the translation of certain situations and depictions in the storyboards to functional elements of the PDF app. An example is, that one story shows -on the first UX framework dimension of meaning- how a farmer is afraid his competences are not acknowledged when a PDF app can reduce dairy farming to activities to mere looking at graphs and management summaries. This is for some farmers a barrier to adopt PDF apps. On the basis of this insight, a functional requirement on “task responsibility” was defined, which ensures that the experienced responsibility can remain with the farmer. More specifically, this requirement states that after an app signals for instance that a cow is behaving differently than normal, the farmer is first asked to take action, rather than the system immediately stating actions or even automating them. Suggestions for proper actions are in this case only given when a farmer asks for them. A smart PDF app can log whenever a farmer asks for these suggestions and takes action accordingly, which causes the system to learn when a farmer feels more comfortable with a PDF app being in the lead and when not. Another requirement coming forth from the dimension of meaning, is to address feelings of insecurity regarding the analyses an app makes. A few so-called “false positives” (e.g. from heat detection sensors) can lead to a skeptical sentiment in

farmers, which can be overcome by simply mentioning what the chances of false positives are in an analysis and due to what possible sources of error. In this way, an app becomes a supporter and "partner" of the farmer rather than a mistrusted instrument with the potential to undermine his position.

Another example, this time on the second UX framework dimension of interactics, has to do with the degree of "disturbance" that a PDF app can cause. The functional design requirement here, is that a farmer can control the setting of how frequently a certain signal is given by the app. If such a design element is overlooked, it may easily cause for a farmer to turn all signaling off which will surely lead to the underperformance of an app. Lastly, an example on the dimension of aesthetics, the app developers should ensure that the relevant information is shown in one glance on a small (smartphone sized) display without the need to scroll.

As a result of the Dutch project, the findings from the initial research have been generalised and summed up in a table of design principles (Figure 3), that can serve as a basis for (ICT) engineers, but also others responsible for app development such as graphic designers, data scientists and product owners. This table depicts the design requirements that come forth from the three UX framework dimensions and are divided into the more functionality-driven requirements (decision-support) and more visual/interface-driven requirements (now called dashboard). The figure below (Figure 3) and its items are exemplary though; these should be fine-tuned to specific apps.

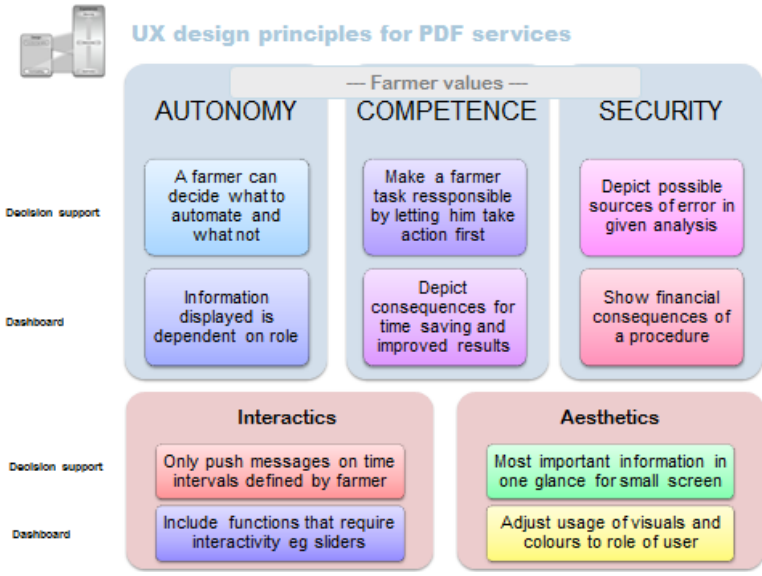


Figure 3: Example of a UX-based design principles framework for app design

Discussion

With increasing rapidity, technological innovations in precision farming are finding their way onto the farm through apps. An accompanying trend is to launch new apps as so-called “minimal viable products” (MVPs): a basic version onto which improvements and functionality are added based on what real users experience. A more traditional method which is also still largely being applied however, is launching an app after it has been tested and perfected before launch. Either way, we find that following the lines of the UX framework to co-design with farmers, helps in all stages to realise an app that adds value, whether it is being introduced to users in early stages of development or not. Furthermore, we found that communicating about value is much easier through storyboards describing the desired interactions needed to create that value, rather than listing the requirements as an abstract set of so called “must-haves” and “nice-to-haves”. A final exercise of turning these value creating interactions into guiding design principles, results into that those actually responsible for making the app, know more concretely what to implement or fine-tune and to justify design decisions. This can also be perceived as a form of risk management, as it helps to reduce the likelihood of a failed launch of a PDF app.

Conclusions

The approach of looking at PDF app development from a holistic perspective of the user, the business model and the technology, as has been done in the Dutch PDF project at hand, is a promising way to safeguard that actual value is being added to daily practice on the farm. In fact, putting farmer values central in the design process can result into essential requirements to precision farming apps, such as acknowledging the farmer’s feeling of competence and responsibility through adjustments in the flow of the app. The described approach can thus support the uptake and adoption of apps by those intended to use them.

This research has until now focused on the applicability of the methods and tools described to the design of PDF apps. It deserves further attention though to research whether our suggested approach indeed causes a (significant) increase in update of PDF apps in practice.

Acknowledgements

This research was supported and financed by the Dutch Top Sector High Tech Systems and Materials. The researchers would also like to thank the farmers that have participated in the research and Accon AVM (Arnhem, the Netherlands) for their review of the storyboards.

References

Hassenzahl, M., Diefenbach, S. & Göritz, A. (2010). Needs, affect, and interactive products – Facets of user experience. Journal of Interacting with Computers 22: pp 353–362

Kort J. in Bulterman, D. (editor) (2012). Together Anywhere, Together Anytime – Technologies for Intimate Interactions. ISBN: 978-90-6196-5619

O'Brien, B., Foley, C., Shortall, J. & Shalloo L. (2015). An economic appraisal of automatic and conventional milking within a grass based seasonal milk production system. In Guarino, M. Berckmans, D., 7th European Conference on Precision Livestock Farming, EC-PLF 2015, 15-18 September 2015: pp 21-29. European Conference on Precision Livestock Farming

The European Innovation Partnership 'Agricultural Productivity and Sustainability' (EIP-AGRI). Focus Group Precision Farming – Final Report. (2015)

Thomson, P. Digital Brand Strategy. (2013). Value Proposition Canvas (Retrieved from: https://www.peterjthomson.com/2013/11/value-proposition-canvas/ on 22st March 2017)

Van der Weerdt, C., Kort, J., de Boer, J. & Paradies, G. (2016). Smart Dairy Farming in practice: design requirements for user-friendly data based services. In Kamphuis, C. & Steeneveld, W., Precision Dairy Farming 2016. 21-23 June 2016. Leeuwarden, the Netherlands. First International Conference on Precision Dairy Farming

Van der Weerdt, C. & M. Vonder. (2013). Smart Dairy Farming Aanpak Requirements-analyse (Eisen en Wensen) (Translated: Plan of Work Requirements Analysis: (must-haves and nice-to-haves)). TNO 2013 R10857, Groningen, The Netherlands

A distributed data-driven business model for Precision Livestock Farming

H. Mahdavi[1], H. Lehr[1]
[1]*Syntesa Partners & Associates, Barcelona, Spain*
hadis@syntesa.eu

Abstract

Precision Livestock Farming (PLF) is an emerging field that develops management tools for real-time and continuous monitoring of animal production, growth, animal health and welfare. To mainstream PLF, a viable business model needs to be defined in which stakeholders along the supply chain experience added value. A distributed business model for PLF has been developed in the *Bright Farm by Precision Livestock Farming* (EU-PLF) project. This paper studies the feasibility of this model for broilers and fattening pigs. In the proposed model, the PLF hardware and software is provided by service providers in charge of installation and maintenance, consultancy and reporting. Stakeholders along the supply chain subscribe to "PLF as a service" to get access to data and derived analysis. To confirm the sustainability of a PLF service within a supply chain, a feasibility implementation was tested by estimating the 'Willingness To Pay/Accept' (WTP/WTA). Choice experiments were used to evaluate the stakeholder's WTP/WTA. Analysis results demonstrated that the WTP/WTA of farmers for PLF as a service is generally low. This is most likely due to a lack of success cases and role models for PLF implementations. The remainder of the supply chain, in particular, feed companies and integrators, acknowledge the value of farm data. The current WTP/WTA restricts the possibility of a full-scale implementation in small group pig farms due to the ROI exceeding the useful lifespan of the technology. On the other hand, a full PLF implementation in a poultry chain as a service is considered to be feasible.

Keywords: Precision livestock farming, smart farm, distributed business model, data-driven

Introduction

Precision Livestock Farming (PLF) is an emerging field that develops management tools for real-time and continuous monitoring of animal production, growth, animal health and welfare. PLF aims to assist farmers in making better daily management decisions by detecting animal needs as early as possible with the help of real-time monitoring sensors. The expectation is that once the animals' needs are identified then satisfied, that the improved well-being of the animals will drive socio-economic advantage for farmers.

Mainstream PLF should be based on a viable business model in which stakeholders along the whole supply chain benefit from the added value, be that tangible, semi-tangible and/or intangible. Generic business models do exist, however, as with any other specialised business operation, PLF requires a unique business model that considers the specific resources that it controls and the capabilities that it possesses. There are various generic forms of business model but eventually, as any other business, PLF calls for its unique business model considering the resources it controls and the capabilities that it possesses.

Standard (traditional) business models have been dominant in companies and sectors for many years. Generalising this model, a product is created by a firm and offered to the marketplace. The value is produced upstream and consumed downstream in a linear flow.

A standard business model for PLF would operate with a farmer (system owner) paying for the technology, installation, and maintenance. Data derived from sensors (monitoring the status and environment of the animals) is the property of the farmer/farm owner. This may be shared with one or many stakeholder/s (e.g. slaughterhouses, vets) based on a contract or agreement. However, the data does not travel further along the supply chain and is typically used to demonstrate compliance by the farmer. As the main or sole consumer of the data, the farmer is generally the only one who enjoys the value-added gains. PLF in its own right as a product would be valuable with a straightforward monetization to measure costing and ensure profitability.

However, previous studies (All-Smart-Pigs, 2013) demonstrated that the PLF hardware and software are too expensive for farmers to buy outright. However, the data captured from farms contains valuable information that could be interesting to other stakeholders along the supply chain. Precision Livestock Farming, therefore, has the potential to be expanded through a distributed (multi-sided) business model with multiple users (other than the farmer) allowing those users to create, deliver, capture and gain value.

Material and methods

Distributed business model for PLF

In a distributed PLF model, the beneficiary is not just the farmers, but also other stakeholders along the supply chain. Feed providers and nutritional companies, for example, will be interested in growth monitoring, health status tracking, feed and water consumption records which will enable real-time feed/nutrition performance overviews.

Real-time overviews will support feeding regimes that improve and optimize the feeding processes to limit growth variations, non-uniformity and improve disease resistance. Improved uniformity will also benefit farmers and abattoirs, with

farmers receiving higher prices for the slaughtered animal within a predefined standard range of weight.

Table 1 lists examples of stakeholder interactions and the advantages of the flow and exchange of information from farms.

Table 1: The interactions generated by flow of information along the chain

Breeders	Feed providers	Integrators	Farmers	Food companies/Retail
Efficiency of the breed material	Impact of feed composition on the animal indicator, performance control	Farm KPIs for quality management	Incidence management, predictability of results	Brand risk management

In the distributed business model for PLF (see Figure 1), the system (hardware and software) will be provided by service providers who will be in charge of the technology, installation, maintenance and active consultancy and reporting. Supply-chain stakeholders would subscribe to “PLF as a service” and get access to the data (and its analysis). This revenue model (subscription fee) is one possibility among the other main business revenue streams described in (Hartmann, Zaki, Feldmann, & Neely, 2014) such as advertising, usage fees, subscription fees, brokerage fees, licensing fees, leasing fees, and asset sales.

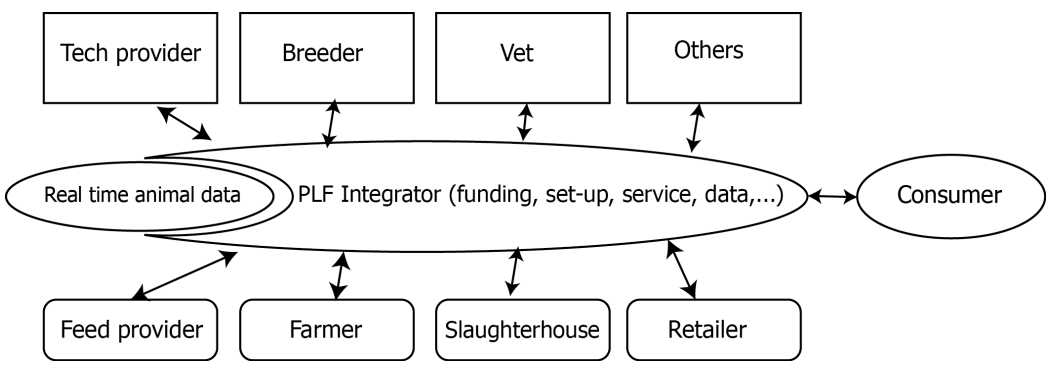


Figure 1: The PLF Business Model, Cost of PLF investment & operation shared along the value creation chain by paying for access to data pool

A feasibility study to ascertain supply-chain stakeholder interest and the potential success of a PLF implementation based on the proposed model would require a reasonable offer that would allow the stakeholders to provide an

economic evaluation and feedback on the likelihood of success. In particular, examining of the Willingness to Accept (WTA) and the Willingness to Pay (WTP) to help achieve this goal.

For this purpose, a choice experiment method was used. The choice experiment is a stated preference valuation method, which can be used to estimate economic values and consumer preferences. By means of an appropriately designed questionnaire, a hypothetical market is described where the good or service in question can be traded. Respondents are then asked to express their maximum willingness to pay for a hypothetical change in the level of provision of the good or service (Alpizar, 2001)(Hanley, Mourato, & Wright, 2001). Each hypothetical change is described by several characteristics, known as attributes.

Following this method, the attributes/indicators were identified with the appropriate levels. For designing the choice sets, a prototyping software was used. The choice-sets hereinafter called "product or mock-up", were designed for different stakeholders of the pig and poultry chain (farmers, feed providers, breeders and integrators of either species). Some products were assigned different levels of access and features and some were focused on aggregated and overview information (breeders and integrators). Table 2 shows a summary of the designed mock-ups and the associated levels.

Table 2: Supply chain step and the designed product levels

Value chain Stakeholder	Farmer	Feed provider	Breeder	Integrator
Product levels	Basic, Standard, Plus	Basic, Standard, Plus	Standard	Standard
Species	Pig, Poultry	Pig, Poultry	Pig, Poultry	Pig, Poultry

Figure 2 shows an example of the main dashboard of the designed Plus product for poultry farmers.

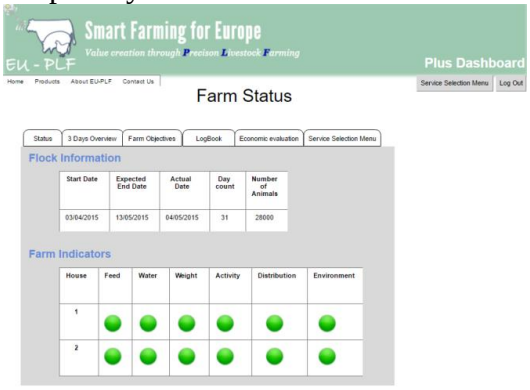


Figure 2: A view of the main dashboard for poultry farms (Plus product)

The data on the WTA/WTP was mainly collected through interviews and questionnaires with the stakeholders. The respondents and participants were from all around Europe including the UK, Germany, Belgium, Spain, Italy, Denmark, Poland, Netherland and Sweden among others.

Results and Discussion

About 60 valid figures were collected from supply chain partners (farmers, breeders, feed mills, technology providers and integrators) about the viability of the distributed business model.
Given that the farm is critical in terms of costs and that there is no clear multiplier between the farm and other supply chain partners (1-2 feed providers per farm, 1-2 breeding companies, 1 potential integrator, 1-3 slaughterhouses, 1-10 retailers), the business model should rely on a self-sufficient cost model per farm. High variability exists among the responses which show the lack of understanding/under-estimation of the value of "big data" in the food chain.
Considering this high variability and not having a statistically-enough number of responses, approximate calculations were made and the stakeholders' willingness to pay was compared with the costs of implementing PLF on farms (based on the designed product models). The results showed that the supply chain (including breeders, feed providers, technology providers, integrators slaughterhouses, and retailers) are willing to pay about €800 per month (€10,000 annually). Farmers, however, showed a WTP much less than €800. Assuming that farmers would pay the same amount (€10,000 annually) a total of 20,000 Euros annually could be collected from the whole supply chain.
It is also assumed that maintenance costs for 20 farms (in the same region or nearby) including a technician or relevant employee visit- every two weeks for 1 incidence and spend half a day per farm, which would be € 2,500 annually per farm. This leaves a total budget of € 17,500 per year. Note that there is no investment cost for farmers, they will just subscribe to the service and will pay a subscription fee. Having these assumptions and data points, the feasibility of implementing the described business model for pigs and poultry was evaluated.

<u>Pig chain</u>
A pig farm of average size with 2400 pig places for fattening pigs was considered for the evaluation. It was also assumed that the buildings, silos, and compartments were already built. Considering the estimated final prices of each of the product levels, the Return on Investment (ROI) for the service provider (who is in charge of the technologies, installations, and maintenance) in the case of the basic product, is relatively high (about 4 years). The ROI for the other

products (Standard and Plus) which were more interesting for the majority of stakeholders is much higher (6.5 years and 11 years respectively).

Poultry chain

A poultry house with the average size of 30,000 animal places was assumed. These 30,000 birds are all housed in one building. It is also assumed that the house, silos, feed hoppers, feed lines and water lines are already built and exist in the farm.

Considering the estimated final prices of the designed products for poultry chain, the calculated ROI for standard and plus products (popular products from the point of view of stakeholders) are 6 and 18 months respectively.

Conclusions

This paper proposed a data-driven business model for PLF. Through this model, the interaction between users (stakeholders) will be facilitated which is promising for improving the productivity and cost-efficiency of animal production, health, and welfare. Another important outcome of a distributed business model for PLF is increased transparency along the supply chain. Consumers are increasingly demanding greater transparency e.g. the farm-to-fork concept (European Commission, 2004) and such a model will pave the way for improved transparency and traceability.

Evaluating the feasibility of implementing PLF with this business model shows that farmer's willingness to pay for PLF as a service is generally very low. This could be due to reasons such as a lack of consideration for the cost scaling of PLF technologies or that the value of information is not tangible enough for farmers. Other stakeholders especially feed providers show interest and are willing to pay for receiving information from the farm they supply. According to the analysis, a full-scale implementation of PLF in pig farms seems very difficult due to a high ROI for the service provider. Solutions to address this problem could be a partial implementation of PLF or co-funding by farmers.

The situation is different for poultry chains and the full implementation of PLF as a service appears to be feasible. This is not only because the implementation of technology is more widely accepted in the poultry sector but also because the poultry farms are already more advanced than pig farms in terms of implementing the technology. This already-established infrastructure makes the costs for implementing PLF much lower than the case for pig farms.

An alternative solution for "PLF as a service" to be successful is to allow it to be owned/governed by PLF farmer's associations. Such systems would then be indirectly owned by farmers themselves which would increase the willingness of farmers to accept the PLF. This would also ensure that the farmer remained at

the heart of the whole system to guarantee the safety of data and the privacy concerns of farmers.

Acknowledgements

This project is funded by the European project EU-PLF (Animal and farm-centric approach to precision livestock farming in Europe), co-financed by the European Commission.

References

All-Smart-Pigs. (2013). *Practical implementation of precision livestock technologies and services at European pig farms using the living lab methodology (All-Smart-Pigs)*.

Alpizar, F. (2001). Using Choice Experiments for Non-Market Valuation. *Transport*, *8*, 1–37. Retrieved from http://www.idrc.org/uploads/user-S/10301141930choiceexperiments.pdf

European Commission. (2004). *From farm to fork - Safe food for Europe ' s consumers*.

Hanley, N., Mourato, S., & Wright, R. E. (2001). Choice Modelling Approaches : a Superior Alternative for Environmental Valuation ? *Journal of Economic Surveys*, *15*(3), 435–462. http://doi.org/10.1111/1467-6419.00145

Hartmann, P. M., Zaki, M., Feldmann, N., & Neely, A. (2014). Big Data for Big Business? A Taxonomy of Data-driven BusinessModels used by Start-up Firms. *Cambridge Service Alliance Whitepaper*, 1–29. http://doi.org/10.1016/j.im.2014.08.008

Session 10

Feed and Cattle

Automatic classification of feeding behaviours in Sarda cattle using tri-axial accelerometry with different time epoch settings

V. Giovanetti[1], M. Decandia[1], M. Acciaro[1], M. Mameli[2], G. Molle[1], A. Cabiddu[1], C. Manca[1], R. Cossu[3], M.G. Serra[1], S.P.G. Rassu[3], C. Dimauro[3]
[1]*AGRIS Sardegna, Loc. Bonassai, Olmedo, 07040, Italy*
[2]*Electronic Systems, Via Sassari 101, 07041 Alghero, Italy*
[3]*Università di Sassari, Dipartimento di Agraria, Viale Italia 39, Sassari, 07100, Italy*
vgiovanetti@agrisricerca.it

Abstract

The grazing behaviour of beef cattle in extensive rangelands can be monitored with sensing technologies which collect information with high temporal detail. The huge amount of data produced rapidly exhausts the battery in the device. To overcome this, an epoch, or size of aggregation window, can be set and applied to the data stream. We evaluated the effect of different epoch settings (5, 10, 30, 60, 120, 180 and 300 s) on the behaviour classification performance for cattle wearing a tri-axial accelerometer device (BEHARUM). A 5 day calibration trial was conducted with Sarda beef cattle equipped with the BEHARUM and allowed to range freely for 4 hrs in a 2 ha paddock of natural pasture. Acceleration data were acquired and recorded as a csv file in a receiving computer. At the same time, cattle behaviour was video-recorded by a fixed camera. Calibration and validation of the system for each epoch under study was performed by comparing acceleration data which was automatically classified into three activities, grazing, ruminating and resting (including other activities), with video-recorded data. A multivariate analysis procedure made it possible to correctly assign 77.6, 82.7, 89.1, 90.8, 92.4, 92.9, 93.4% of the 5, 10, 30, 60, 120, 180, 300 s epochs, respectively, to the three activities. Increasing the time epoch improved the correct classification of behaviour, and extended the battery life of the device.

Keywords: Sensors, ICT, ruminants, pasture, multivariate analysis

Introduction

Monitoring changes in the foraging behaviour of free-ranging ruminants provides knowledge that can help farmers to understand the relationships between animal (i.e. nutritional requirements, health, etc.) and pasture (i.e. sward state) and their potential effect on daily intake (Penning & Rutter, 2004). Over

the years, many devices have been developed for this purpose, the most promising of which for the near future are based on accelerometer sensors. Their use for on-farm dairy herd management is under development.
Wireless three-dimensional accelerometers provide a non-invasive, automatic measure of normal behaviour patterns; however, limited research has been performed to evaluate the accuracy of these devices in cattle at pasture or the impact of different recording settings on categorisation of specific cattle behaviour patterns (Robert *et al*., 2009).
Moreover, these devices sample the acceleration signal at high frequencies, which generates vast amounts of data and carries a cost in terms of battery consumption. To overcome this, an epoch, or size of aggregation window, can be set and applied to the data stream. Recorded data can then be processed to develop a linear (Giovanetti *et al*., 2017; Yoshitoshi *et al*., 2013) or quadratic (Watanabe *et al*., 2008) discriminant analysis of transformed variables which automatically classifies different behaviours.
For this reason, in the present research, different data-recording options were tested to optimise the performance of a tri-axial accelerometer. The device, named BEHARUM, was positioned under the animal's lower jaw. The objective of the experiment was to determine whether the accuracy, sensitivity, specificity, precision and Cohen's k coefficient differed for different epoch settings in order to optimise device performance.

Materials and methods

Description of BEHARUM device

The BEHARUM device includes a halter equipped with a three-axial accelerometer sensor positioned under the animal's lower jaw. Animal head and jaw movements are detected through accelerations measured in the X (longitudinal), Y (horizontal) and Z (vertical) axis (Figure 1).

Figure 1. Halter equipped with a tri-axial accelerometer sensor.

The acceleration sensor was installed in a compact micro-electromechanical system (MEMS) which samples raw acceleration data at a frequency of 62.5 Hz and encodes them through an analogue-to-digital converter with a resolution of 8 bits into levels ranging from 0 to 255. The microcontroller then selects three converted values per second per axis (Giovanetti *et al*., 2017). This device sends the converted acceleration data (LoRa wireless system) to a nearby receiver computer equipped with an antenna or to a remote computer through a local server using the GSM services.

Data collection

A 5-day calibration trial was conducted at the Bonassai experimental farm of AGRIS, located in the NW of Sardinia (40° 40' 16.215" N, 8° 22' 0.392" E, 32 m a.s.l). On each day of the experiments, a Sarda beef cow was fitted with the BEHARUM device and allowed to range freely for 4 hrs in a 2 ha paddock of natural pasture. Acceleration data were acquired and recorded by a receiving computer as a csv file. At the same time, cattle behaviour was video-recorded by a fixed camera.

Data processing

Mean, variance, inverse coefficient of variation (ICV; mean/standard deviation) and number of accelerations of the recorded data were calculated for each axis as well as for the resultant of the three axes (Watanabe et al., 2008) for the following epoch settings: 5 s, 10 s, 30 s, 60 s, 120 s, 180 s, 300 s. Video recordings were manually coded with the prevailing behaviour during each epoch and classified as grazing, ruminating or resting according to Gibb (1998). Grazing activity included the act of searching for food while walking with the head down without evidence of biting, or standing still with the head down while biting and chewing either with the head down or the head up. Ruminating activity included regurgitation, chewing and swallowing of a bolus, in the lying or standing position. Resting activity included all other activities which basically involved lying down or standing without rumination, and travelling.

The merged sensor and behavioural data were analysed for each epoch using two multivariate statistical techniques (Mardia et al. 2000): canonical discriminant analysis (CDA), and discriminant analysis (DA). CDA tested whether the three behaviours were significantly separated by using different epochs, whereas DA was used to assign behaviours to the three different groups.

DA performance was evaluated in terms of sensitivity, specificity, precision and accuracy which were calculated on the basis of the error distribution in assignment with the following equations:

Sensitivity = TP/(TP + FN); Specificity = TN/(TN+FP); Precision = TP/(TP+FP); Accuracy= (TP+TN)/(TP+TN + FP + FN),

where TP, TN, FP and FN are true positive, true negative, false positive and false negative counts, respectively.
Finally, the Cohen's k coefficient (Fleiss, 1981) was calculated for each behaviour and overall to evaluate the agreement between observed and model-predicted data, corrected for agreement that would be expected by chance. The k values were judged according to the criteria proposed by Landis and Koch (1977).

Results and discussion

The BEHARUM device offers potential to monitor cattle behaviour remotely, and optimising the epoch setting could make it possible to increase the duration of data recording without compromising classification accuracy. In the present experiment, the dataset consisted of 13456 records in the 5 s epoch, decreasing to 226 in the 300 s epoch due to time collection.
CDA significantly discriminated the three behaviours (Hotelling's test $P < 0.0001$) by extracting two canonical functions (CAN1 and CAN2) in each epoch setting. CAN1 discriminated the resting activity from the grazing and ruminating activities, whereas CAN2 differentiated the grazing from the ruminating behaviour. This expected result confirms that resting is markedly different from the other two behaviours because it does not involve any jaw movement related to feeding activity. Figure 2 shows that a long epoch setting gives better separation between behavioural groups. The performance of DA in classifying the behavioural activities is presented in Table 1. The precision values indicate the proportion of predicted positive cases that were correct and hence the probability that the BEHARUM detects a behaviour that the cow is actually performing. The highest precision values for grazing behaviour occurred in the 300 s epoch, for resting in the 180 s epoch, and for ruminating in the120 s epoch.

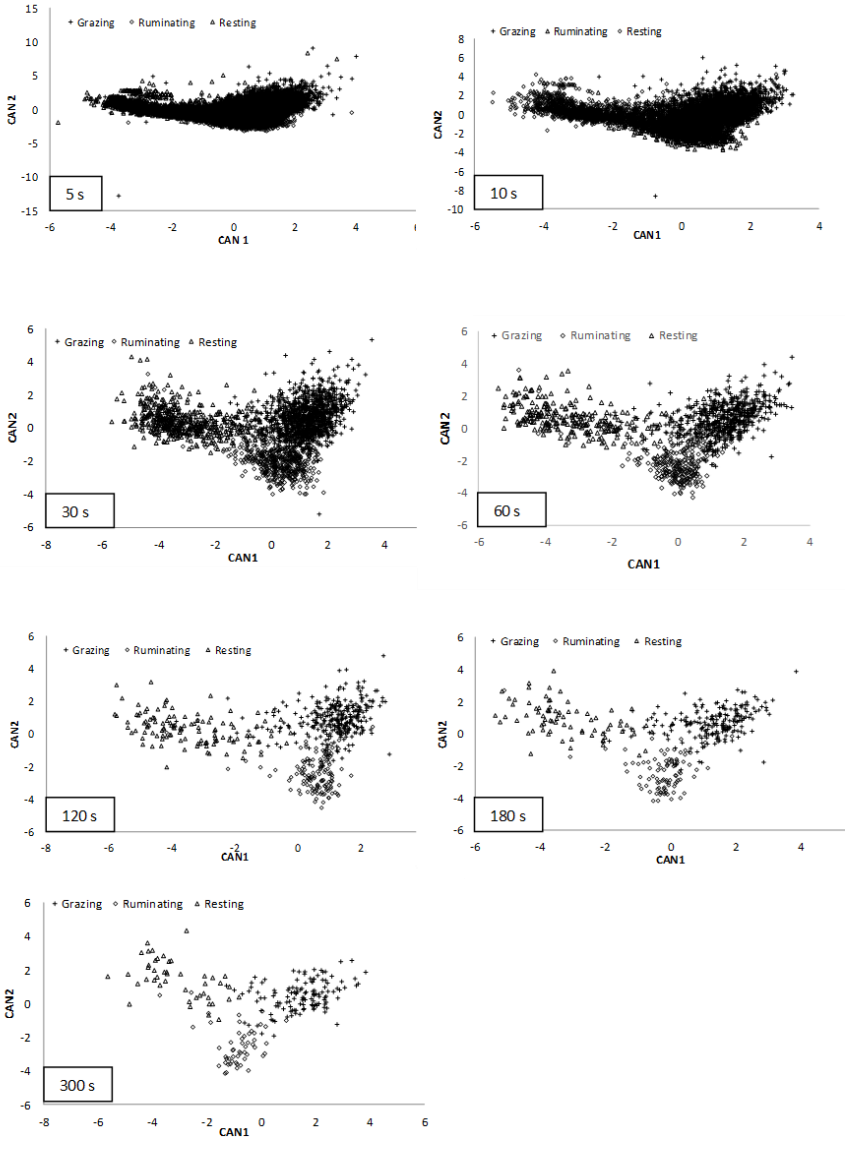


Figure 2. Plot of canonical variables (CAN 1, CAN 2) generated from discriminant analysis for different time epoch settings (5 s, 10 s, 30 s, 60 s, 120 s, 180 s, 300 s).

The precision of BEHARUM for identifying grazing activity in the longest epoch settings is comparable to the mean precision found at the 120 s epoch setting by Delagarde & Lamberton, (2015) in dairy cows fitted with a uniaxial accelerometer device (Lifecorder), originally designed for human health improvement. The reliability of the BEHARUM device is also confirmed by the high accuracy values, which indicate whether the values are close to the true values being predicted, and were in excess of 95% for the three behaviours at 180 s and 300 s.

The sensitivity and specificity values for grazing, ruminating and resting behaviour indicate the rate of true positives and true negatives detected by the BEHARUM system, i.e. whether the behaviour is occurring or not, compared with reference values. Sensitivity was highest in the 300 s epoch and specificity in the 180 s epoch for grazing, while ruminating and resting showed the highest sensitivity and specificity values at 180 s. The statistical agreement determined with the k coefficient, which represents a measure of chance (or not) agreement between observed values and values predicted by the model for each behaviour, was particularly high and similar (k = 0.9) to the 180 and 300 s epoch for grazing, 60 s, 120 s, 180 s, 300 s epoch for ruminating and 30 s, 60 s, 120 s, 180 s, 300 s epoch for resting. The overall accuracy, precision and k coefficient were particularly high for the three behaviours at 120 s, 180 s and 300 s epoch lengths, indicating no substantial differences in classification among these epoch settings. For shorter data recording periods (5 s, 10 s, 30 s and 60 s) the behaviour classification performance was lower than for longer epochs and may reduce the battery life of the BEHARUM device. These results are in contrast with those obtained by other authors who reported better performance with similar epoch settings. For example, Robert *et al*., (2010) reported that accelerometers provided an accurate measure of cattle behaviour (lying, standing and walking), with a 3 s and 5 s epoch setting being more accurate for monitoring animal activity than a 10 s time epoch (overall accuracy 98.1, 97.7 and 85.4%, respectively). Similar results were obtained by Dutta *et al*., (2015) with a 5 s epoch as well as by Gonzales *et al*., (2015) with a 10 s epoch in grazing cattle. Other authors obtained better results when using 60 s-based data with overall precision levels of about 95% (Yoshitoshi *et al*., 2013; Watanabe *et al*., 2009).

Table 1. Sensitivity, specificity, precision, accuracy and k coefficient in the assignment of behaviour activities, predicted on the basis of accelerometer data, for the different epoch settings (5, 10, 30, 60, 120, 180, 300 s) and overall.

		Sensitivity (%)	Specificity (%)	Precision (%)	Accuracy (%)	k
Grazing	5 s	88.6	77.2	77.3	82.5	0.6
	10 s	91.1	80.4	81.2	85.6	0.6
	30 s	93.7	86.8	88.0	90.3	0.8
	60 s	95.0	89.0	90.2	92.1	0.8
	120 s	96.0	88.4	90.2	92.4	0.8
	180 s	96.5	93.4	94.1	95.0	0.9
	300 s	97.6	93.1	94.6	95.6	0.9
Ruminating	5 s	57.3	93.2	80.6	81.3	0.7
	10 s	65.4	94.3	82.9	85.7	0.8
	30 s	77.8	96.4	88.6	91.4	0.8
	60 s	80.8	96.9	90.2	92.6	0.9
	120 s	84.4	98.3	94.7	94.7	0.9
	180 s	88.3	97.6	92.2	95.3	0.9
	300 s	87.3	97.7	92.3	95.1	0.9
Resting	5 s	85.0	92.7	74.7	91.2	0.7
	10 s	85.6	95.4	83.9	93.2	0.8
	30 s	90.5	97.3	90.6	95.8	0.9
	60 s	92.0	97.7	92.0	96.5	0.9
	120 s	90.0	98.0	92.3	96.3	0.9
	180 s	93.2	98.3	94.3	97.1	0.9
	300 s	91.3	98.3	93.3	96.9	0.9
Overall	5 s			77.6	77.5	0.6
	10 s			82.7	82.2	0.7
	30 s			89.1	88.8	0.8
	60 s			90.8	90.6	0.8
	120 s			92.4	91.7	0.9
	180 s			92.9	93.7	0.9
	300 s			93.4	93.8	0.9

Conclusions

This study showed that tri-axial accelerometers placed under the animal's jaw were capable of discriminating grazing, ruminating and resting behaviours in cattle at pasture. The multivariate statistical approach accurately predicted feeding behaviour with the highest sensitivity, specificity, precision, accuracy and k coefficient for the 120 s, 180 s and 300 s epoch settings. Increasing the time epoch length improves correct classification of behaviour and extends the battery life of the device. Further research is needed to strengthen the calibration of the BEHARUM device with more animals tested in different environments. As the next step, validation trials are planned to investigate the applicability of the BEHARUM device even in marginal areas, where cattle graze on Mediterranean rangeland and bushland.

Acknowledgements

We would like to thank the Government of Sardinia (Italy) for its financial support (Projects CRP-17287 PO Sardegna, FSE 2007-2013 LR 7/2007). The authors are also grateful to S. Picconi and S. Pintus, who provided technical assistance and the other collaborators from the laboratories and farm of Bonassai research station and from the University of Sassari who contributed to this work.

References

Delagarde, R., Lamberton, P., 2015. Daily grazing time of dairy cows is recorded accurately using the Lifecorder Plus device. *Applied Animal Behaviour Science* **165**:25–32.

Dutta, R., Smith, D., Rawnsley, R., Bishop-Hurley, G., Hills J., Timms, G., Henry, D., 2015. Dynamic cattle behavioural classification using supervised ensemble classifiers. *Computers and Electronics in Agriculture* **111**:18–28.

Fleiss, J.L., 1981. The measurement of interrater agreement. In: *Statistical Methods for Rates and Proportions*. 2nd Edition, John Wiley, NewYork, 212-236.

Gibb, M.J., 1998. Animal grazing/intake terminology and definitions. In: *Proc. Workshop Concerned Action. AIR3–CT93–0947h*. Occasional Publ. No. 3. Teagasc, Dublin, Ireland.

Giovanetti, V., Decandia, M., Molle, G., Acciaro, M., Mameli, M., Cabiddu, A., Cossu, R., Serra, M.G., Manca, C., Rassu, S.P.G., Dimauro, C., 2017. Automatic classification system for grazing, ruminating and resting behaviour of dairy sheep using a tri-axial accelerometer. *Livestock Science*, **196**:42–48.

González, L.A., Bishop-Hurley, G.J., Handcock, R.N., Crossman, C., 2015. Behavioral classification of data from collars containing motion sensors in grazing cattle. *Computers and Electronics in Agriculture*, **110**:91–102.

Landis, J., Koch, G., 1977. The measurement of observer agreement for categorical data. *Biometrics* **33**:159–174.

Mardia, K.V., Bookstein, F.L., Moreton, I.J., 2000. Statistical assessment of bilateral symmetry of shapes. *Biometrika* **87**:285–300. doi:10.1093/biomet/87.2.285.

Penning, P.D., Rutter, S.M., 2004. Ingestive Behaviour. In: *P.D. Penning, ed., Herbage Intake Handbook*, The British Grassland Society, Reading, 151-175.

Robert, B., White, B.J., Renter, D.G., Larson, R.L., 2009. Evaluation of three-dimensional accelerometers to monitor and classify behaviour patterns in cattle. *Computers and Electronics in Agriculture*. **67**:80–84.

Yoshitoshi, R., Watanabe, N., Kawamura, K., Sakanoue, S., Mizoguchi, R., Lee, H.J., Kurokawa, Y., 2013. Distinguishing cattle foraging activities using an accelerometry-based activity monitor. *Rangeland Ecology Management* **66**:382–386.

Watanabe, N., Sakanoue, S., Kawamura, K., Kozakai, T., 2008. Development of an automatic classification system for eating, ruminating and resting behaviour of cattle using an accelerometer. *Japanese Journal of Grassland Science* **54**:231–237.

Traditional mixed linear modelling versus modern machine learning to estimate cow individual feed intake

C. Kamphuis, J.W. van Riel, R.F. Veerkamp, and R.M. de Mol
Wageningen University & Research, Livestock Research, PO Box 338, the Netherlands
Claudia.Kamphuis@wur.nl

Abstract

Three modelling approaches were used to estimate cow individual feed intake (**FI**) using feeding trial data from a research farm, including weekly recordings of milk production and composition, live-weight, parity, and total FI. Additionally, weather data (temperature, humidity) were retrieved from the Dutch National Weather Service (KNMI). The 2014 data (245 cows; 277 parities) were used for model development. The first model (**M1**) applied an existing formula to estimate energy requirement using parity, fat and protein corrected milk, and live-weight, and assumed this requirement to be equal to energy intake and thus FI. The second model used 'traditional' Mixed Linear Regression, first using the same variables as in M1 as fixed effects (**MLR1**), and then by adding weather data (**MLR2**). The third model applied Boosted Regression Tree, a 'modern' machine learning technique, again once with the same variables as M1 (**BRT1**), and once with weather information added (**BRT2**). All models were validated on 2015 data (155 cows; 165 parities) using correlation between estimated and actual FI to evaluate performance. Both MLRs had very high correlations (0.91) between actual and estimated FI on 2014 data, much higher than 0.46 for M1, and 0.73 for both BRTs. When validated on 2015 data, correlations dropped to 0.71 for MLR1 and 0.72 for MLR2, and increased to 0.71 for M1 and 0.76 for both BRTs. FI estimated by BRT1 was, on average, 0.35kg less (range: -7.61 – 13.32kg) than actual FI compared to 0.52kg less (range: -11.67 – 19.87kg) for M1. Adding weather data did not improve FI estimations.

Keywords: precision feeding, dairy cows, Big Data, prediction, machine learning

Introduction

Feed efficiency in dairy cattle is gaining interest due to the limited availability of natural resources (De Mol et al., 2016) and the challenge to feed over 9 billion people by 2050 (FAO, 2016). Feed efficiency is a measure on the efficient

conversion of feed intake into milk production (Lu et al., 2015). Feed intake (**FI**) can be measured using dedicated feeding equipment, e.g., roughage intake control systems, but these systems are exclusively used under experimental conditions. Actual daily feed intake of dairy cows under commercial circumstances, thus, remains unknown.

During the past decades farm sizes have increased, milk yields have risen and automation and sensor technologies for milking and other farm tasks (e.g., observing cows in oestrus) have become increasingly popular on dairy farms (Mottram, 2016). This increase in automation and sensor technology has also increased the availability of the amount and sources of data. A shift from traditional methods to analyse data to new modelling approaches is, therefore, expected to occur (Mottram, 2016). One of these new modelling approaches are Big Data analytics. The mainstream definition of Big Data involves three Vs (Sonka and Cheng, 2015): (1) Volume, or the amount of available data (2) Velocity, or the speed and frequency of data arrival and processing (Devlin, 2012; Zaslavsky et al., 2012) and the capability to respond to events (near) real-time, and (3) Variety, or the availability of different (un)structured formats of data, e.g., spreadsheets, drone images, and pictures. Over time, other Vs have been added like variability, veracity (trustworthiness of data), visualisation, and value (McNulty, 2014). The tools used in Big Data analytics include data-driven techniques like machine learning.

To explore the usefulness of Big Data analytics for the estimation of cow individual FI, this study compared three different modelling approaches for estimating FI. The first model estimated energy requirements based on parity, live-weight, and milk production, using the assumption that energy requirement equals energy intake. The second model used traditional Mixed Linear Regression to predict feed intake, and the third model was a machine learning algorithm called Boosted Regression Tree. Since Variety is one of the three characteristics used in the mainstream definition of Big Data, the latter two modelling approaches were repeated with weather information as additional data source.

Materials and Methods

Experimental data

Data were retrieved from 10 feeding trials conducted in 2014 and/or 2015 at the Wageningen University & Research farm in Lelystad. During each trial, FI (kg dry matter /day) was recorded on a daily basis as the sum of roughage intake (kg dry matter /day) and concentrate (kg /day) intake, where the latter was converted into kg dry matter by multiplying the intake with 0.89. This value was considered the Gold Standard and further referred to as ‘actual FI’. For each

calendar week, daily cow individual FI recordings were converted into an average FI. The same approach was used to calculate an average daily live-weight per calendar week. Data on milk yield and composition were recorded once a week. From these data fat and protein corrected milk (**FPCM**) was calculated using (CVB, 2008; Klop et al., 2016):

$$FPCM\ (kg/day) = Milk\ yield * (0.337 + fat\% * 0.116 + protein\% * 0.06), \quad (1)$$

where milk yield is the recorded milk yield expressed in kg per day, fat% and protein% are the percentages of fat and protein, respectively. Averages of actual FI and live-weight of the same week that milk yield and composition were recorded were added. Lastly, for each cow, parity and the week in milk were added for each calendar week.

In addition to FI and cow information, weather data from Lelystad Airport (~10km distance from the research farm) were retrieved from the Royal Dutch Meteorological Institute (KNMI). This institute records freely accessible weather variables on a daily basis. From all available variables, the minimum, maximum, and average temperature and relative humidity per day were selected. Based on these recorded variables, the daily temperature (and relative humidity) range, and the difference between todays average temperature (and relative humidity) with the average temperature (and relative humidity) over the past seven days were derived. Weather information was then coupled with FI and cow information based on date, and thus, all cows had once-a-week data recordings of FPCM, live-weight, parity, DIM, and weather information available.

Cows with less than four records (that is, less than one month of data) were excluded from further analysis. Live-weight recordings and FCPM values that were outside the mean ± four times the standard deviation were considered outliers and set at missing. Cow-weeks that had missing values for any of the recorded or derived parameters were excluded (28.3%). These exclusion criteria resulted in 407 cows and 3,787 cow-weeks from seven feeding trials available for further analysis. Table 1 summarizes the number of cows, cow-weeks, and treatments per trial, as well as the range in parity per trial, the range in DIM per trial, and the year in which the trial was conducted. Cows could be included in multiple trials, and in trials crossing years. Therefore, the number of unique cows in this study (n = 300) was lower than the 407 cows reported in Table 1. The number of unique cows in 2014 was 245; in 2015 there were 155 unique cows.

Table 1: Characteristics of trials used for training and testing including the number of cows, cow-days, and treatments (Treatm.) per trial (Trial), the range of parity and days in milk (DIM) per trial, and the year(s) in which the trial was conducted.

Trial	Treatm. (n)	Cows (n)	Cow-days (n)	Parity range	DIM range	Year
1	4	136	399	1 – 7	70 – 160	2014
2	3	52	75	1 – 6	42 – 207	2014–2015
3	3	96	2,594	1 – 7	7 – 364	2014–2015
4	1	10	65	3 – 5	6 – 56	2014
5	1	15	39	1 – 5	21 – 56	2014
6	3	39	177	2 – 9	14 – 140	2015
7	5	59	438	1 – 5	7 – 63	2014–2015
Total	20	407	3,787			

Statistical analysis

Several models (Table 2) were developed using data from 2014. Each of these models was tested on the same data used for training, as well as on new, independent, data from 2015. The first model (**M1**; Table 2) used an existing model to estimate energy requirement, and assumed this requirement to be equal to energy intake. Energy requirement was calculated using the Dutch net energy evaluation for dairy cows (Van Es, 1975; CVB, 2008):

$$VEM/day = (42.4 * LW^{0.75}) + (442 * FPCM)) * (1 + (FPCM - 15) * 0.00165) \quad (2)$$

Where LW represents a cow's live-weight (in kg), and FPCM refers to the fat and protein corrected milk (in kg; formula 1). Since further details on used feeding and treatments within these trials were unknown, we assumed that provided feed had 975 VEM/kg dry matter. Therefore, required VEM/day (from formula 2) was divided by 975 to compute FI / day.

The second model used the Mixed Linear Regression approach (Table 2). The first variant of this model (**MLR1**) used FI as dependent variable, and the same variables used as M1 as fixed effects, where parity was included as a three-level factor (parity 1, 2, and ≥3). Trial, treatment within trial, cow, week in milk, and month of the year were included as random effects. The second variant of the Mixed Linear Regression model (**MLR2**) extended the MLR1 with weather information by adding temperature and relative humidity data as fixed effects.

The third model used machine learning to estimate FI (Table 2), using a nonlinear predictive method called Regression Tree (James et al., 2015). It involves segmenting the predictor space using binary splits into smaller regions that contain training observations that are similar. Typically, the mean of all

training observations falling into such a small region is used as predicted outcome for a new observation (not used for training) that belongs to that same region. The power of trees lies in the simple method, and visualising the tree makes the model itself easy to interpret. However, single trees are often large and over-fitted, and consequently lack predicting accuracy on new, unseen observations. Improving the predictive performance of trees is possible, e.g., by aggregating many trees (James et al., 2015). Boosting is such an approach to generate many trees and aggregate them into one single outcome. Boosting creates multiple small trees sequentially, where each new tree uses the residuals from the previous tree as response (James et al., 2015). The first variant of this third model applied Boosted Regression Tree (**BRT1**) using FI as independent variable, and the same variables as M1, where parity was included as a three-level factor (1,2, and ≥3) variable, and with week in milk and month of the year added to the model. The second variant of this third model (**BRT2**) extended BRT1 with weather information by adding temperature and relative humidity data. Both ensemble trees consisted of 1,000 sub-trees with each sub-tree having a maximum number of four splits.

Table 2: short description and variables included per model.

Model	Description	Variables
M1	Energy requirement according to formula 1 and feed intake according to formula 2	parity, live-weight, fat and protein corrected milk
MLR 1	Mixed Linear Regression without weather info	Fixed effects: * Random effects: trial, treatment within trial, cowid, week in milk, month of the year
MLR 2	Mixed Linear Regression with weather info	Fixed effects: *, temperature[1], humidity[2] Random effects: trial, treatment within trial, cowid, week in milk, month of the year
BRT1	Boosted Regression Tree without weather info	*, week in milk, month of the year
BRT2	Boosted Regression Tree with weather info	*, temperature[1], humidity[2], week in milk, month of the year

* same variables as listed for model M1; 1 includes average temperature of the past week, and the absolute difference between today's temperature and the average temperature of the past week; 2 includes average humidity of the past week, and the absolute difference between today's humidity and the average humidity of the past week

To evaluate performance of each model in predicting FI, the Pearson's correlation between predicted FI and actual FI was calculated for each model for both the training set (2014 data), and the test set (2015 data). For both MLR1 and MLR2 (Table 2) only coefficients of the fixed effects were used to predict FI. Additionally, the mean difference between predicted and actual FI was calculated for the test set only. This was done for all observations combined, per parity category (1, 2, and ≥3), and per lactation stage (<100, 100-200, and >200 days in milk).

All analyses were conducted using RStudio (using R version 3.1.1; R Core Team 2016; James et al., 2015) extended with the following packages: RODBC (Ripley and Lapsley, 2016), plyr (Wickham, 2011), lme4 (Bates et al., 2015), Hmisc (Harrell, 2016), data.table (Dowle et al., 2015), and gbm (Ridgeway, 2015).

Results

The average actual FI of cows was 21.2kg for both the training (2014) and test data (2015). Table 3 summarizes the correlations between actual and estimated FI by the different models, for both the training (2014) and the test (2015) data. Both MLR models have high correlations between actual and estimated FI for the training set, indicating a good fit. Correlations for M1 and both BRT models on the training data were lower. When models were applied to observations not used for training, correlations between actual and estimated FI dropped for both MLR models. In contrast, correlations for M1 and both BRT models increased. Correlations were similar between models with and without weather information, regardless whether training or test data were used. All models had comparable correlations when applied on the test set, and all models estimated, on average, FI to be lower than actual FI. Estimated FI from MLR2 deviated most, on average, from the actual FI. Although M1 had a low mean difference (-0.52, Table 3), it did have the highest range in difference between actual and estimated FI; estimated FI ranged to be almost 12kg less than actual FI to almost 20kg too much. The range in difference between actual and estimated FI was lowest with ~20kg for both MLR models.

Table 3. Per model the correlation between estimated feed intake (FI) and actual FI on the training (2014) and on the test (2015) data, and the mean and range of the difference (both in kg) between the estimated and actual FI on the test data (2015).

Model	Training set	Test set		
	Correlation	Correlation	Mean difference (kg)	Range difference (kg)
M1	0.46	0.71	-0.52	-11.67 – 19.87
MLR1	0.91	0.71	-1.23	-7.70 – 12.32
MLR2	0.91	0.72	-1.73	-8.24 – 11.76
BRT1	0.73	0.76	-0.35	-7.61 – 13.32
BRT2	0.73	0.76	-0.35	-7.61 – 13.32

Table 4 summarizes correlations for different parity categories and lactation stages. Both BRT models have high correlations between actual and estimated FI for first parity cows, in contrast to the MLR models. Also, BRT models had the highest correlations for cows earlier in lactation, whereas correlation dropped for both BRT models for cows later in lactation. The M1 and both MLR models have the highest correlation for cows that are 100 to 200 days in lactation. Again, there is no difference in correlation between models that do not include weather information (MLR1, BRT1) versus those that had this information included (MRL2, BRT2).

Table 4. Per model the correlation between estimated feed intake (FI) and actual FI using the test data (2015) per parity group, and per category of days in milk (DIM). The number of records per category of parity or DIM is listed between brackets

Model	Parity			DIM		
	1 (98)	2 (461)	≥3 (831)	<100 (544)	100-200 (299)	>200 (547)
M1	0.67	0.77	0.71	0.60	0.77	0.63
MLR1	0.67	0.76	0.71	0.58	0.75	0.64
MLR2	0.66	0.76	0.71	0.58	0.75	0.65
BRT1	0.82	0.79	0.72	0.78	0.69	0.38
BRT2	0.82	0.79	0.72	0.78	0.69	0.38

Discussion

The current study is not the first one estimating cow individual FI using machine learning. Van der Waaij et al. (2016) analysed a dataset very similar to the one we used, with the exception that they had additional sensor information

(rumination) and a differentiation between roughage and concentrate intake. But there are three more differences with that study worthy to discuss: firstly, they included cow identification as proxy for the influence of genotype on FI and reported a positive influence of this variable in predicting FI. In contrast, we left cow identification out of the equation, since BRT will likely use that variable as root node which will likely result in improved cow individual FI prediction. However, generalization to new data (that is, unseen cow identification numbers) will not work since the model will not recognize this new 'value'. Secondly, adding weather information did not contribute to a better FI prediction in our study, whereas Van der Waaij et al. (2016) reported temperature having a 'positive influence'. Unfortunately, they did not specify the magnitude of that positive contribution nor provided results of a model without weather information, leaving the question unanswered whether temperature adds significantly to FI prediction. Thirdly, Van der Waaij et al. (2016) used a Neural Network, and reported this network to be unable to predict FI in case of missing data. Given that sensor data are incomplete by definition, Neural Networks may not be the appropriate analytical tool to be used in practice.

The majority of the data used in the current study (68.5%) originated from a single feeding trial crossing years (Experiment 3, Table 1). Thus, data used for training (2014) were not independent from data used for testing (2015) which may have overestimated results. Still, both MLRs and BRTs were trained and tested on same data, and thus, results are relative to each other. The MLR models performed well on the training set, but correlations dropped substantially when applied on the test set, indicating a possible overfit of these regression models. In contrast, BRT appeared to be more robust and less prone to overfitting, since correlations on the test set were similar to those of the training set. All models underestimated actual FI, with the M1 having the widest range in differences between actual and estimated FI (Table 3). Also large differences in correlations between parity groups and lactation stages were seen, for all three modelling approaches. BRT models appear to estimate FI for first parity cows and those early in lactation much better than M1 and MLR models, whereas MLR and M1 seem to outperform BRT for cows later in lactation (Table 4). Future research should investigate whether the differences between model performance on the test set are significant, why all models consistently underestimate actual FI, and what is causing the differences between modelling approaches for different parity groups or lactation stages.

The data used in the current study were pre-processed such that all three modelling approaches could handle the data (e.g., records with missing values for any of the recorded or derived variables were excluded to allow mixed linear regression analysis). By doing so, we ensured training and testing of different models to be conducted on the same data, but we may have limited the potential

of the BRT models in two ways: firstly, we excluded almost 30% the records with missing data for one or more predictor variables, whereas these incomplete records may still hold potentially valuable information. Machine learning approaches like BRT are known for their capability to deal with these incomplete data. Secondly, by excluding almost 30% of the data we reduced the volume considerably, whereas machine learning works requires large amounts of data. Saying this, even if we would have included all data, critics could argue that even then we would not have enough data for machine learning and that we have linked this study to Big Data incorrectly. On the other side, the volume characteristic is highly subjective, depending on the industry and application, and a specific threshold on this characteristic is lacking (Sonka and Cheng, 2015). In the near future, data of the current study will be extended with 15 years of feeding trials, conducted at several different research farms, and including additional data sources, like breeding values for FI, roughage and concentrate percentages fed, and other sensor data. This will certainly increase volume, but will also add complexity due to increased variety and velocity of the available data.

Conclusion

Three modelling approaches were used to estimate cow individual FI. The 'traditional' MLR models had high correlations on the training data, but these dropped substantially when the models were applied to the test data. In contrast, the 'modern' BRT models had lower correlations on the training data, but appeared to be more robust since correlations remained similar on the test set. Moreover, FI estimated by BRT1 was, on average 0.35kg less than actual FI, compared with the commonly applied M1 model that had an average predicted FI more than 0.5kg less than actual FI. Adding weather information did not improve FI estimations. To better meet the three Vs of Big Data, and potentially improve performance of machine learning algorithms that thrive on large volumes of data, future research will focus on including more farms, more feed experiments conducted during more years, and adding data from more sources.

Acknowledgements

This project is part of the project KB-27-001-001 Big Data for healthy resources utilization, which is funded by the Dutch Ministry of Economic Affairs. Colleagues at Wageningen University & Research are acknowledged for sharing the data.

References

Bates, D., M. Mächler, B. Bolker, and S. Walker. 2015. Fitting Linear Mixed-Effects Models Using lme4. 2015 67(1):48.

CVB. 2008. Table Booklet feeding of ruminants.

De Mol, R. M., R. M. A. Goselink, J. W. Van Riel, H. M. Knijn, and A. T. M. Van Knegsel. 2016. The relation between eating time and feed intake of dairy cows. Pages 387-392 in Precision Dairy Farming 2016. C. Kamphuis and W. Steeneveld, ed. Wageningen Academic Publishers, Wageningen, the Netherlands, Leeuwarden, the Netherlands.

Devlin, B. 2012. The Big Data Zoo - Taming the beasts: the need for an integrated platform for enterprise information. 9sight Consulting. from http://9sight.com/pdfs/Big_Data_Zoo.pdf

Dowle, M., A. Srinivasan, T. Short, and S. Lianoglou, 2015. data.table: Extension of Data.frame. from https://CRAN.R-project.org/package=data.table

FAO, 2016. Retrieved 13 December 2016 from http://www.fao.org/livestock-environment/en/.

Harrell, F. E., 2016. Hmisc: Harrell Miscellaneous. from https://CRAN.R-project.org/package=Hmisc.

James, G., D. Witten, T. Hastie, and R. Tibshirani. 2015. An introduction to statistical learning with applications in R. Springer Texts in Statistics. Springer New York, Heidelberg, Dordrecht, London.

Klop, G., B. Hatew, A. Bannink, and J. Dijkstra. 2016. Feeding nitrate and docosahexaenoic acid affects enteric methane production and milk fatty acid composition in lactating dairy cows. Journal of Dairy Science 99(2):1161-1172.

Lu, Y., M. J. Vandehaar, D. M. Spurlock, K. A. Weigel, L. E. Armentano, C. R. Staples, E. E. Connor, Z. Wang, N. M. Bello, and R. J. Tempelman. 2015. An alternative approach to modeling genetic merit of feed efficiency in dairy cattle. Journal of Dairy Science 98(9):6535-6551.

McNulty, E., 2014. Understanding Big Data: the seven V's. Retrieved 24 March, 2017 from http://dataconomy.com/2014/2005/seven-vs-big-data/.

Mottram, T. 2016. Animal board invited review: Precision livestock farming for dairy cows with a focus on oestrus detection. Animal 10(10):1575-1584.

Ridgeway, G. 2015. gbm: Generalized Boosted Regression Models. from https://cran.r-project.org/web/packages/gbm/gbm.pdf.

Ripley, B. and M. Lapsley, 2016. ODBC connectivity. from https://cran.r-project.org/web/packages/RODBC/vignettes/RODBC.pdf.

Sonka, S. and Y.-T. Cheng. 2015. Big Data: More than a lot of numbers! Department of Agricultural and Consumer Economics, University of Illinois Urbana-Champaign 5: 201.

Van der Waaij, B. D., R. L. Feldbrugge, and R. F. Veerkamp. 2016. Cow feed intake prediction with machine learning. Pages 377-382 in Precision Dairy Farming 2016. C. Kamphuis and W. Steeneveld, ed. Wageningen Academic Publishers, Wageningen, the Netherlands, Leeuwarden, the Netherlands.

Van Es, A. J. H. 1975. Feed evaluation for dairy cows. Livestock Production Science 2(2):95-107.

Wickham, H. 2011. The Split-Apply-Combine Strategy for Data Analysis. 2011 40(1):29.

Zaslavsky, A., C. Perera, and D. Georgakopoulos. 2012. Sensing as a servive and big data. Pages 21-29 in Proc. International Conference on Advances in Cloud Computing (ACC-2012).

Using accelerometry to evaluate the weight data of the Walk over Weigh system in beef cattle

J. J. Roberts[1] and L. Moine[2]
[1]*Precision Livestock Management Group, Central Queensland University, Bruce Hwy Rockhampton, Australia*
[2]*Agrosup Dijon, 26 Boulevard du Docteur Petitjean, Dijon, France*
j.j.roberts@cqu.edu.au

Abstract

Wireless network technologies are important and useful for monitoring cattle health and productivity in extensive production systems. Walk over Weigh (WoW) systems remotely monitor animal weight and radio frequency identification tags.

WoW systems exhibit great potential in extensive systems for herd and feed management due to the versatility of their potential application (i.e. weight trends, calving, maternal lineage) and relative implementation ease. They are especially useful where producers cannot regularly monitor animals and the landscapes due to time and geographical constraints, for example in northern Australia.

Weight data recorded by a WoW can be inaccurate because of animal behaviour. Inaccurate weight may be recorded when an animal is running or when multiple animals are on a WoW platform at once.

Preliminary research to determine if accelerometers could be used to filter out inaccurate weight data in a herd of beef cattle was conducted. A tri-axial accelerometer was mounted on a TRU-TEST™ WOW!™ platform to monitor movement and duration of cattle on the platform. WoW records were compared to conventional weights (traditional monitoring) and visual surveillance of animal's behaviour when travelling over the scales.

Behaviours monitored included running, walking, single and multiple animals. Analysis was undertaken using R®, which showed the minimum, maximum and mean duration of cattle on the WoW platform differed for the four behaviours monitored. Data recorded from running and multiple animals were distinguishable. This initial study highlights the potential to integrate automatic analysis into WoW systems to improve the quality of data available to producers.

Keywords: Walk over Weigh, accelerometer, cattle behaviour, precision livestock management.

Introduction

Despite world leadership in beef production, the Australian cattle industry is experiencing difficulties, especially related to production variability. A large portion of Australia, especially in Queensland, the Northern Territory and the north half of Western Australia, is specialised in beef cattle production. Because of low stocking rates, extensive areas, varying quality of vegetation and a tropical climate, Northern Australian production has comparatively low live weight gains and reproductive rates compare to temperate counterparts. In 2015, northern herds had weaning rates as low as 50 and up to 80% (Behrendt and Weeks, 2017). While this is enough for replacing animals, the pregnancy rate during the first lactation can sometimes be very low (between 25 and 50 %) (Schatz *et al.*, 2008, Zhang *et al.*, 2014). Furthermore, weight gains of northern Australia production systems are around 104 kg lwt/cow/year, much lower than the rest of Australia which ranges from 210 to 340 kg lwt/cow/year (MLA, 2016). It has been acknowledged that this is an area with the potential for significant production improvement (Aldridge *et al.*, 2016; Behrendt and Weeks, 2017). Furthermore, despite the major losses incurred in this harsh environment, checking the livestock directly on a regular basis is simply not feasible or financially viable (Aldridge *et al.*, 2016).

In such situations where the harsh environment affects both production of meat and reproductive capabilities of a herd, the improvement of herd performances, including reproductive performance and meat production is a consequent issue and a priority for cattle breeders. The notion of precision livestock is logical for this situation. Indeed, using wireless network technologies combined with behavioural studies appears to be a solution. One of these technologies is WoW; it is an automated system that can weigh and identify an animal as it walks over a platform. Recent examples of using WoW for potential industry applications for this technology have focused on determining birth dates derived from weight changes (Aldridge *et al.* 2016) and maternal parentage through temporal association of weight records (Charmley, *et al.* 2006; Menzies *et al.* 2017) who investigated different ways of using a WoW to determine maternal parentage of calves born in extensive beef herds.

Unfortunately, the data recorded by the WoW are not always accurate and this issue is not new. In previous work by the investigators, it was observed that some behaviours led to incorrect weights Examples were when an animal travels

over the platform too quickly or multiple animals have their feet on the platform simultaneously.

Aldridge *et al.* (2016) made several suggestions including slowing the rate of passage with the inclusion of a crush or step leading up to, and a step after, the scale platform. These engineering solutions would prevent multiple animals from walking on the scale simultaneously. Another proposed solution was to consider improving the Tru-Test™ software. The collection of relevant data to identify the presence and or extent of WoW data error in the field is a necessary first step. This research aims to identify the potential to use accelerometry to differentiate accurate and inaccurate weight measurements through monitoring key behaviours and weight data.

Material and methods

This research was undertaken at the Central Queensland Innovation and Research Precinct at Central Queensland University, Rockhampton, Queensland, Australia. The research was approved by the Central Queensland Animal Ethics Committee, approval number 20119.

Cattle

Eight, nine month old heifers were monitored for the duration of this research. Five of the heifers were Brahmans and three Droughtmasters. Cattle were grazed on pasture and had access to one water source, which is only accessible via a WoW platform. In the months prior to this research the cattle were peer trained for the WoW system. The peer training involved socialising the heifers with experienced cows and calves for several weeks. The experienced cattle demonstrated walking across the WoW platform, resulting in the heifers crossing the platform without hesitation by the commencement of this research.

Weighing system and accelerometer

Cattle were weighed conventionally and with the WoW. Conventional weighing used TRU-TEST™ scales and data logger in a crush. In conventional weighing, the weight of an animal is recorded by the data logger when the scales reach stability. Conventionally measured weights of the cattle were recorded 10 times on nine days over a period of 22 days.

The WoW system included a set of TRU-TEST™ WOW™ scales coupled with a Radio Frequency Identification (RFID) reader and data logger. Weights are recorded as cattle step off the weighing platform. The scales were located before a spear gate in a race leading into the paddock's only fresh water source.

A tri-axle piezoelectric accelerometer, X16-1D Gulf Coast Data Concepts, LLC, was mounted to the base of the WOW platform. The accelerometer was connected to a Raspberry Pi™ 3 Model B, microcomputer linked to the WoW. The vibrations of the accelerometer from movement in the platform triggered the Raspberry Pi™ to record the signal. The recording lasted for 28 seconds with a sample rate of 70 $m.s^{-2}$. Time stamps were used to align accelerometer data to RFID for identifying the movement of the individual cattle.

Cattle weighing events

For each weighing event, the heifers were first weighed using the conventional method. From there, the cattle were moved towards a compound with the WoW system. The heifers were encouraged to go over the WoW platform to enter the water trough compound with or without human pressure. This was repeated. The water trough was made inaccessible for the first entrance into the compound and released for the second visit. This was done to increase data collected without the influence of weight gain due to water intake. After the second visit to the compound, the cattle were given a small amount of hay to supplement them as it was the dry seasons when pastures are relatively low in nutrients.

The WoW system remained fully functional for the entire 23 days. This allowed for extra data collection from the WoW system. However, weights measured outside of the main data collection events did not have comparable conventionally measured data.

Data analysis

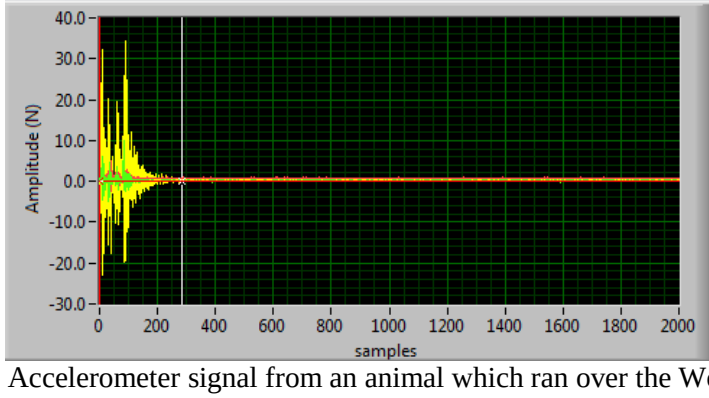


Figure 1: Accelerometer signal from an animal which ran over the WoW scale.

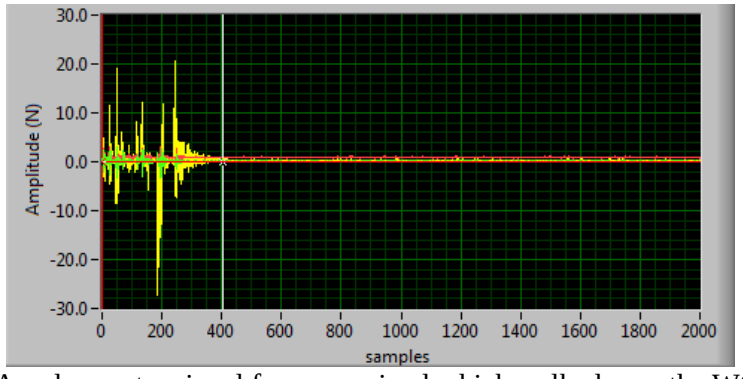


Figure 2: Accelerometer signal from an animal which walked over the WOW scale.

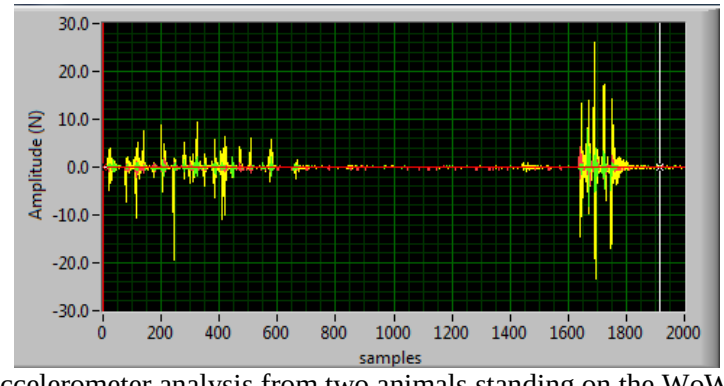


Figure 3: Accelerometer analysis from two animals standing on the WoW platform at the same time.

Raw accelerometer data are presented as a text file. This file contains all the values, according to the three dimensional axis, which represent the vibrations of the platform during each recorded event. A custom program was developed at Central Queensland University to process the accelerometer data. An example of the accelerometer signal data related to the three key behaviours as cattle passed over the WoW platform are presented in Figures 1-3. Figure 1 presents a signal of a running heifer. The duration is shorter and the amplitude is larger. Figure 2 presents that of a walking heifer, which has a shorter duration that in Figure 3. Figure 3 presents the signal of two animals walking on the scale during one data collection event. The duration of the passage is identifiable, through the introduction and conclusion of peaks and troughs in the data.

The data, summarised in Table 1, was analysed in a using R® and Rstudio®. A total of 77 observations were collected. Of these, 86% represent walking behaviours and 73% represent data collected from events where only one animal was on the WoW platform. The data were filtered to remove weights recorded as

zero. These occur when no weight is measured, but an ear tag is recorded. This resulted in the removal of 14 observations.

Results and discussion

Cattle Live weights

The difference between the conventional and WoW weights which were measured within minutes of each other was calculated for each comparable observation. The WoW weight measures were considered as inaccurate when the difference between the two weights was greater than 2 % of the static weight.

Cattle behaviour on the platform

The passage over the WoW platform was assessed according to two criteria: the number of animals on the scale (1 or more) and the behaviour (running or walking). In figure 4 the mean of the duration of walking heifers when the heifers are walking is higher than for running heifers with 6.22 and 2.43 s respectively. Additionally, the standard deviation is lower for running cattle. Thus, from this preliminary dataset, it appears duration, as measured by an accelerometer, is providing useful information.

Figure 5 represents the duration of an event according to the number of animals on the scale. The duration of a single or multiple animal event is significantly different. The passage of the animals is clearly longer when there is more than one animal on the scale. However, the range of values of the ‘two animals” criteria is a consequence of the herd mentality. Indeed, they generally come all together to drink. So they follow each other onto the scale. After visually observing the cattle activity, it was noted that sometimes there was even more than two animals recorded in the same even due to this tendency of cattle to walk note-to-tail: the platform can support the back legs of the first animal, all four legs of the second animals and the two front legs of the third.

The mean duration per animal is presented in Figure 5. The herd duration was compared with the individual animal duration. When the WoW weight was more than 2% different to the conventional weight and the duration of the event is greater than the mean, there is more than one animal on the scale. When the WoW weight is inaccurate and the duration is lower than the mean, the animal was running on the scale.

Table 1. Summary of the number of data records collected or each event of heifers crossing the WoW. Data was filtered to remove weights recorded as zero.

	Unfiltered records	% (unfiltered)	Filtered records	% filtered
Walking events	66	85.7	60	95.2
Running events	11	14.3	3	4.8
One animal	56	72.7	49	77.8
Two animals	21	27.3	14	22.2
Total	77	100	63	100

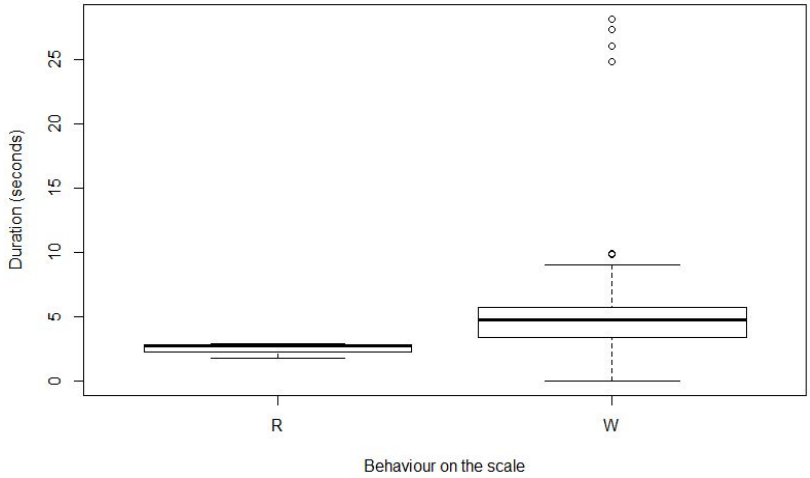


Figure 4. Duration of cattle on the WoW platform according to running (R) or walking (W) behaviour.

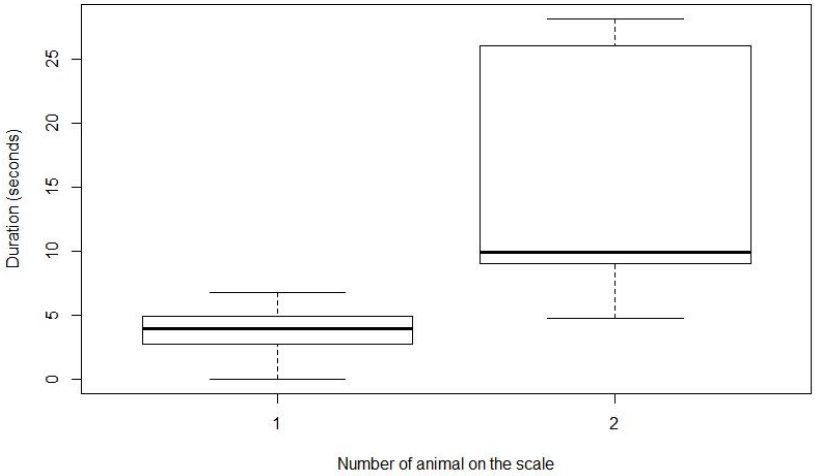


Figure 5. Duration of cattle on the WoW platform according to the number of animals on the scale: a single animal (1) or multiple animals (2).

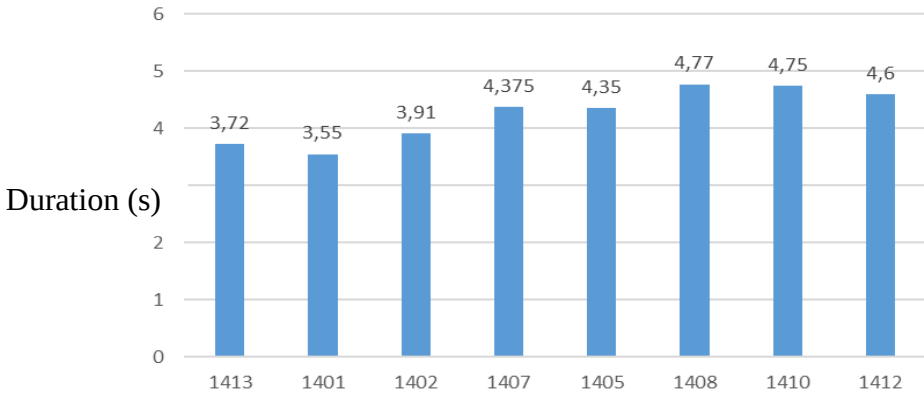


Figure 6: Mean duration of individual animals crossing a WoW platform, with ID on the x axis and mean duration labelled.

Conclusion

Duration was able to provide insight into the accuracy of animal weights. What is more impressive at this early stage is the visual representation of the signal indicates a difference in behaviours. While duration is a simple attribute to measure, the next step is to analyse the accelerometer signal in more depth, beyond duration and focusing on the signal pattern itself. There is the potential for algorithm development for individual animals. The quite clear differences in the four behavioural categorise monitored highlight that if pursued further, this could lead to increased information on data validity, health and production related to weighing the animal that has been recorded autonomously by the RFID. Additionally, a technology such as this could be a great used in observing health status of livestock from afar if their ‘usual’ pattern of movement changes. Indeed, further development of accelerometers to investigate gait, duration on the platform and amplitude of vibrations could lead to herd diagnostics for a production systems severely lacking in the ability to monitor and manage herd health closely.

Acknowledgements

This project was supported by Mr Don Menzies, Mr Greg Capern and the Institute of Future Farming, Central Queensland University.

References

Aldridge, M.N., Lee, S.J., Taylor, J.D., Popplewell, G.I., Job, F.R., and Pitchford, W.S. 2016. The use of walk over weigh to predict calving date in extensively managed beef herds. *Animal Production Science* **57** 583-591.

Behrendt, K., Weeks, P. 2017, MLA Market Information report – How are global and Australian beef producers performing? Meat and Livestock Australia Limited, Australia.

Charmley, E., Gowan, T. L., Duynisveld, J. L. 2006. Development of a remote method for the recording of cattle weights under field conditions. *Australian Journal of Experimental Agriculture*, **46**, 831-835.

Menzies, D., Patison, K. P., Corbet, N. J., & Swain, D. L. 2017. Using temporal associations to determine maternal parentage in extensive beef herds. *Animal Production Science*.

Pastell, M., Aisla, A.M, Hautala, M., and Poikalainen, V., Praks, J. Ahokas, J. 2006. Measuring lameness in dairy cattle using force sensors. In: *Agricultural engineering for a better world: XIV CIGR World Congress: AgEng Bonn, 64th VDI-MEG International Conference Agricultural Engineering: FAO Workshop global issues.*

Schatz, T.J., and Hearnden, M.N. 2008. Heifer fertility on commercial cattle properties in the Northern Territory. *Australian Journal of Experimental Agriculture* **48** 940-944.

Zhang, Y.D., Johnston, D.J., Bolormaa, S., Hawken, R.J., and Tier, B. 2014. Genomic selection for female reproduction in Australian tropically adapted beef cattle. *Animal Production Science* **54** 16-24.

Effect of feeding out frequency of mixed feed on feeding behaviour, feed intake, and milk production in an automatic milking herd

K. H. Sloth[1], C. Coletti[2], A. Peña Fernández[3], D. Bossen[4], E. Tullo[2], I. Fontana[2], M. Guarino[2]
[1]*GEA Farm Technologies GmbH, Nørskovvej 1B, DK-8660 Skanderborg, Denmark*
[2]*Department of Environmental Science and Policy, Università degli Studi di Milano, Via Celoria 2, 20133 Milan, Italy*
[3]*Department of Biosystems, Division M3-BIORES: Measure, Model & Manage Bioresponses, KU Leuven, Kasteelpark Arenberg 30, 3001 Heverlee, Belgium*
[4]*Agri Nord, Markedsvej 6, DK-9600 Aars, Denmark*
KarenHelle.Sloth@gea.com

Abstract

Excellent feed management is one of the main drivers to achieve high production outputs in Precision Dairy Farming (PLF). In this context, increased automation offers possibilities to serve fresh feed at a higher frequency to motivate cows to have more meals and eat more feed. A trial was set up in a commercial dairy herd where each of two experimental treatments was applied twice to two groups of lactating cows. The treatments included (1) partially mixed ration (PMR) divided into six servings of equal size per day (one every four hours) and (2) PMR divided into twelve servings of equal size per day (one every two hours). Every experimental period lasted seven days and was preceded by a seven days transition period with the new feeding out frequency applied. Mixed models were used to evaluate the effect of the experimental treatments on three feed event-based feeding behaviours and three meal-based feeding behaviours, dry matter and energy intake, daily milk yield and number of milkings. In this study, feeding the PMR divided into twelve servings per day resulted in a small but significant increase in average daily feed intake per cow. The feed was consumed during more feed events and meals, however, of shorter duration and shorter total feed time. In short, cows ate more in less time with twelve feed deliveries. The increase in feed intake and change in feeding behavior did not convert into increased milk attendance or milk production as we found no effect of feeding frequency on number of milkings per day or daily milk yield. Group, parity, days in milk and repetition included in the statistical models proved to be important factors for most of the response variables.

Keywords: PLF, automatic feeding, RTLS, feed intake, milk yield, number of milkings

Introduction

Excellent feed management is one of the main drivers to achieve high production and different types of automation in Precision Livestock Farming (PLF) represent possibilities for improving on-farm feeding management. In precision dairy farming improving individual feed intake of cows is an ongoing focus topic. Indeed, offering main part of the ration in smaller servings at a higher frequency may motivate cows to eat more and more often. DeVries and Keyserlingk (2005) pointed out that delivery of fresh feed is a strong driver in stimulating group-fed cows to eat. Other studies support the positive effect of frequent feed deliveries as it gives more equal access to fresh feed for all cows in a group (DeVries et al., 2005), and less change in the feed ration over time (Endres and Espejo, 2010) due to less feed sorting (DeVries et al., 2005; Sova et al., 2013). Moreover, some studies have shown positive influence of frequent feeding on the digestion of feed. A more even distribution of daily feeding time may contribute to less diurnal variation in rumen pH (Shabi et al., 1999) and higher fiber digestibility (Dhiman et al., 2002).

In automated milking herds continuous cow traffic flow is important to fully optimize the utilization of the automatic milking capacity. Oberschätzl-Kopp et al. (2016) found increased feeding and milking attendance and less waiting time in front of the feed bunk when the mixed ration was delivered more often (six times versus two). In a similar study Oostra et al. (2005) found no difference in milking attendance but less time spent queueing up per visit in the automated milking system when feeding six times compared to two. Using an automated feeding system Mattachini et al. (2015) took frequent feed deliveries to a new level comparing six versus eleven feed deliveries in an automated milking herd. This study used interval video scans to quantify feeding time. However, Real-Time-Positioning-Systems (RTLS) now offer the possibility to quantify cows' whereabouts 24-7 (Tullo et al., 2016) and convert these whereabouts into detailed individual cow time budgets (Sloth et al., 2015). We believe this technology has potential for visualizing important daily aspects of cow responses to feeding management on farm. Therefore, the purpose of this study was to quantify the effects of high (six times) and very high (twelve times) feeding frequency on RTLS classified feeding behaviour, feed intake, daily milk yield and milking attendance in a farm with automated feeding and milking system.

Materials & Methods

Experimental design

The feeding trial was performed at a commercial automatic milking herd with 220 cows (Holstein, Swedish Red-and-White, and crossings). The dataset was

collected over four experimental periods of seven days duration in 2015 (see Table 1).

Table 1. Trial design in terms of repetition, experimental periods, number of cows per group and number of feed deliveries applied.

Repetition	Experimental period	Group	Number of cows	Feed deliveries per day
1	April 15th – April 21st	2029	84	6x
	2015	1019	88	12x
	April 29th – May 5th	1019	90	6x
	2015	2029	86	12x
2	June 4th – June 10th	2029	95	6x
	2015	1019	93	12x
	June 18th – June 24th	1019	94	6x
	2015	2029	95	12x

Two groups (1019, 2029) of lactating dairy cows were included. The experimental treatments were applied twice to each group (two repetitions) and included (1) partially mixed ration (PMR) divided into six equally sized servings per day (once every four hours) and (2) PMR divided into twelve equally sized servings per day (once every two hours). Every experimental period was preceded by a seven day transition period with the new feeding frequency applied. The cows were housed in two equally sized free-stall environments with mattress equipped cubicles (dried sawdust as bedding) and post-and-rail system along the feed bunks. Cow traffic was free in group 1019 and guided (milk first) in group 2029. Between the first and the second repetition of the trial, a milking pre-selection gate was installed in group 2029 changing the guided cow traffic from ‘milk first’ to ‘selective milk first’. Parity and days in milk in group 1019 were 1.6 ± 0.8 and 145 ± 89 and in group 2029 1.7 ± 1.1 and 164 ±134 (mean ± standard deviation), respectively. Animal densities cubicle- and feed-bunk-wise were 1.00 ± 0.02 animals per cubicle and 52.5 ± 1.3 cm feed bunk space per animal in group 1019 and 1.08 ± 0.02 animals per cubicle and 48.7 ± 1.0 cm feed bunk space per animal in group 2029 (mean ± standard deviation).

Feeding behaviour

Feeding behaviour variables were derived from RTLS data provided by the GEA CowView system based on classification of cow positions within activity zones e.g. feed event equal to cow being positioned at the feeding table. Overall, six feeding behaviour variables were investigated: average number of feed events, average duration of feed events, average total total feed event time (= average total time spent at the feeding table), average number of meals, average meal

duration, and average total daily meal time. The mixed density approach by Tolkamp et al. (1998) was used to create the meal variables based on the feed event data. It implies the need for a herd level meal criterion, which was estimated to 3.06 $\log_{10}$ seconds (=19.1 minutes) using a three-component mixture model (FMM procedure, SAS) with two normal and one Weibull distributions. At animal level, a new meal was generated every time an interval between two feeding events exceeded duration of the herd level meal criterion. Before summarizing the feeding variables to individual animal average values per experimental period, outliers in meal-based feeding variables were filtered out using the median absolute deviation (MAD) method according to Leys et al. (2013) on $\log_{10}$ transformed meal durations within animal. The level of two times MAD (95 % level) was chosen to remove extremely short and long meal durations.

Feed ration and feed intake

The full ration fed to the lactating dairy cows included the PMR and two individually adjusted concentrate types. Two batches of the PMR were prepared daily in a stationary mixer (Cormall Multimix 2010, Cormal A/S, Sønderborg, Denmark) at 7 am and 5 pm, respectively. The mixed ration was stored in the stationary mixer which automatically supplied the feed distribution system, an automatic Free Stall Feeder M2000 (GEA Farm Technologies Mullerup A/S, Ullerslev, Denmark) during day and night. Both concentrate types were fed in the milking robots and supplied individually according to milk yield, parity and stage of lactation. Amounts of the concentrate types supplied were recorded at individual animal level via the dairy herd management program. The PMR consisted of: grass silages, corn silage, rolled barley, concentrate, feed salt, feed chalk, mineral premix and water. A minor adjustment of the amount of the different cut grass silages in the PMR was performed between the first and second repetition. Weights of all feed ingredients were recorded daily at mixing and weight of PMR supplied was monitored at group level. Furthermore, weight of feed residuals was recorded on removal. Feed residuals weighed during the experimental periods were limited: 1.3 ± 2.7 % in group 1019 and 1.1 ± 1.4 % in group 2029 (mean ± standard deviation). Dry matter and net energy for lactation of the PMR was calculated using feed batch analyses or table values for delivered minus feed residuals assuming same relative composition. As the proportions of young and old cows in the two groups were unbalanced, we chose to factor the feed intake capacity of cows in 1st lactation to 0.81 of older cows when estimating individual daily intake of the PMR (Østergaard et al., 2003). Dry matter and net energy for lactation of concentrate were calculated using feed information given by the feed supplier. For statistical evaluation, daily records of

total dry matter and energy intake were averaged to single animal-level values per experimental period.

Milk attendance and milk yield

Number of milkings per day and daily milk yield were recorded at animal level via the automatic milking system. Each group of cows was served by one 2-box MiOne robot (GEA Farm Technologies GmbH, Bönen, Germany). Cows with more than 10 hours since last milking were fetched for milking twice daily. For statistical evaluation, daily records of number of milkings and milk yield were averaged to single animal-level values per experimental period.

Statistical evaluation

The general null hypothesis to be investigated was that changing feeding frequency would not affect the cows' feeding behaviour, feed intake, number of milkings per day or daily milk yield. To examine this, a multivariable mixed model for each response variable was produced (MIXED procedure, SAS) including the following fixed main effects: Group affiliation (1019, 2029), parity (1, 2, 3+), days in milk (0-89, 90-220, >220), repetition (1, 2), and feeding out frequency (6x, 12x). Cow was fitted as random effect. Full model least-square mean values (LSMEANS, SAS) with 95%-confidence intervals were generated as estimates of treatment effect levels.

Results & Discussion

Feeding behavior

In this study, feeding out the PMR divided into twelve servings per day resulted in a small but significant increase in average daily feed intake per cow. The feed was consumed during more feed events and meals, however, of shorter duration and shorter total feed time (see Table 2). In short, cows ate more in less time with twelve feed deliveries. Some published studies have found increased feeding time when increasing the number of feed deliveries: DeVries et al. (2005) comparing 1x with 2x feeding and 2x with 4x feeding per day, and Oberschätzl-Kopp et al. (2016) comparing 2x with 6x feeding. Other studies have found either no significant differences in feeding time (Mäntysaari et al., 2006; 1x feeding compared with 5x) or only differences in behaviors the first hour after time of feeding out (Mattachini et al., 2015; 6x feeding compared with 11x). Concerning feed intake, Mäntysaari et al. (2006) found increased feed intake when feeding 1x compared to 5x per day, while Mattachini et al. (2015) found no difference in feed intake.

Table 2. Effects of six versus twelve feed deliveries of the PMR on cow feeding behavior and total feed intake in an automatic milking herd. Estimated main effects are full model least-square mean values; 95%-confidence intervals in brackets ([ ]).

Response variable	Feeding out frequency		F-test,
	6x	12x	*P*-value
N feed events, count/day	88.0 [84.0-92.0]	79.7 [75.7-83.7]	<0.0001
Feed event duration, seconds	243 [233-252]	213 [204-223]	<0.0001
Total feed event time, hours/day	4.72 [4.58-4.87]	4.58 [4.43-4.72]	0.0004
N meals, count/day	7.14 [6.91-7.38]	7.73 [7.50-7.97]	<0.0001
Meal duration, minutes	55.7 [53.4-57.9]	52.5 [50.2-54.7]	<0.0001
Total meal time, hours/day	6.13 [5.93-6.33]	6.22 [6.02-6.42]	0.1324
Dry matter intake, kg/day	22.5 [22.2-22.7]	22.7 [22.5-22.9]	0.0023
NEL[1], MJ/day	153.0 [151.4-154.6]	154.7 [153.0-156.3]	0.0073

[1]Net energy intake for lactation

There may be many reasons for differences between our results and other studies beside the specific feeding frequencies investigated. First of all, the applied estimation method of individual PMR intake is rather rough using group level records instead of individual feed troughs with weight scales producing electronic records of individual feeding time and feed intake. Furthermore, no surveillance of the feed value of either PMR or refusals was performed during the trial to control for day-to-day variation in especially roughage components. When comparing with other studies, another important point could be the very low amount of residual feed recorded in the present study. Sova et al. (2013) suggest based on their findings in a large observational study, that frequent feeding and feeding for lower refusal rates may promote consumption of an unsorted diet close to that intended. However, the experimental results of French et al. (2005) showed that feeding for low feeding refusals changed the feeding behavior of the cows to consume the same amount of feed in less time. We suspect that the splitting of the PMR into as many as twelve smaller servings and having almost no feed residuals may have created periods during the day resembling limit feeding with possibly some competition for feed motivating the cows to eat more, more often and faster than at six servings per day.

Milk attendance and daily yield

The increase in feed intake and change in feeding behavior did not convert into increased milk production or milk attendance as we found no effect of PMR feeding frequency on daily milk yield or number of milkings per day (see Table 3). For comparison, Oberschätzl-Kopp et al. (2016) found a significantly higher milking frequency but no difference in daily milk yield when feed was delivered six times per day compared to two times while Mattachini et al. (2015) found no difference in milking frequency but a tendency for higher milk yield when feeding six times per day compared to eleven times per day. Furthermore, Mattachini et al. (2015) suggested that the higher feeding frequency may have disturbed the lying behavior of the cows influencing animal welfare and milk production. If limit feeding with some degree of competition for feed in addition to possibly disturbed resting behavior was the case in our study, then this could possibly explain the difficulty in converting a small increase in feed intake into higher milk production.

Table 3. Effects of six versus twelve feed deliveries of the PMR on cow milk yield and number of milkings per day in an automatic milking herd. Estimated effects are main effect model least-square mean values; 95%-confidence intervals in brackets ([ ]).

Response variable	Feeding out frequency		F-test,
	6x	12x	*P*-value
Milk yield, kg/day	26.7 [25.7-27.8]	26.5 [25.4-27.5]	0.2288
Number of milkings, count/day	2.20 [2.13-2.28]	2.19 [2.12-2.26]	0.5948

Effects of parity and days in milk

Results from the feeding behaviour models showed that younger cows (1st and 2nd lactation) had more feed events and meals and longer total feeding event and meal times than older cows. Furthermore, cows in early and mid-lactation had significantly more meals, more total feeding time and total meal time than cows in late lactation. Feed event duration and meal duration were longest for cows in mid-lactation. These effects are not completely similar to what have been found in another recent feeding trial (Sloth et al., 2017) which underlines specificity in herd response to feeding management in general. Feed intake models estimated higher feed intake in early and mid-lactation than in late lactation and cows in 1st lactation to have lower feed intake compared to older cows. However, both of these effects are clearly related to the supplementation plan for concentrate in the robots and the estimation approach used for individual consumption of PMR in this trial. Cows in early and mid-lactation had more milkings and produced more milk per day compared to cows in late lactation. The fixed effect of parity showed that the number of milkings and milk production was significantly higher in 2nd lactation

than in 1st, 3rd and older lactations in this herd. Poor average performance of the oldest group of cows may be due to recent expansion of the herd, keeping older low producing cows longer than normal and possibly lower milk allowance for low producers in the milking robots.

Effects of group affiliation and repetition

In general, group1019 had higher feed intake distributed across more but shorter meals and less total feeding time compared to group 2029. Also, group 1019 had a significantly higher number of milkings per day. This may be related to difference in cow traffic and/or the marginally lower animal density concerning feed space, cubicles and milking robotic-wise in this group. The significant effect of repetition in five out of the six feeding behavior models and number of milkings per day was most likely due to differences in feed and/or barn environmental factors like change in cow traffic in group 2029 between first and second repetition and possibly differences in temperature and humidity between the repetitions. However, repetition as main effect was not significant in the dry matter or energy intake models, nor in the milk yield model.

Quantification of feeding behavior using RTLS

Defined feeding event as well as meal variables based on RTLS data were explored and used to quantify changes in feeding behaviour in this study. Total feed event time and total meal time differs, because meals by definition include short intra-meal time intervals where the cow leaves the feed bunk to change feeding position and a bit longer intra-meal time intervals when eating is interrupted by a drinking activity. In this way, meals reflect periods in time where the cow is highly motivated to eat. Generally, we feel safer using detailed feed event variables because of variation in non-feeding intra-meal time intervals in meals. Other studies report feeding activity or feeding time along with number of meals, meal duration and total meal time (DeVries et al., 2003; Hosseinkhani et al., 2008).

Conclusion

In this study, feeding the PMR divided into twelve servings per day resulted in a small but significant increase in average daily feed intake per cow. The feed was consumed during more feed events and meals, however, of shorter duration and shorter total feed time. In short, cows ate more in less time with twelve feed deliveries. The increase in feed intake and change in feeding behavior did not convert into increased milk attendance or milk production as we found no effect of feeding frequency on number of milkings per day or daily milk yield. Group,

parity, days in milk and repetition included in the statistical models proved to be important factors for most of the response variables.

Acknowledgement

This project has received funding from the European Union's Seventh Programme for Research, Technological Development and Demonstration under Grant Agreement No 311825.

References

DeVries, T.J., M. A. G. von Keyserlingk, D. M. Weary, and K. A. Beauchemin. 2003. Measuring the feeding behavior of lactating dairy cows in early to peak lactation. J. Dairy Sci. 86: 3354-3361.

DeVries, T. J. and M. A. G. von Keyserlingk. 2005. Time of feed delivery affects the feeding and lying patterns of dairy cows. J. Dairy Sci. 88, 625-631.

DeVries, T. J., M. A. G. von Keyserlingk, and K. A. Beauchemin. 2005. Frequency of feed delivery affects the behavior of lactating dairy cows. J. Dairy Sci. 88, 3553-3562.

Dhiman, T. R., M. S. Zamen, I. S. MacQueen, and R. L. Boman. 2002. Influence of corn processing and frequency of feeding on cow performance. J. Dairy Sci. 85, 217-226.

Endres, M. I. and L. A. Espejo. 2010. Feeding management and characteristics of rations for high-producing dairy cows in freestall herds. J. Dairy Sci. 93, 822-829.

French, P. J. Chamberlain, and J. Warntjes. 2005. T176 Effect of feed refusal amount on feeding behavior and production in Holstein cows. J. Dairy Sci. 88, Suppl. 1, p. 175.

Hosseinkhani, A., T. J. DeVries, K. L. Proudfoot, R. Valizadeh, D. M. Veira, and M. A, G. von Keyserlingk. 2008. The effects of feed bunk competition on the feed sorting behavior of close-up dry cows. J. Dairy Sci. 91, 115-1121.

Leys, C., C. Ley, O. Klein, P. Bernard and L. Licata, 2013. Detecting outliers: Do not use standard deviation around the mean, use absolute deviation around the median. Journal of Experimental Social Psychology (2013), http://dx.doi.org/10.1016/j.jesp.2013.03.013

Mattachini, G., E. Riva, J. C. A. M. Pompe, G. Provolo. 2015. Automatic monitoring of cow behavior to assess the effects of variations in feeding delivery frequency. Pages 473-481 in: Proc. Precision Livestock Farming 2015, Session 12 Feed and Cattle, 7th European Conference on Precision Livestock Farming, September 15-18 2015, Milan, Italy.

Mäntysaari, P., H. Khalili, and J. Sariola. 2006. Effect of feeding frequency of a total mixed ration on the performance of high-yielding dairy cows. J. Dairy Sci. 89, 4312-4320.

Oostra H., J. Stefanowska, and K. Sallvik. 2005. The effects of feeding frequency on waiting time, milking frequency, cubicle and feeding fence utilization for cows in an automatic milking system. Acta Agriculturae Scandinavica, Section A – Animal Science 55(4), 158-165.

Oberschätzl-Kopp, R., B. Haidn, R. Peis, K. Reiter, H. Bernhardt. 2016. Studies on dairy cow behavior with automatic feeding in a herd milked by AMS. Landtechnik 71 (2), 55-65.

Shabi, Z., I. Bruckental, S. Zamwell, H. Tagari, and A. Arieli. 1999. Effects of extrusion of grain and feeding frequency on rumen fermentation, nutrient digestability, and milk yield and composition in dairy cows. J. Dairy Sci. 82, 1252-1260. SAS Institute Inc., SAS® 9.4.

Sloth, K. H., D. Frederiksen, and S. Klimpel. 2015. Estimated cow time-budgets using a Real Time Location System. Pages 740-748 in: Proc. Precision Livestock Farming 2015, Posters, 7th European conference on Precision Livestock Farming, September 15-18 2015, Milan, Italy.

Sloth, K. H., C. Coletti, A. Peña Fernández, D. Bossen, E. Tullo, I. Fontana, M. Guarino. 2017. Effects of frequent feed pushes of mixed feed on feeding behaviour, feed intake, and milk production in an automatic milking herd. 8th European Conference on Precision Livestock Farming (EC-PLF), September 12 -14 2017, Nantes, France. Accepted.

Sova, A. D., S. J. LeBlanc, B. W. McBride, and T. J. DeVries. 2013. Associations between herd-level feeding management practices, feed sorting, and milk production in freestall dairy farms. J. Dairy Sci. 96, 4759-4770.

Tolkamp, B. J., D. J. Allcroft, E. J. Austin, B. L. Nielsen, and I. Kyriazakis. 1998. Satiety splits feeding behavior into bouts. J. Theor. Biol. 194, 235-250.

Tullo, E., I. Fontana, D. Gottardo, K. H. Sloth, and M. Guarino. 2016. Technical note: Validation of a commercial system for the continuous and automated monitoring of dairy cow activity. J. Dairy Sci. 99, 7489-7494.

Østergaard, S., T. Kristensen, O. Aaes, V. F. Kristensen, M. Jensen, S. Clausen. 2003. 16. Planlægning af økonomisk optimal fodring af malkekøer. In: DJF rapport Husdyrbrug nr. 54. Kvægets ernæring og fysiologi. Bind 2. Fodring og produktion. Edited by F. Strudsholm and K. Sejersen. Published by: Danmarks JordbrugsForsking, Ministeriet for Fødevarer, Landbrug og Fiskeri. P. 371-405.

Session 11

Oestrus and calving

The use of sensor data before parturition as an indicator of resilience of dairy cows in early lactation

R.M. de Mol[1], I.D.E. van Dixhoorn[1], J.T.N. van der Werf[1], C.G. van Reenen[1], S. van Mourik[2]
[1]*Wageningen Livestock Research, P.O. Box 338, 6700 AH, Wageningen, The Netherlands*
[2]*Wageningen University, P.O. Box 16, 6700 AA, Wageningen, The Netherlands*
rudi.demol@wur.nl

Abstract

The transition period is a critical phase in the life of dairy cows. Metabolic and infectious disorders occur mostly in the first weeks after calving. These disorders can be considered as critical transitions for which early-warning indicators might be available following the theory of resilience of biological systems. Sensor data might be useful to notice early-warning signals like slower recovery from perturbations, increased autocorrelations and increased variance. Sensor data (measuring activity and behaviour) and extensive reference data were collected for a group of 22 dairy cows during a period from 2 weeks prior to expected parturition until 6 weeks after parturition. During this period the cows were scored daily for health status. The number of days of diminished health (DDH) were used a health measure of a cow. The correlations of the log-transformed DDH with several sensor quantities were determined. Correlations with average values were significant (*) for inactive time and eating time. Correlations with variances were significant (*) for ear temperature and number of steps. Correlations with autocorrelations were not significant. Correlations with nonperiodicity were significant for eating time (*), number of steps (**), motion index (**) and lying time (***); where nonperiodicity was defined as the mean squared error of the correlogram with a sinusoid with a 24h cycle and an amplitude of 0.25. The high correlations before parturition of some sensor data with nonperiodicity might be used as indicator for critical transitions after parturition. Further research is needed to validate whether a regular life may prevent disorders in dairy cows

Keywords: dairy cows, transition, sensors, circadian rhythm, early warning

Introduction

The transition period is a critical phase in the life of dairy cows. The transition period is marked by changes in endocrine status that pave the way for parturition

and lacto-genesis and is defined as the period between 3 weeks pre-partum and 3 weeks post-partum (Grummer, 1995). It is a demanding period for dairy cows which makes them vulnerable for the development of metabolic and infectious diseases (Huzzey *et al.*, 2007). Especially in the first weeks after calving, cows experience a high incidence of diseases and metabolic disorders, such as hypocalcaemia, hypomagnesaemia, ketosis as well as retained placenta, displacement of the abomasum, metritis and laminitis (Urton *et al.*, 2005). Metabolic stress occurs when cows fail to adapt physiologically to an increase in nutrient requirements needed for parturition and milk synthesis and secretion. This metabolic stress causes health disorders together with dysfunctional inflammatory responses and the experienced oxidative stress (Sundrum, 2015).

Great progress has been made in understanding the biology of energy metabolism and immune function as well as how to provide the behavioural and nutritional needs of transition dairy cows (LeBlanc *et al.*, 2006). Also epidemiological studies have revealed critical risk factors for these diseases. Based on this knowledge, generic veterinary herd health management programs have often been developed to shift from curative to preventive health management (Derks *et al.*, 2013). Although successes have been achieved in diminishing incidences of milk fever, clinical respiratory diseases in adults, contagious mastitis and clinical parasitism, the incidence of most common and important diseases remain stable (LeBlanc *et al.*, 2016). According to LeBlanc 30%-50% of dairy cows are affected by some sort of metabolic or infectious disease around the time of calving (LeBlanc, 2014). Apparently cows still have difficulties in adapting to all changes and disturbances occurring inside and outside the animal during the transition period resulting in this high incidence of peri-parturient disorders (Sundrum, 2015). Hence, transition management should be improved, however the solution is not completely evident (van Saun and Sniffen, 2014).

Herd health management often focusses on solutions at group level. Feeding regimes, especially total mixed rations are formulated according to the average performance of a group within the herd. Production or age groups within dairy herds are exposed to the same feeding and housing conditions despite the fact that individual cows can vary considerably in their needs, due to differences in weight, milk yield, age, social rank, etc. Also group size, grouping strategy and group feeding behaviour have large impact on the competition between animals for feed, feed intake and (resting) space (Grant and Albright, 1995). Competition itself is also perceived differently depending on the social rank degree. Also the ability to cope with metabolic stress varies considerably between individual cows (Kessel *et al.*, 2008). So there is individual variation between animals in their adaptive capacity to the changes and this variation can be further influenced by environmental, management, feeding, housing factors. The many possible

causes that contribute to development of metabolic disorders and the large variation in management between farms indicate that transition management should always be analysed within its specific (farm) context. The most limiting factors that contribute to the overstressed ability of all present animals to adapt to their living conditions are the key factors that need to be improved. Current herd health management often focusses on fertility, milk production and udder health, less often on claw health, young stock and housing aspects (Derks *et al.*, 2013). It is clear that animals within a herd will be better able to adapt in order to survive, if appropriate resources and living conditions are offered which meet the individual requirements at the different stages of their lives and if nutritional and other disturbances are reduced to a minimum (Sundrum, 2015).

Optimal management requires continuous and comprehensive monitoring of appropriate indicators reflecting the adaptive capacity of cows together with farm management analysis indicating the crucial risk and critical success factors at farm level. At this moment there are no indicators that identify cows at risk for developing transition period related disorders. Management programs would especially benefit if early identification of individual cows at risk for disease is embedded. This would allow for early intervention and optimization of the transition period at individual level. Providing the behavioural needs and room to obtain the nutritional needs for all animals within a herd, would improve adaptive capacity of all animals, and thus diminishing health problems.

Based on the theory of resilience of biological systems (Walker *et al.*, 2004, Scheffer *et al.*, 2009) we hypothesize that the level of vulnerability of an individual cow can be quantified by describing dynamical aspects of continuously measured physiological and behavioural variable. Suggested indicators in Scheffer *et al.* (2012) are variance, autocorrelation and others.

To examine the risk to develop diseases early in the lactation period, we modelled the relationship between dynamic patterns of high-resolution, continuous physiological and behavioural data recorded in individual cows before calving with the score of post-partum clinical disturbances within dairy cows.

Material and methods

Animals, housing and diet

A group of 22 Dutch Holstein-Friesian dairy cows of mixed age within a Dutch dairy farm situated in the east of The Netherlands was selected for the experiment. The experiment took place between the 14th of April 2014 and the 26th of July 2014. The selection was based on the expected day of parturition. Experimental period per cow lasted from 2 weeks prior to expected parturition until 6 weeks after parturition. The cows were part of the herd of 180 cows, with

an average production of 10.040 kg milk (with 4.25% fat and 3.58% protein) per year. These lactating and dry cows were housed in different groups in a freestall barn with cubicles. Dry cows were kept in a separate group. When the cows showed signs of impending calving, they were moved to individual straw bedded maternity pen within the same building. They were added to one of the three production groups directly after calving. The three production groups were milked with 3 milking robots of DeLaval and were similar with regards to production level. For each group 55 cubicles were available and the feeding dunk gave room to 43 cows. Group size and composition was dynamic, as animals were moved between pens before and after the transition period, but cows remained in the same group after calving until next dry period. The cows were fed twice daily with a Total Mixed Ration (TMR) consisting of corn silage, hay silage, with concentrates added (protein and mineral supplement) adjusted to the production level of the group. Dry cows were fed dry cow diet consisting of TMR. Water was available ad libitum. For the duration of the experimental period feed composition was kept constant.

Clinical examination

A score was calculated based on clinical examination of each cow that was performed daily for the period of 2 weeks before until 6 weeks after parturition. During clinical examination, heart rate, breathing rate, rectal temperature, rumination (chews per minute), udder condition and much more, were measured and overall condition was evaluated according to these measurements (combined with blood values) as described by (Hajer *et al.*, 1988). Clinical examinations were performed by three specialized dairy cow veterinarians. Blood samples were taken every two days.

Score of diminished health

Each aberrant clinical finding related with metabolic stress or disease was scored as 1 per day. The scores were added to one single total score of diminished health per cow. As production diseases are all interrelated, and should not be considered in isolation (Mulligan and Doherty, 2008, Sundrum, 2015), we calculated days of diminished health (DDH) as one feature, adding up all clinically detected disturbances from 1 day until 6 weeks after calving, based on the clinical findings.

Data acquisition

During the 2-week period before calving and 6 weeks after calving, continuous and high-frequent behavioural and body temperature data were obtained with the use of three sensors:

1. IceQube sensors for recording activity: per quarter the number of minutes lying and standing (adding up to 15), the number of steps, the number of lying bouts and motion index (a measure of the total acceleration measured).
2. SensOor sensors for measuring behaviour (eating, ruminating and activity level) and ear temperature: 60 minutes per hour are divided into number of minutes eating, ruminating, high active, low active and inactive; average temperature per hour is recorded.
3. BellaAg Bolus sensors for measuring rumen temperature every 10 minutes.

Data analysis / statistical analysis

For each sensor variable the average, variance and autocorrelation were calculated over all measurement values during a period starting 15 days before calving up to and including the day before calving. The average, variance and autocorrelation were also calculated during a period from day 1 up to day 7 after calving. For this research, the nonperiodicity was introduced. Nonperiodicity was defined as the mean squared error of the correlogram with a sinusoid with a 24h cycle and an amplitude of 0.25. The nonperiodicity was based on the observation that the correlogram of hourly sensor data was showing a stable diurnal rhythm in the case of healthy cows whereas this pattern in general was not visible in the correlogram of cows with serious health disorders. The nonperiodicity was calculated over the same two periods. All these quantities - average, variance, autocorrelation and nonperiodicity- were correlated with DDH after calving using Pearson's correlation coefficients.

Results and discussion

Sensor variables were collected before and after calving. IceQube data on quarter level were summed to get data at hour level, BellaAg bolus temperature data per 10 minutes were averaged per hour. Average, variance, autocorrelation (with lag 1) and nonperiodicity were calculated for each hourly sensor variable. To illustrate the calculation of nonperiodicity, correlograms are included in Figure 1 for two cows: cow 8829 with a low number of DDH (0) and cow 8389 with a high number of DDH (65). The correlograms of the high resilience cows (low number of DDH) show a periodicity, which is less or not visible in the correlograms of the low resilience cow. The calculated nonperiodicity for IceQube lying time is 0.003 for cow 8829 and 0.027 for cow 8389.

Clinical observations resulted in DDH per cow in the transition period. DDH per cow varied between 0 and 121. The DDH were log-transformed for the analysis as the distribution was skew. To illustrate some results, scatter plot of log(1+DDH) versus nonperiodicity for all sensor variables are included in Figure 2.

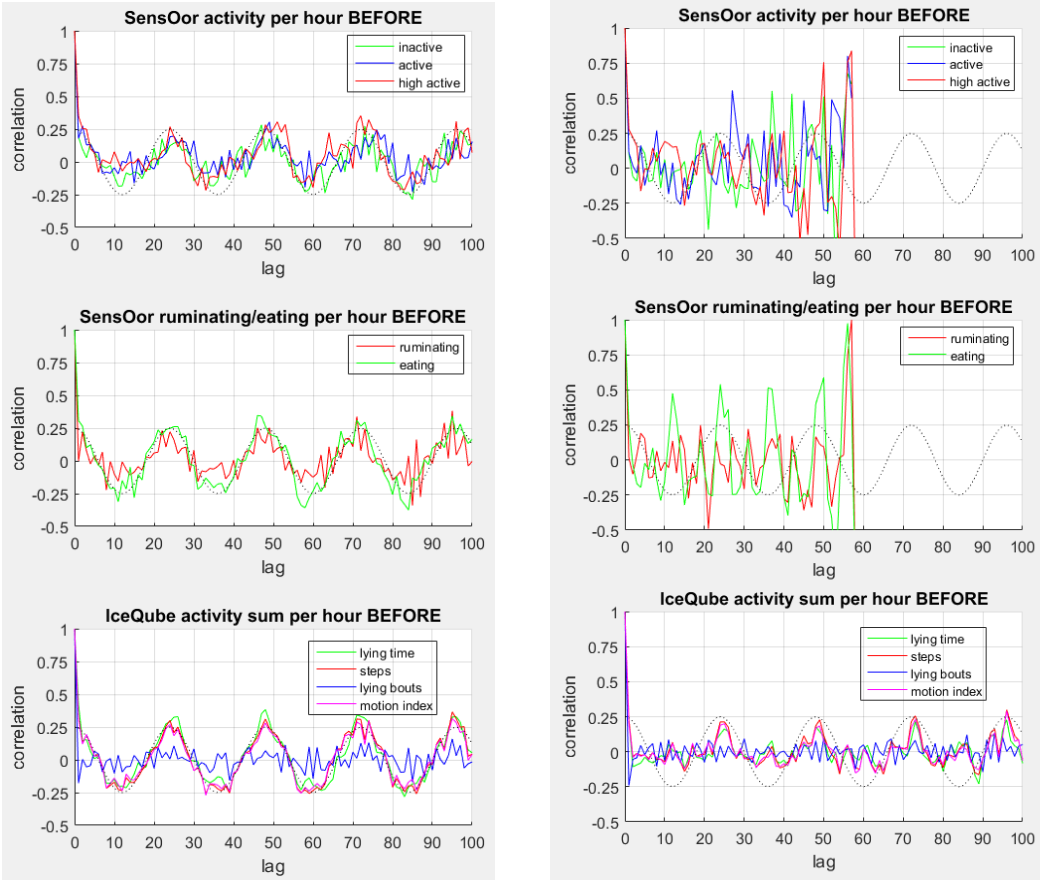


Figure 1: Examples of correlograms of sensor data (SensOor activity: upper, eating/ ruminating: middle and IceQube activity: lower) before calving of cow 8829 with high resilience (left) and cow 8389 with low resilience (right), combined with a sinusoid with a 24h cycle and an amplitude of 0.25 (dotted lines)

The number of points in each subplot of Figure 2 depends on the availability of sensor data before calving (not all sensors were available in time). These plots suggest a positive relationship between DDH and nonperiodicity for several sensor variables. Pearson's correlations between DDH and quantitative sensor values were calculated to quantify this observation. Significant correlations were found in several cases (Table 1).

Significant correlations ($P<0.05$) between DDH and sensor quantities were found for the average of SensOor inactive and eating time, the variance of SensOor temperature and IceQube number of steps, and the nonperiodicity of SensOor

eating time. Moderately significant correlations (P<0.01) were found for the nonperiodicity in IceQube number of steps and motion index. Highly significant correlations (P<0.001) were found for the nonperiodicity in SensOor eating time. The correlations with average values suggest that a higher inactive time and lower eating time before calving are negative for the health status of a cow after calving. The correlations with variances are less easy to interpret. The correlations with nonperiodicity suggest that leading a regular life before calving is positive. But of course it is not clear whether this is a cause or an effect. Further research on more farms in broader conditions is needed to investigate this relation further.

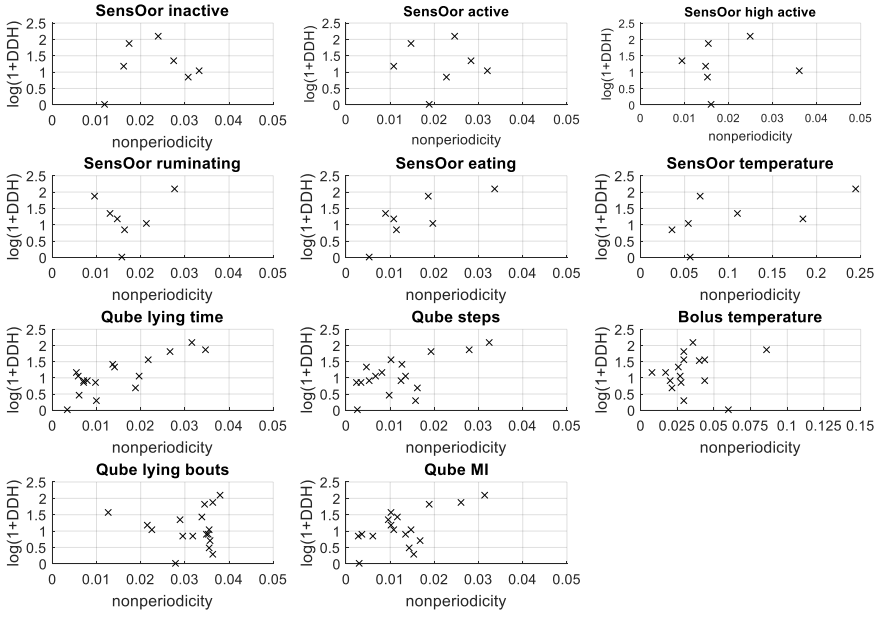


Figure 2: Scatter plots of log(1+DDH) versus nonperiodicity for all sensor variables: SensOor level of activity (inactive, active, high active), ruminating, eating and (ear) temperature; IceQube (aggregated to hour level) lying time, steps, lying bouts and motion index (MI) and BellaAg Bolus (average per hour) temperature

Table 1: Significant correlations between days of diminished health (DDH) after calving and quantitative values of continuously recorded sensor variables recorded from 15 days before calving to the last day before calving (inclusive)

Sensor measurement	Value	Correlation with log(1+DDH)	P-value
Inactive time	average	0.67	<0.05
Eating time	average	-0.76	<0.05
Ear temperature	variance	0.67	<0.05
Number of steps	variance	-0.51	<0.05
Eating time	nonperiodicity	0.78	<0.05
Lying time	nonperiodicity	0.79	<0.001
number of steps	nonperiodicity	0.63	<0.01
motion index	nonperiodicity	0.62	<0.01

The correlations between DDH and quantitative values of sensor variables have also been calculated for the period after calving (Table 2). The number of significant correlations is higher in this case. But in this case quantitative values might have been calculated for ill cows. So these correlations cannot be used as predictors for health problems but suggest that quantitative values might be used for early warning.

Table 2: Significant correlations between days of diminished health (DDH) after calving and quantitative values of continuously recorded sensor variables recorded just after calving

Sensor measurement	Value	Correlation with log(1+DDH)	P-value
Inactive time	average	0.67	<0.05
Eating time	average	-0.77	<0.01
Ear temperature	average	-0.71	<0.01
Number of steps	average	-0.76	<0.001
Motion index	average	-0.74	<0.001
Eating time	variance	-0.69	<0.05
Standing time	variance	-0.56	<0.05
Number of steps	variance	-0.65	<0.05
Motion index	variance	-0.62	<0.05
Eating time	nonperiodicity	0.81	<0.01
Lying time	nonperiodicity	0.49	<0.05

Possible solutions for management improvement should focus on facilitating and stimulating adaptive capacity of dairy cows and minimizing the gap between nutritional requirements and provision for all cows within the herds. It is suggested that dairy cows will more easily succeed in adapting and in avoiding dysfunctional

processes in the transition period when the gap between nutrient and energy demand and their supply is restricted (Sundrum, 2015).
The better the cows are prepared or equipped with adaptation tools to withstand this demanding challenge, the less health disorders will occur, resulting in better milk and reproductive performance as well as increased life expectancy (through decreased culling rates).
Previous studies have shown that dry matter intake and feeding behaviour during the week before calving, can identify cows at risk for metritis after calving (Huzzey *et al.*, 2007). Also it has been found that aggressive interactions at the feed bunk or avoiding aggressive interactions are related to the development of metritis after calving (Huzzey *et al.*, 2007). Indicating that individual behavioural characteristics within competitive environment distinguish between the vulnerability for the development of diseases.
Early warning signals in the dynamics of a system approaching a bifurcation are, according to (Scheffer *et al.*, 2009), slower recovery from perturbations, increased autocorrelation and increased variance. Here we focus on the latter two of these signals. Other signals are also known form literature (Scheffer *et al.*, 2012).

Conclusions

In this experiment we studied the possibilities and limitations of individual monitoring with sensors. Dynamic, quantitative parameters for high-resolution physiological and behavioural measures continuously measured during the dry period have predictive value for the risk of cows to develop diseases during the early lactation period. Our results suggest that quantitative parameters derived from sensor data may reflect the level of resilience of individual cows. The high correlations before parturition of some sensor data with nonperiodicity might be used as indicator for critical transitions after parturition. Further research is needed to validate whether a regular life may prevent disorders in dairy cows.

Acknowledgements

This project was funded by the province of Overijssel and the Dutch “Melkveefonds”.

References

Derks, M., T. van Werven, H. Hogeveen, and W. D. J. Kremer. 2013. Veterinary herd health management programs on dairy farms in the Netherlands: Use, Execution, And relations to farmer characteristics. *Journal of Dairy Science* **96**(3):1623-1637.

Grant, R. J. and J. L. Albright. 1995. Feeding behavior and management factors during the transition period in dairy cattle. *Journal of Animal Science* **73**(9):2791-2803.

Grummer, R. R. 1995. Impact of changes in organic nutrient metabolism on feeding the transition dairy cow. *Journal of Animal Science* **73**(9):2820-2833.

Hajer, R., J. Hendrujse, L. J. E. Rutgers, M. M. Sloet van Oldruitenborgh-Oosterbaan, and G. C. van der Weijden. 1988. *Het klinisch onderzoek bij grote huisdieren.* (Clinical examination of farm animals) Wetenschappelijke uitgeverij Bunge, Utrecht.

Huzzey, J. M., D. M. Veira, D. M. Weary, and M. A. G. Von Keyserlingk. 2007. Prepartum behavior and dry matter intake identify dairy cows at risk for metritis. *Journal of Dairy Science* **90**(7):3220-3233.

Kessel, S., M. Stroehl, H. H. D. Meyer, S. Hiss, H. Sauerwein, F. J. Schwarz, and R. M. Bruckmaier. 2008. Individual variability in physiological adaptation to metabolic stress during early lactation in dairy cows kept under equal conditions. *Journal of Animal Science* **86**(11):2903-2912.

LeBlanc, S. J. 2014. Reproductive tract inflammatory disease in postpartum dairy cows. *Animal* **8**(SUPPL. 1):54-63.

LeBlanc, S. J., K. D. Lissemore, D. F. Kelton, T. F. Duffield, and K. E. Leslie. 2006. Major advances in disease prevention in dairy cattle. *Journal of Dairy Science* **89**(4):1267-1279.

Mulligan, F. J. and M. L. Doherty. 2008. Production diseases of the transition cow. *Veterinary Journal* **176**(1):3-9.

Scheffer, M., J. Bascompte, W. A. Brock, V. Brovkin, S. R. Carpenter, V. Dakos, H. Held, E. H. Van Nes, M. Rietkerk, and G. Sugihara. 2009. Early-warning signals for critical transitions. *Nature 461*(7260):53-59.

Scheffer, M., S. R. Carpenter, T. M. Lenton, J. Bascompte, W. Brock, V. Dakos, J. Van De Koppel, I. A. Van De Leemput, S. A. Levin, E. H. Van Nes, M. Pascual, and J. Vandermeer. 2012. Anticipating critical transitions. *Science* **338**(6105):344-348.

Sundrum, A. 2015. Metabolic disorders in the transition period indicate that the dairy cows' ability to adapt is overstressed. *Animals* **5**(4):978-1020.

Urton, G., M. A. G. von Keyserlingk, and D. M. Weary. 2005. Feeding Behavior Identifies Dairy Cows at Risk for Metritis. *Journal of Dairy Science* **88**(8):2843-2849.

van Saun, R. J. and C. J. Sniffen. 2014. Transition Cow Nutrition and Feeding Management for Disease Prevention. *Veterinary Clinics of North America - Food Animal Practice* **30**(3):689-719.

Walker, B., C. S. Holling, S. R. Carpenter, and A. Kinzig. 2004. Resilience, adaptability and transformability in social-ecological systems. *Ecology and Society* **9**(2).

Is it possible to perform non-contact measurement of body temperature on the bovine eye?

B. Eveslage-Rüter, G. Claußen, E.F. Hessel
Georg-August University of Göttingen, Department of Animal Sciences, Gutenbergstraße 33, 37075 Göttingen, Germany
earkena@gwdg.de

Abstract
Automation and precision livestock farming (PLF) are playing an increasingly important role in modern animal husbandry. Potential means of automation are also increasingly being considered in health monitoring, which is essential for successful calf and cattle rearing. Therefore, the present investigation was conducted at a calf fattening unit and a dairy farm to test the suitability of an innovative measuring device for the non-contact measurement of body temperature, compared with the rectal temperature. The present results of the non-contact body temperature measurement were not satisfactory. As a result of the lack of precision and accuracy, the specificity and sensitivity is to be rated as low. If the innovative measuring device were to be used for health monitoring, it can be assumed that a large proportion of sick animals would not be detected or that healthy animals would be classified as sick. Further research and improvement of accuracy are necessary before the device can be used within the context of PLF.

Keywords: Cattle, Eye, Body temperature, Infrared temperature

Introduction

Successful calf rearing lays the foundation for the next generation of dairy cows. Today's calf is tomorrow's cow. Therefore, the health of calves and cattle should be the focus of increased attention, for the calves' immune system is still lacking, particularly in the first weeks of life, and the animals are susceptible to diarrhoea and respiratory infections. In order to reduce losses of calves and cattle as well as veterinary costs, it is important to detect diseases as early as possible (Rademacher, 2011). Over the past few years, there has been a growing trend towards automation in livestock farming and the term "Precision Livestock Farming" (PLF) has become a matter of increasing discussion. Therefore, methods are being considered that in the future might be used, for example, to perform automatic body temperature measurement at the automatic calf feeder or, in the case of cattle, at the automated milking system (AMS) or at the concentrate feeder.

The objective of the present study was, therefore, to test the suitability of an innovative method (Thermofocus Animal®) for the non-contact measurement of body temperature on the bovine eye. Measurement on the eye has been researched previously by several other studies. However, an infrared camera was always used for this purpose. The measuring point was in the ventral, nasal angle of the eye, as blood flow is particularly strong there, with many capillaries meeting at the surface (Stewart et al., 2005 and 2008, Soroko et al., 2016). In a study by Schaefer et al. (2011), the area of the eye plus one centimetre around the eye was evaluated for the measurement and could be used for the early detection of sick calves. In a study by Johnson et al. (2011), however, it was discovered that measurement on the eye can be affected by external influences such as exposure to sunlight or varying distance and is therefore insufficient on its own for the determination of body temperature.

Material and methods

Experimental setup

The experiments were conducted on a calf fattening unit (CFU) and on a dairy farm (DF).

The CFU purchased the calves at the age of 14 days from different farms within Germany. Up to the legally stipulated maximum age of 8 weeks (TierSchNutztV, 2006), the animals were kept in individual stalls on Bongossi slatted flooring.

In addition, the experiment was performed on a DF with cattle of different age groups. In the first 14 days after birth (TierSchNutztV, 2006), the calves were kept in individual stalls on straw litter. After this period, the female animals are moved to new stalls in groups of up to 4 calves and the male calves are sold to a bull fattener. The older cattle are kept on straw in different sized groups.

Several cows were also included in the experiment. These are kept tethered and are put out to pasture every day from spring to autumn.

Data collection

On the CFU, the experiment was conducted within the context of a veterinary measure. To determine the body temperature, the calves were led to the feeding fence by one person and manually held in place there. This person was then able to measure the rectal temperature using a veterinary thermometer. A second person recorded the eye temperature with the infrared thermometer "Thermofocus Animal®" manufactured by the Italian company Tecnimed. Depending on the temperament of the experimental animal, it was held in place by one person alone or with the help of a further person. For measurement, the device was taken in one hand and brought to the cow's eye. Upon pressing the measuring button on the device, two semicircles of light were visible, which

converged as the device was moved towards the eye and formed a circle at a distance of around 3cm (Figure 1). After releasing the measuring button, the Thermofocus Animal® had to be kept still for around one second in order to complete the measurement. The measured body temperature could then be read off the display on the device. The measurement was then repeated four times in the same way, so that 5 repeat measurements were obtained per animal.

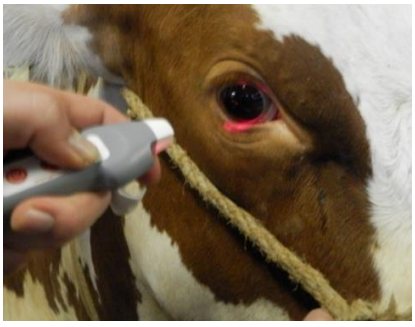


Figure 1: Non-contact body temperature measurement on the bovine eye with the Thermofocus Animal®

For the temperature measurements on the DF, the cattle were tethered to the feeding fence with a halter. The measurements were then performed on the heifers. In the case of the cows on the dairy farm, the measurements were taken in the tethered position, so that only the head had to be kept still to enable an unimpaired temperature measurement on the eye. The measurements were performed by one and the same person on the two farms.

Statistical evaluation

A total of 109 calves aged 29.51 (± 5.82) days were available for this investigation on the CFU, which meant that 545 IR temperature measurements on the eye were available. On the DF, 160 IR temperature measurements on the eye were performed on 32 cattle. In the statistical analysis, on the one hand the precision of the infrared measurements with the Thermofocus Animal® and, on the other, their accuracy in relation to the rectal measurements as the gold standard were investigated. For precision - as a measure of the agreement between independent measurement results under fixed conditions - the standard deviation of the 5 repeat measurements of the IR eye temperature was taken. Accuracy is the relative measure of the deviation between individual measurement value of the IR eye temperature and rectal temperature. In addition, linear regression was used to calculate the connection between rectal temperature and IR eye temperature.

Results and discussion

Rectal temperature and infrared temperature of the bovine eye

The mean rectally measured body temperature of the calves is 38.43 (±0.48) °C and the mean infrared eye temperature 37.25 (± 0.63) °C. The mean IR eye temperature is thus 1.18 °C below the rectal temperature. The measurement values of the Thermofocus Animal® scatter much more strongly, with a coefficient of variation (CV) of 1.7%, than the measurement values of the rectal temperature measurement (CV=1.14%) (Fig. 2). On the DF, the mean rectal body temperature measured is 38.70 (±0.40) °C and the mean infrared eye temperature 38.11 (±1.07) °C. The mean IR eye temperature is 0.59 °C below the rectal temperature. Here, too, the measurement values of the IR thermometer Thermofocus Animal® scatter much more strongly, with a coefficient of variation (CV) of 2.80%, than the measurement values of the rectal temperature measurement (CV=1.03%) (Figure 2).

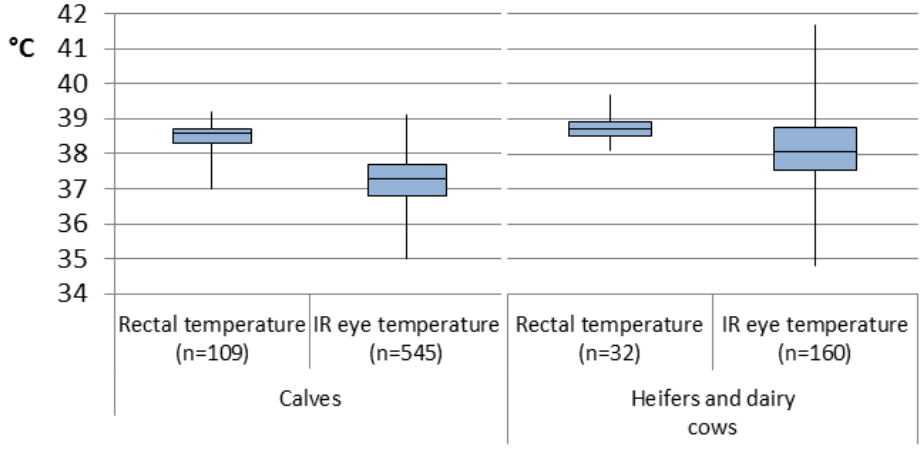


Figure 2: Boxplots of rectal temperature as well as of IR eye temperature of calves as well as of heifers and dairy cows

Precision and accuracy of the infrared temperature measurement

Precision was calculated on the basis of the 5 repeat measurements of IR eye temperature. This produced values of 0.35 (± 0.17) °C on the CFU and 0.42 (± 0.23) °C on the DF. Figure 3 shows the distribution of the precision of all 109 calves and the 32 cattle. In 25% of the calves this is greater than 0.46 °C, in 25% of the animals of the DF greater than 0.58 °C.

There may have been a drop in precision in this study, due to errors in carrying out the non-contact temperature measurement. On the one hand, the person carrying out the measurements may themselves have caused errors during measurement, e.g. failure to maintain the correct distance when taking the eye

measurement. Movement of the animals may also be reflected in deviations of measurement values. For the earliest possible detection of elevated body temperatures in calves, a precision of on average 0.35 °C, or 0.42 °C in cattle, would not appear to be sufficient. Calves have a normal body temperature of 38.5 – 39.5 °C (Stöber, 1990). Any elevation, even by as little as 0.1 °C, can point to a febrile disease such as bovine flu. Early detection is extremely important for sick animals to be treated effectively and to ensure that the infection is not passed on to other calves in the group (Müller, 2012).

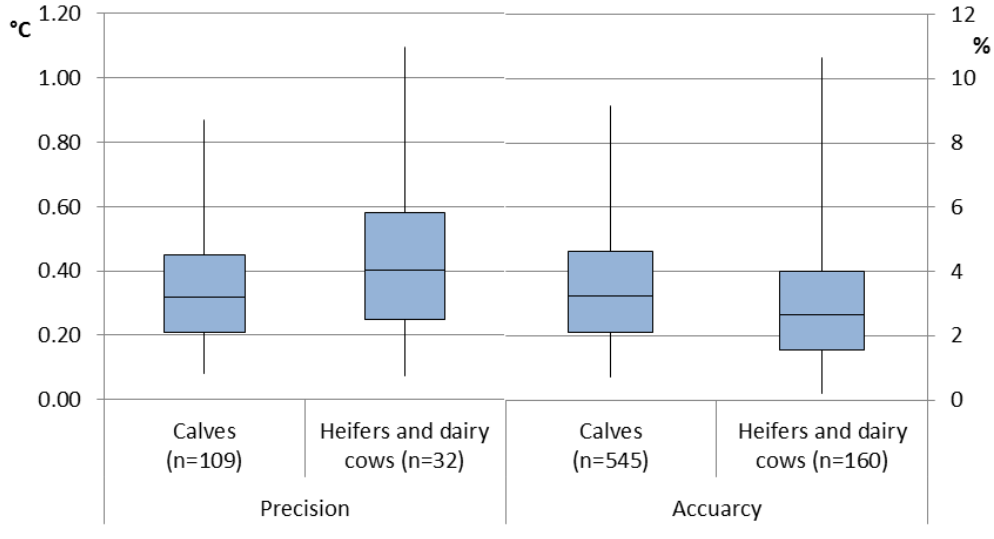


Figure 3: Distribution of the precision of 5 repetitions of IR eye temperature as well as the accuracy of single measurements

Alongside precision, which gives the spread within the 5 repeat measurements, the accuracy of the measurement is also of great importance (Figure 3). On average, the accuracy of the infrared eye measurement is 3.35% (1.24 °C) in the calves, with a mean of 2.86% (1.13 °C) on the DF.
In some of the measurements the IR temperatures are in agreement with the rectal temperature, however maximum deviations between IR temperatures and rectal temperature are 9.10% (3.2 °C) on the CFU and 10.63% (4.05 °C) on the DF. The accuracy is stated as 0.2 °C by the manufacturer Tecnimed.

Linear regression

A connection between rectal temperature and IR eye temperature, presented with the aid of linear regression is not really present, at $R^2 = 0.0030$ (CFU) and $R^2 = 0.0015$ (DF) (Figure 4). This means that a prediction about actual body

temperature cannot be made on the basis of the IR eye temperature. It remains to be investigated whether the eye is a suitable site for determining body temperature at all. The suitability of the eye for the non-contact measurement of body temperature cannot be conclusively resolved. Furthermore, the reasons for the lack of precision between the repeat measurements should also be examined.

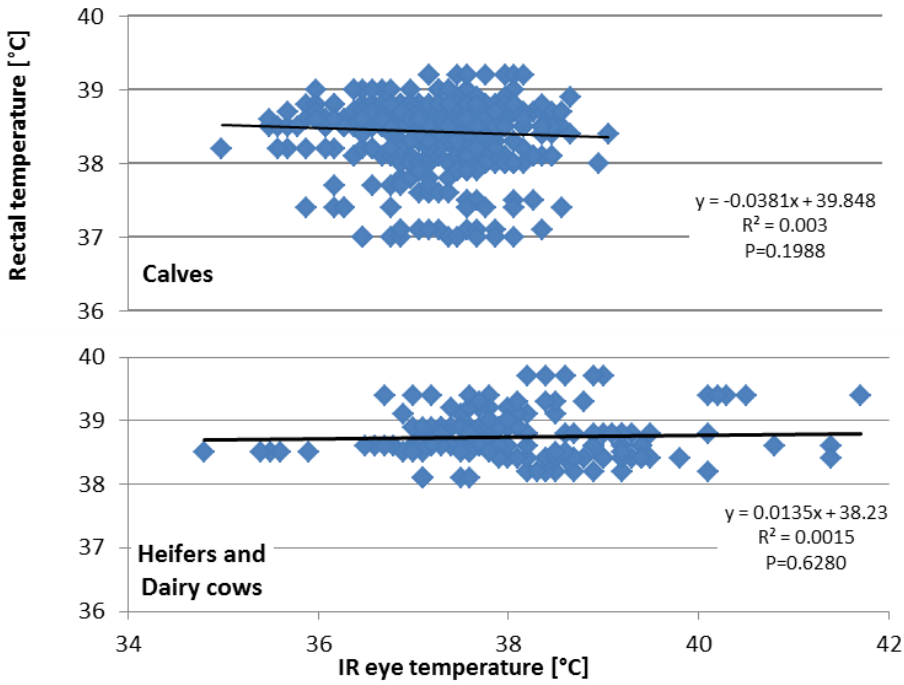


Figure 4: Regression of IR eye temperature on rectal temperature

Conclusions

On the basis of the present results, it is concluded that the investigated method for non-contact measurement of body temperature does not yield satisfactory results. As a result of the lack of precision and accuracy, the specificity and sensitivity is to be rated as low. If health monitoring were to be carried out with the Thermofocus Animal®, it can be assumed that a large proportion of sick animals would not be detected or that healthy animals would be classified as sick. Further research and improvement of accuracy are necessary before the device can be considered suitable for use in practice.

References

Johnson, S.R., Rao, S., Hussey, S.B., Morley, P.S., Traub-Dargatz, J.L. (2011): Thermographic Eye Temperature as an Index to Body Temperature in Ponies. In: Journal of Equine Veterinary Science 31 (2011), S. 63 – 66, doi:10.1016/ J.jevs.2010.12.004

Müller, K. (2012): Leitfaden zum Atemwegweiser für Kälber und Rinder – die enzootische Bronchopneumonie. Klinik für Klauentiere in Berlin in Zusammenarbeit mit Intervet Deutschland GmbH, einem Unternehmen der MSD Tiergesundheit http://www.msd-tiergesundheit.de/binaries/MSD_Leitfaden_Atemwegserkrankungen_A5-finale_Freigabe_tcm82-191196.pdf

Rademacher, G. (2011): Kälberkrankheiten – Ursachen und Früherkennung, Neue Wege für Vorbeugung und Behandlung, 4. Auflage, S. 9 – 32, Stuttgart: Eugen Ulmer Verlag, ISBN: 978-3-8001-7553-6

Schaefer, A.L., Cook, N.J., Bench, C., Chabot, J.B., Colyn, J., Liu, T., Okine, E.K., Stewart, M., Webster, J.R. (2011): The non-invasive and automated detection of bovine respiratory disease onset in receiver calves using infrared thermography. In: Research in Veterinary Science 93 (2), November 2011, S.928 – 935, doi:10.1016/j.rvsc.2011.09.021

Soroko, M., Howell, K., Zwyrzykowska, A., Dudek, K., Zielińska, P., Kupczyński, R. (2016): Maximum Eye Temperature in the Assessment of Training in Racehorses: Correlations with Salivary Cortisol Concentration, Rectal Temperature, and Heart Rate. In: Journal of Equine Veterinary Science 45 (2016), S. 39 – 45, http://dx.doi.org/10.1016/j.jevs.2016.06.005

Stewart, M., Webster, J.R., Schaefer, A.L., Cook, N.J., Scott, S.L. (2005): Infrared thermography as a non-invasive tool to study animal welfare. In: Animal Welfare 14 (2005), S. 319 – 325

Stewart, M., Stafford, K.J., Dowling, S.K., Schaefer, A.L., Webster, J.R. (2008): Eye temperature and heart rate variability of calves disbudded with or without local anaesthetic. In: Physiology and Behavior 93 (2008), S. 789 – 797

Stöber, M. (1990): Kennzeichen, Anamnese, Grundregeln, Allgemeine Untersuchung. In: Rosenberger, G. (1990): Die klinische Untersuchung des Rindes., 3. Auflage, S. 131 – 135, Berlin und Hamburg: Verlag Paul Parey, ISBN: 3-489-56516-9

TierSchNutztV (2006): Tierschutznutztierhaltungsverordnung §8 (Besondere Anforderungen an das Halten von Kälbern im Alter von über zwei bis zu acht Wochen in Ställen) http://www.gesetze-im-internet.de/tierschnutztv/BJNR275800001

An artificial neural network predictive model for assessing thermal stress in beef cattle using thermal radiation

R. V. Sousa[1] and L. S. Martello[1]
[1]*Faculty of Animal Science and Food Engineering, University of São Paulo, Av. Duque de Caxias Norte 225, Pirassununga-SP, Brazil*
rafael.sousa@usp.br

Abstract

Non-invasive techniques based on thermal radiation were investigated as an alternative method for assessing heat stress in animal production. The objective of this work was to develop a model based on artificial neural networks (neural model) to estimate the rectal temperature of beef cattle through the body surface infrared temperature measured with embedded low-cost sensors. Experiments were performed with two groups of Nellore cattle confined in different periods. For development of the neural model, the inputs were infrared thermographic images collected from the face surface of animals and the air temperature and humidity. The neural model was based on a multi-layer non-feedback architecture and used supervised learning. Subsequently, the model generated was tested with inputs from low-cost embedded sensors: an infrared pyrometer and a digital sensor which supplied the air temperature and humidity. In the model generation step, the statistical analysis of the measured and estimated rectal temperature showed a correlation coefficient of 0.85. In the second step, the neural model fed with embedded sensor data showed a correlation coefficient of 0.69. The results strengthen the potential for generalisation of the neural model and validate its application as a means of estimating the rectal temperature of animals based on embedded low-cost sensors.

Keywords: infrared thermography, animal welfare, non-invasive measurement, soft computing, artificial intelligence, smart sensor

Introduction

It has long been known that climatic and environmental conditions, in particular, have a significant impact on the performance of feedlot cattle. Performance is adversely affected by high ambient temperature, humidity and solar radiation, with a reduction in dry matter intake, increase in body temperature and decreased weight gain (Mader & Griffin, 2015). Physiological responses such as body temperature are good indicators of animal welfare (Burfeind *et al*., 2012; Gaughan & Mader, 2013). However, the approach to animal status assessment

traditionally includes manual and visual scoring which is laborious, invasive and stressful for the animal (Wathes *et al*., 2008). Thus, the development of models for predicting thermal stress which consider not only environmental factors but also the physiological response of the animal are more useful for inferring animal health and welfare (Scharf *et al*., 2011; Martello *et al*., 2015).

Among the non-invasive tools, infrared thermography has been studied for use in instrumentation systems to monitor body surface temperature profiles and their correlation with other animal welfare factors (Wathes et al., 2008). Some very positive results are being achieved in studies of systems based on non-invasive sensors combined with predictive models based on soft computing techniques to allow assessment of animal welfare (Huang *et al*., 2010; Sousa *et al*. 2016). Brown-Brandl *et al*., (2005) constructed and evaluated five different models for predicting thermal stress in cattle: two statistical models, two fuzzy inference systems and one artificial neural network. The models based on soft computing tools, artificial neural network and fuzzy logic, produced better results. Shao & Xin (2008) used a real-time image processing system to detect movement and classify the thermal stress status of group-housed pigs based on their resting behavioural patterns. Hernández-Julio *et al*. (2014) evaluated techniques for modelling the physiological responses, rectal temperature and respiratory rate of black and white Holstein dairy cows. The model based on artificial neural networks showed the best performance, followed by the models based on neurofuzzy networks and regression. Sousa *et al*. (2016) proposed a fuzzy classifier which resulted in better estimates of the thermal stress level when compared with the traditional temperature–humidity index and previously developed fuzzy-based systems.

The objective of this study was to investigate a method for predicting a physiological variable related to the thermal stress of animals by non-invasive techniques, more specifically, a model based on artificial neural networks (neural model) to estimate the rectal temperature of beef cattle through the body surface infrared temperature measured with embedded low-cost sensors. In addition to the infrared temperature, the model also uses the temperature and humidity of the air.

Materials and methods

The neural model was developed in two phases and a different group of cattle confined for data collection purposes was used in each phase (two feedlots). The measurements performed with the first group were used to construct the neural model. The second group of measurements was used to evaluate the neural model using data collected by a microcontroller board built with cheap embedded sensors.

Feedlot and data acquisition

The study was carried out at the facilities of Faculty of Animal Science and Food Engineering (FZEA) of the University of São Paulo (USP) in Pirassununga, SP, Brazil, located at 21°57′02″S, 47°27′50″W at a mean elevation of 630 m above sea level. The average annual temperature is 22°C, with approximately 1360 mm of rain per year. The study was conducted according to the Institutional Animal Care and Use Committee Guidelines of FZEA/USP (NRC, 2003).

In the first phase, eight Nellore steers (18 months old) were evaluated over a period of eight days. In the second phase, data was collected from fifty-five Nellore steers (20 months old) in a single day. In both phases the cattle were allocated to individual pens (5 x 8 m) with a soil floor, automatic water fountains and sheltered feed bunks. The pens had additional shade for the animals (20 m^2/head) which were fed a daily diet containing 85% concentrate and 15% roughage on an ad libitum basis.

The schedule for measurements in the first phase was planned according to the animal handling work, with animals restrained in the squeeze chute (cattle crush) at least four times a day. The rectal temperature (RT) was measured manually using a digital thermometer (VMDT01, Viomed, China). Infrared images as shown in Figure 1 were obtained from the face of the animal using a camera (TI 20-9 Hz, Fluke Corporation, Everett, USA) with an emissivity value of 0.97 for infrared temperature measurements from this region (IRT). A data logger (HOBO U12, Onset Computer Corporation, USA) was installed at the centre of the pens at 2 m above the floor, at approximately the same level as the animal's head. Among other weather data, wet bulb temperature (WBT, ^{o}C) and relative humidity (RH, %) were considered in this study, based on the results of several studies which show a high correlation between these variables and thermal stress (Mader, 2006; Dikmen and Hansen, 2009).

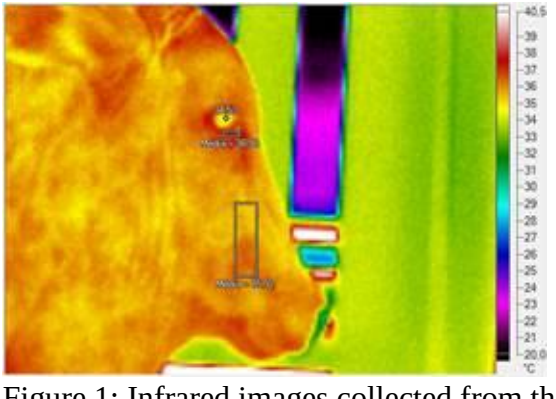


Figure 1: Infrared images collected from the face of the animal

Data collection in the second phase was performed by an Arduino UNO microcontroller board (Arduino, Italy) with two sensor modules (embedded sensors) as shown in Figure 2. The DHT22 sensor module (Aosong Gaungzhou Elestronics Co., China) was used to measure air temperature and relative humidity. The infrared pyrometer GM-550 (Benetech, China) was set to an emissivity of 0.97 and used to measure the face temperature of animals in place of the infrared camera. The data collected for each of the fifty-five animals in a single day were transferred and stored in real time on a portable computer. Figure 2 shows the microcontroller board with embedded sensors.

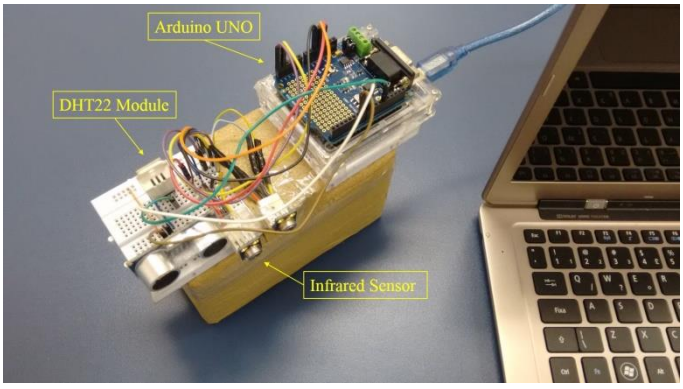


Figure 2: Microcontroller board with embedded sensors.

Development and evaluation of the model

The neural model was implemented through the Neural Network Toolbox from Matlab software version R2010b (Mathworks Inc., USA) according the Fitting methodology. Neural model development used non-feedback and multi-layered architecture with a sigmoid transfer function in the hidden layer and a linear transfer function in the output layer. The model was run (simulated) a few times to fine-tune some of the parameters using supervised training and taking as inputs the variables IRT, WBT and RH to estimate the RT output. In this procedure, supervised training used 70% of the data from the first phase. The Levenberg-Marquardt method, the mean squared error and a maximum of 1000 iterations were used for training. The remaining 30% of the data was used for the validation step during the training process.

Artificial neural networks were trained with the number of neurons (N) in the hidden layer set to 7, 10, 15, 20, 30, 50 and 100. In addition, as the data is randomly selected the performance of the model is subject to the set chosen for training. The choice of less representative data can therefore generate a poor model. Thus, a method was applied in which one hundred neural networks were trained for each configuration of the number of neurons with random divisions of the data.

From the parameterisation described, seven hundred neural models were generated and compared. The model's performance was evaluated by comparison between the estimated and measured rectal temperature using linear regression and the parameters: slope, intercept, mean error, root mean square error (RMSE) and determination coefficient (R^2).
The models with the best performance were selected from the first phase and run with the second phase data to evaluate the neural models with unseen data obtained with low-cost sensors. The same statistical parameters used in the first phase were calculated from the relationship between the estimated and measured rectal temperatures.

Results and discussion

As mentioned earlier, the proposed architecture for a neural model was trained with different numbers of neurons (N). Each model related to N was simulated a hundred times using different random data set collected in the first phase to give comparison parameters. The best models for each N were selected according the best value of R^2. The statistical parameters related to these best models are shown in Table 1.

Table 1: Statistical results related to the phase of development of the model

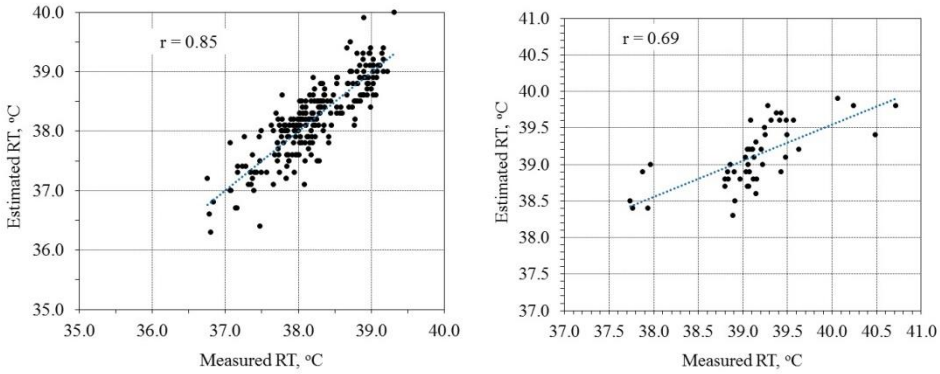
	N = 7	N = 10	N = 15	N = 20	N = 30	N = 50	N = 100
Slope	0.99	0.99	0.93	0.94	1.01	0.90	0.75
Intercept	0.20	0.22	2.80	1.91	-0.34	3.88	9.39
Mean error (^oC)	0.25	0.26	0.25	0.26	0.24	0.26	0.34
RMSE (^oC)	0.32	0.33	0.32	0.33	0.31	0.32	0.44
R^2	0.74	0.73	0.74	0.74	0.76	0.75	0.58

Table 1 shows that the models based on architectures with 7, 10 and 30 neurons in the hidden layer presented greater homogeneity in the parameters. Specifically, the model with 30 neurons showed better performance for the parameters slope, mean error, RMSE and R^2. The interception parameter for 30 neurons presented a similar value to the other two models.
As described above, the input data for the evaluation phase are related to unseen data by the neural model in the training procedure. In the second phase, the inputs IRT, WBT and RH for each animal were collected by the embedded sensors and applied to the seven best models selected in the earlier phase. When the best models were tested against the data, they presented the performance parameters shown in Table 2. These statistical parameters were calculated from the relationship between the estimated and measured rectal temperatures.

Table 2: Statistical results related to the phase of evaluation of the model

	N = 7	N = 10	N = 15	N = 20	N = 30	N = 50	N = 100
Slope	0.56	0.97	0.57	0.64	0.66	0.70	0.73
Intercept	17.42	1.18	16.90	14.42	13.37	1.88	10.48
Mean error (^oC)	0.26	0.31	0.25	0.29	0.30	0.31	0.36
RMSE (^oC)	0.32	0.40	0.31	0.36	0.37	0.38	0.43
R^2	0.43	0.48	0.45	0.42	0.42	0.40	0.35

The results reported in Table 2 show that the best model was obtained for the architecture with 10 neurons. This model presents significantly better values for slope, intercept and R^2 than the other models.
The linear relationship between the estimated and measured rectal temperatures obtained in the model development phase and the model evaluation phase are shown in Figure 3a and 3b respectively.



(a) (b)

Figure 3: The linear relationship between measured rectal temperature and estimated rectal temperature: model development phase (a); and model evaluation phase (b). The points represent individual measurements, the line represents the linear regression, and r represents the correlation coefficient.

It can be seen from Figures 3a and 3b that the correlation coefficients are significantly different: the first is 0.85 (Figure 3a) and the second is 0.69 (Figure 3b). It was observed that there was also a deterioration of the intercept parameter once the regression line is displaced. This fact is confirmed by the comparison between the values of the intercept parameters found in Tables 1 and 2 for N equals 10.
The intercept parameter is 0.22 for the neural model development phase (Table 1) and 1.18 for the neural model evaluation phase (Table 2). It was hypothesised that the displacement of the regression line may be affecting the other

performance parameters, which can be explained by the low precision of the embedded sensors in relation to the thermographic camera and the climate data recorder. This hypothesis should be investigated in order to guide the improvement of the proposed system by means of a calibration process which improves data collection or by using sensors with higher accuracy.

Conclusions

A methodology is presented for development of a predictive model of thermal stress in beef cattle based on an intelligent neural network which predicted the rectal temperature by means of weather (dry bulb temperature and relative humidity) data and non-invasive physiological measurement of body surface temperature using infrared radiation. The model was evaluated against data collected with low-cost sensors in a second feedlot phase and presented adequate performance, but lower than the higher-accuracy sensors used for data collection during development of the model. However, it was found that the methodology showed potential and a hypothesis for its improvement was developed.

References

Mader, T.L., Griffin, D., 2015. Management of cattle exposed to adverse environmental conditions. *Veter. Clin. North Am.: Food Anim. Practice* 31 (2), 247–258.

Burfeind, O., Suthar, V.S., Heuwieser, W., 2012. Effect of heat stress on body temperature in healthy early postpartum dairy cows. *Theriogenology* 78 (9), 2031–2038.

Gaughan, J.B., Mader, T.L., 2013. Body temperature and respiratory dynamics in unshaded beef cattle. *Int. J. Biometeorol*. 1–8.

Wathes, C.M., Kristensen, H.H., Aerts, J.M., Berckmans, D., 2008. Is precision livestock farming an engineer's daydream or nightmare, an animal's friend or foe, and a farmer's panacea or pitfall? *Comput. Electron. Agric*. 64 (1), 2–10.

Scharf, B., Leonard, M.J., Weaber, R.L., Mader, T.L., Hahn, G.L., Spiers, D.E., 2011. Determinants of bovine thermal response to heat and solar radiation exposures in a field environment. *Int. J. Biometeorol*. 55 (4), 469–480.

Martello, L.S., da Luz e Silva, S., Gomes, R.C., Corte, R.R.P.S., Leme, P.R., 2015. Infrared thermography as a tool to evaluate body surface temperature and its relationship with feed efficiency in Bos indicus cattle in tropical conditions. *Int. J. Biometeorol*. 60, Issue 1, 173–181.

Brown-Brandl, T.M., Jones, D.D., Woldt, W.E., 2005. Evaluating modelling techniques for cattle heat stress prediction. *Biosyst. Eng*. 91 (4), 513–524.

Shao, B., Xin, H., 2008. A real-time computer vision assessment and control of thermal comfort for group-housed pigs. *Comput. Electron. Agric.* 62 (1), 15–21.

Hernandez-Julio, Y.F., Yanagi Jr., T., de F. Avila Pires, M., Lopes, M.A., de Lima, R.R., 2014. Models for prediction of physiological responses of Holstein dairy cows. *Appl. Artif. Intell*. 28 (8), 766–792.

Sousa, R.V., Canata, T.F., Leme, P.R., Martello, L.S., 2016. Development and evaluation of a fuzzy logic classifier for assessing beef cattle thermal stress using weather and physiological variables. *Comput. Electron. Agric*. 127 (1), 176–183.

Dikmen, S., Hansen, P.J., 2009. Is the temperature-humidity index the best indicator of heat stress in lactating dairy cows in a subtropical environment? *J. Dairy Sci*. 92 (1), 109–116.

Mader, T., 2006. Environmental factors influencing heat stress in feedlot cattle. *J. Anim.* 712–719

Progesterone and betahydroxybutyrate in line measurements for a better description and understanding of Holstein cows fertility in field conditions

C. Saby-Chaban[1], W. Zhang[1], R. Fournier[2], R. Servien[3], N. Villa-Vialaneix[4], F. Corbière[1], S. Chastant-Maillard[1]
[1]*INRA/ENVT UMR 1225 IHAP, National Veterinary School, Toulouse, France*
[2] *MSD Animal Health, Beaucouzé, France*
[3]*INRA/ENVT UMR 1331 Toxalim, Research Center in Food Toxicology, Toulouse, France*
[4] *INRA, UR875 MIAT, Castanet Tolosan, France*
s.chastant@envt.fr

Abstract

PLF devices allow to follow up large populations of animals in a non-invasive way over long periods of time and under field conditions. The objective of this work was to describe the ovarian activity and metabolic status during the postpartum period in dairy cows and their impact on further fertility in commercial herds. Data from 760 cows housed in 21 French farms were collected over the first 140 days postpartum (dpp). Milk progesterone was assayed on average every 2.7 days from 20 to 140 dpp whereas BHB was assayed every 3- 4 days during the first 21 dpp. Date and success of artificial insemination (AI) were recorded. Overall, 22.9% (174/760) cows resumed cyclicity (progesterone > 5 ng/ml) after 45 dpp (prolonged anovulatory interval postpartum), ovulation was delayed (follicular phase > 14 days) in 27.9% (212/760), luteolysis was delayed (a luteal phase > 20 days) for 26.1% of the cows (199/760) whereas 34.3% (261/760) suffered from an early luteolysis (a short luteal phase < 10 days). A total of 74.3% (565/760) cows showed at least one atypical pattern of cyclicity. The prevalence of biochemical ketosis (BHB> 0.15 mmol/L) is higher in cows with at least one cyclicity abnormality (p-value=0.02). In cows without any atypical pattern, a shortening in calving to first insemination interval (83.2 dpp vs 97.1 dpp; p-value<0.001) and calving to conception interval (120.7 dpp vs 143.6 dpp; p-value<0.001) were observed. Atypical patterns of ovarian activity are thus of high frequency in Holstein cows, associated to metabolic issues and significantly impact on fertility.

Keywords: Dairy cow, progesterone, betahydroxybutyrate, fertility,

Introduction

During the last month of pregnancy, ovarian activity decreases with a progressive follicular wave spacing,and even a complete stop of wave patterns

during the last 21 days of pregnancy (Driancourt, 2001). Normal follicular waves appear again within one week after calving (Roche *et al.*, 1991). However, ovulation, that effectively characterizes cyclicity recovery, occurs at very variable postpartum delays (Royal *et al.*, 2000; Petersson *et al.*, 2006b). Moreover, after this first ovulation, ovarian cycles do not necessarily follow in a regular way, that is a succession of a follicular phase being 3 to 14 days long and a luteal phase 10 to 19 days long. Other durations of the two phases together with first ovulation occurring later than 45 days postpartum (dpp) characterize atypical patterns of ovarian cyclicity (Royal *et al.*, 2000; Opsomer *et al.*, 2000). In addition to the frequency of the different abnormalities, the question of their subsequent consequences on reproductive performances arises.

The aim of this project was to describe the ovarian cyclicity resumption in dairy cows under field breeding conditions in France, to evaluate the impact of atypical patterns on fertility. Since the onset of lactation implies a huge increase in cow energy requirements, dairy cows are at high risk of ketosis during the postpartum period: this study also aimed to evaluate the frequence of ketosis in the field, together with its association with atypical patterns of ovarian cyclicity and further reproductive performances Available data (especially those in French breeding conditions) were often collected from experimental herds and/or from a small number of farms, on a limited number of animals, and/or with a low frequency of sampling, limiting the accuracy of the description (Cutullic *et al.*, 2011; Disenhaus *et al.*, 2008; Ledoux *et al.*, 2011 ; Opsomer *et al.*, 2000 ; Petersson *et al.* 2006a).

Material and methods

Data collection

Twenty-one French commercial herds equipped with Voluntary Milking System (VMS, DeLaval International, Tumba, Sweden) were included in the study. The mean number of cows by herd was 109 [min-max: 64-203] with 1.8 VMS per farm. Their milking robots were coupled to Herd Navigator system (HN, DeLaval International, Tumba, Sweden), repeatedly assaying milk progesterone (P4) and beta hydroxybutyrate (BHB) concentrations. Biomodels control HN automatic in-line sampling and measuring at varying intervals (Nielsen *et al.*, 2005; Friggens *et al.*, 2008). BHB is measured during the first three months of lactation. Progesterone assays begin at 20 days postpartum until the confirmation of pregnancy. A total of 153 715 milk P4 records and 78 362 milk BHB records were collected between April 2014 and July 2015 during 4 029 Holstein cow's lactations. Data on calving date, parity, milk production, insemination dates and pregnancy check were also registered.

The study focused on the period between the calving date and 140 days postpartum ("daily milk production filter"; table 1). Data were then selected as follows. In case of gaps between two consecutive progesterone assays longer than 10 days, the whole lactation was deleted from the study ("Progesterone filter", table 1). For the 760 lactations retained, progesterone was assayed every 2.8 ± 0.5 days (mean ± sd) between day 20 and day 140 postpartum. For the analysis of BHB risk factor, only lactations with a minimum of three BHB measurements during the 21 days postpartum were kept ("BHB filter", table 1):740 lactations were retained with on average a BHB assay every 1.4 ± 0.5 days. Table 1 describes the number of assays and cows after application of each filter.

Table 1: Number of progesterone (P4), β-hydroxybutyrate records (BHB) lactations, and cows retained by filtering criteria.

Criteria	P4	BHB	Lactations
Raw database	153 715	78 362	4029
Daily milk production filter [day 0- day 140 pp]	46 753	40 302	1102
Progesterone filter	38 539	28 837	760
BHB filter	37 632	28 343	740

Data smoothing

After applying daily milk production and progesterone filters (Table 1), the remaining progesterone data were processed. Periods during which progesterone was higher than 5 ng / mL were called "luteal phases" and periods during which progesterone is lower than 5 ng/mL , "follicular phases".

The first step consisted of estimating true onset and end date of each phase (time when the progesterone crosses the threshold value of 5 ng/mL) by the application of a linear interpolation method. Then, in the second step, fake follicular and luteal phases were deleted (luteal phase duration less than 3 days and follicular phase less than 2 days because biologically meaningless).

Definitions

The various patterns of abnormal cyclicity resumption are defined in Table 2. Cows with BHB concentration higher than 0.15 mmol/L at least once during the first 21 days of lactation were considered as affected by biochemical ketosis (BHB + group). The others were considered non affected (BHB – group).

Table 2: Definitions of atypical patterns (modified from Royal *et al.*, 2000, Opsomer *et al.*, 2000 and Petersson *et al.*, 2006a).

Delayed cyclicity (DC)	Progesterone levels ≤ 5 ng/mL during the first 45 days postpartum (included)
Delayed ovulation (DO)	Progesterone levels ≤ 5 ng/mL during more than 14 days (included) between two luteal phases
Delayed luteolysis (DL)	Progesterone levels ≥ 5 ng/mL during more than 20 days (included)
Early luteolysis (EL)	Progesterone levels ≥ 5 ng/mL during less than 10 days (included)

Statistical analysis

Data editing, filtering, trait definition and statistical analysis were carried out in R software version 3.3.2. (R Core Team, 2016). The normality was evaluated with the Shapiro–Wilk test. Data were analyzed using univariate tests (chi square and t-tests).

Results and discussion

Prevalence of atypical patterns

A total of 74.3% (565/760) cows exhibited at least one atypical pattern of cyclicity over the first 140 days of lactation.

The prevalences of the different patterns observed in the present study (Table 3) are in part different from those described in literature. Reported prevalence of delayed ovulation ranges between 3.7 and 12% (Opsomer *et al.*, 2000; Royal *et al.*, 2000; Cutullic *et al.*, 2008; Shrestha *et al.*, 2004) versus 28.7% in our study. The most stricking difference is for early luteolysis, whose prevalence was 34.3% in our study whereas very rare (0.5% to 3.7%) according to Opsomer *et al.*, (2000), Shrestha *et al.*, (2004), Cuttulic *et al.*, (2012) and Ranasinghe *et al.*, (2011); in those studies, the first luteal phase was always excluded, in contrast with the present work. In some other studies dealing with patterns of ovarian resumption in cows, short luteal phases were even not looked for (Disenhaus *et al.*, 2008; Cuttulic *et al.*, (2012); Ledoux *et al.*, 2011). Conversely, prevalences of delayed luteolysis (26.1%) and delayed cyclicity (22.9%) are coherent with those reported in earlier studies, ranging respectively from 11.9 to 35% and from 13 to 21% (Opsomer *et al.*, 2000; Royal *et al.*, 2000; Disenhaus *et al.*, 2008; Cuttulic *et al.*, 2012; Ledoux *et al.*, 2011; Shrestha *et al.*, (2004); Ranasinghe *et al.*, 2011)

Table 3 Prevalence of the different types of atypical patterns of ovarian cyclicity resumption (n=760 cows). One cow can have developed several types of abnormalities within one postpartum period.

Pattern	Cows	%
Delayed cyclicity	174	22.9
Delayed ovulation	212	29.7
Delayed luteolysis	199	26.1
Early luteolysis	261	34.3

Ketosis as a risk factor for atypical pattern of ovarian cyclicity

Overall, 17% of the cows developed biochemical ketosis over the first 21 days postpartum in our population. This figure is coherent with the observation of Philippe and Raboisson (2012) in French dairy herds, with 19% of cows affected based on BHB milk concentration. Ketosis has also a significant negative effect on the risk of cyclicity abnormality: only 11.5% of the cows with normal pattern vs 19.0% of females with at least one atypical pattern were BHB+ (p-value=0.02). Cows with at least on atypical pattern represent 83% of BHB+ group against 72% of BHB- group. However, no significant difference was evidenced when each anomaly was considered separately.

This result, based on ketosis diagnosed based on biochemical criteria is consistent with those of Walsh et al (2007) and Shin et al (2015) who described an impact of subclinical ketosis on the time of ovarian resumption. Considering clinical ketosis, Opsomer et al (2000) measured a 11-fold increase of the risk of delayed ovulation.

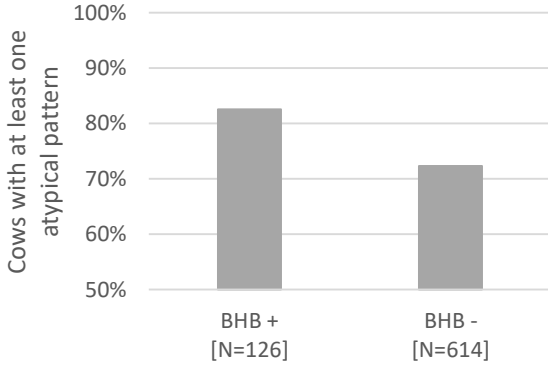


Figure 1: Percentage of cows with at least on atypical pattern in BHB + and BHB – groups (p-value=0.02)

Impact on fertility

Calving to first insemination interval was shorter for cows that resumed ovarian cyclicity postpartum following a normal pattern compared to cows suffering from at least one abnormality (83.2 dpp vs 97.1 dpp; p-value < 0.001; figure 2A). A significant increase was also observed for calving to conception interval (120.7 dpp vs 143.6 dpp; p-value<0.001; figure 2B).

Few studies evaluated the impact of the pattern of postpartum ovarian resumption on further fertility. A negative impact of atypicity was evidenced in Great-Britain twenty years ago with a + 7.5 and + 12.5 days increase of calving to first insemination (Lamming and Darwash (1998), Royal et al (2000) respectively) and a +18 days increase in calving to conception interval (Lamming and Darwash 1998). Ranasinghe et al (2011) also observed an increase in these intervals in Holstein dairy cows in case of different postpartum anomaly resumptions.

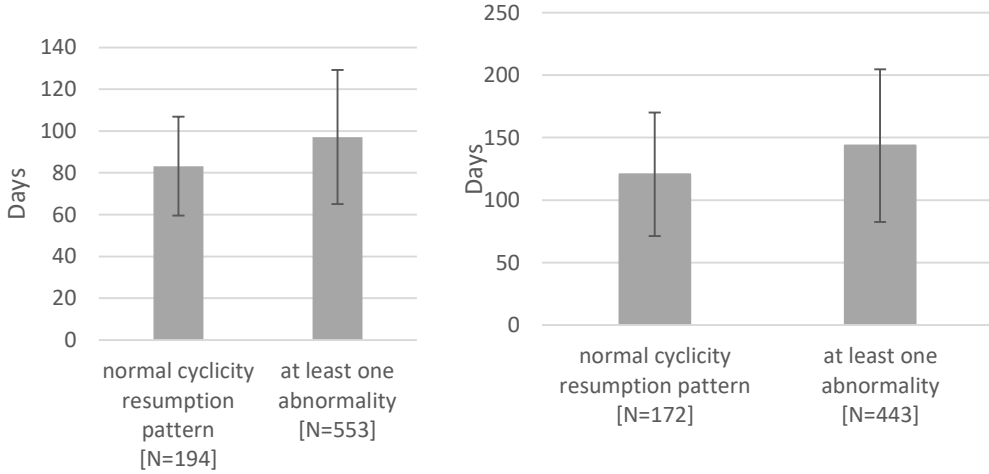


Figure 2 : Calving to first insemination (at left) and calving to conception (at right) intervals depending on the normality of ovarian resumption pattern (p<0.001)

Conclusions

This study evidenced not only the high prevalence of abnormalities in ovarian cyclicity resumption in modern Holstein dairy cows in field conditions in France, but also downstream their significant impact on further fertility and upstream ketosis as a risk factor. In that context, PLF tools contribute to a precise phenotyping of cows postpartum, allowing an early detection of cows at higher risk of infertility, and in consequence a precocious and appropriate care.

Acknowledgements

The authors thank DeLaval France for providing the list of farmers using the Herd Navigator system in France and all the farmers who participated at the study.

References

Cutullic E., Delaby L., Gallard Y. and Disenhaus C. 2011. Dairy cows' reproductive response to feeding level differs according to the reproductive stage and the breed. *Animal* **5**(5):731-40

Disenhaus C., Cutullic E., Blanc F., Gatien J., Agabriel J., Hetreau T., Michel G., Paccard P., Badinand F., Egal D. and Ponsart C. 2008. Caractéristiques comparées de la cyclicité après vêlage de différentes races bovines. *Rencontres Recherches Ruminants* **15**, 383-386

Driancourt M.A. 2001. Regulation of ovarian follicular dynamics in farm animals. Implications for manipulation of reproduction. *Theriogenology*.**1;55**(6):1211-39.

Friggens N.C., Bjerring M., Ridder C., Hojsgaard S. and Larsen T. 2008. Improved Detection of Reproductive Status in Dairy Cows using Milk Progesterone Measurements. *Reproduction in Domestic Animals* **43** (Suppl 2), 113-121.

Lamming G.E. and Darwash A.O. 1998 The use of milk progesterone profiles to characterise components of subfertility in milked dairy cows. *Animal Reproduction Science*. **11;52**(3):175-90.

Ledoux D., Touze J.L., Richard C., Ponter A.A., Bosc M.J. and Grimard B. 2011. Abnormal patterns of resumption of cyclicity after calving in Holstein cows : risk factors, relationships with the ultrasound appearance of the ovaries and with gestation failure after AI. *Revue Medecine Vétérinaire* **162**, 98-106

Nielsen N.I., Friggens N.C., Chagunda M.G.G. and Ingvartsen K.L. 2005. Predicting risk of ketosis in dairy cows using in-line measurements of beta-hydroxybutyrate: A biological model. *Journal of Dairy Science* **88**, 2441-2453

Opsomer G., Gröhn Y.T., Hertl J., Coryn M., Deluyker H. and De Kruif A. 2000. Risk factors for postpartum ovarian dysfunction in high producing dairy cows in Belgium: a field study. *Theriogenology* **53**(4):841-57

Petersson K.J., Gustafsson H., Strandberg E. and Berglund B. 2006a. Atypical progesterone profiles and fertility in Swedish dairy cows. *Journal of Dairy Science* **89**(7):2529-38.

Petersson K.J., Strandberg E., Gustafsson H. and Berglund B. 2006b. Environmental effects on progesterone profile measures of dairy cow fertility. *Animal Reproduction Science* **91**, 201–214

Philippe P. and Raboisson D. 2012. Prévalence de la cétose subclinique dans les troupeaux bovins laitiers de l'Ouest de la France. *Renc. Rech. Ruminants* **19**

Ranasinghe R.M., Nakao T., Yamada K., Koike K. and Hayashi A., Dematawewa C.M. 2011. Characteristics of prolonged luteal phase identified by milk progesterone concentrations and its effects on reproductive performance in Holstein cows. *Journal of Dairy Science*. **94**(1):116-27

Roche J.;F., Boland M.P. 1991. Turnover of dominant follicles in cattle of different reproductive states. *Theriogenology* **35**:81-90.

Royal M.D., Darwash A.O., Flint A.P.F., Webb R., Wooliams J.A. and Lamming G.E. 2000. Declining fertility in dairy cattle: changes in traditional and endocrine parameters of fertility. *Animal Science* **70**, 487-501

Shin E.K., Jeong J.K., Choi I.S., Kang H.G., Hur T.Y., Jung Y.H. and Kim I.H. 2015. Relationships among ketosis, serum metabolites, body condition, and reproductive outcomes in dairy cows. *Theriogenology*. **15;84**(2):252-60.

Shrestha H.K., Nakao T., Higaki T., Suzuki T. and Akita M. 2004. Resumption of postpartum ovarian cyclicity in high-producing Holstein cows. *Theriogenology*. **61**(4):637-49.

Walsh R.B., Kelton D.F., Duffield T.F., Leslie K.E., Walton J.S. and LeBlanc S.J. 2007. Prevalence and risk factors for postpartum anovulatory condition in dairy cows. *Journal of Dairy Science* **90**(1):315-24.

Can liveweight kinetics be used to predict the beginning of the breeding period in dairy cows?

T. Decers[1] and M. Ferrand[2]
[1]*France Conseil Elevage, 42 rue de Châteaudun, 75009 Paris, France*
[2]*Clasel, 141 Boulevard des Loges, 53940 Saint Berthevin, France*
thomas.decers@france-conseil-elevage.fr

Abstract

The energy balance is known to influence fertility (M.J. de Vries et al., 2000) and Thorup et al., 2013, concluded that the energy balance can be studied by means of real-time liveweight measurements. This paper seeks to assess whether daily liveweight measures from an automatic milking system (AMS) can be used to indicate when the breeding period can start.

Data from AMS and milk recording and advisory organisations (MRAO) were combined. The AMS could not be used directly and it was necessary to clean the data of load cell drift and to aggregate weights by ten-day lactation period in order to smooth daily variability. Finally we diversified our study database with other sources relating to animals.

1,195 Prim'Holstein lactations were used to link liveweight measurements and milk production in order to explain when the cows could be efficiently put to the bull or inseminated.

Liveweight kinetics was not the only factor in our study, but an important one in determining the positive artificial insemination (AI) date. This data processing enables us to propose an indicator for dairy farmers to enable them to identify the best period to breed their cows, the BoB, or Beginning of Breeding. This indicator could make it possible, firstly to reduce the number of straws needed for the latest fertilisable cows, and, secondly, to reduce the interval between two calves for the earliest ones.

Keywords: dairy cows, real-time liveweight, breeding period, fertility

Introduction

It is not always easy to assess when the breeding period starts. De Vries et al., 2010 showed that fertility is influenced by energy balance. AI must be delayed in dairy cows with a very negative balance, in which case AI semen is wasted. AI could be carried out earlier to reduce the interval between calvings for cows with a low postpartum interval before restoration of a positive energy balance. The energy balance can be estimated in two different ways: *i)* body condition score (Thorup et al., 2012) and *ii)* frequent body weight measurements (Thorup et al.,

2013). The fact that three brands of milking robot weigh dairy cows during milking makes it possible to investigate daily liveweight measurements. From these inputs, this paper examined whether it could be possible to indicate when dairy cows are fertile.
Since 2011, France Conseil Elevage, the umbrella organisation for French MRAO, has been developing software to populate our databases with all AMS brands (Ori-Automate®). It converts each AMS data format into our format. We can share data such as identification, reproduction, official milk recording (MRAO to AMS) and milk yield, liveweight, concentrate intake and animal activity (AMS to MRAO). This system is not used consistently throughout France, but we hope to improve its dissemination with this new indicator and upgraded versions of the software.

Materials and methods

Data available

Data supplied by AMS are first saved in regional databases. The MRAO can then transfer data saved in regional databases to the national database. Once the connection is working, data is imported continuously and automatically. This database allows national R&D studies. However, some of the connections for copying data from regional databases into the national database are not currently enabled. The system is operational in Brittany, Normandy and eastern France and data since 2014/01/01 have been included in the study.
Additional data, such as date of birth, calving date, breed, rank of lactation, AI date and pregnancy diagnosis completed the study database. The completeness of the study was limited by this data because it required manual extraction.
All data analyses were performed with R Statistical Software (version 3.3.0).

Data wrangling and cleaning

Cleaning and qualification of the AMS data

Cleaning of the AMS data was carried out at herd level to remove the drift due to weighing platform anomalies. Data were summarised by week to detect anomalies of two types. The first was a drift over time without rational explanation (Figure 1) and the second was linked to a specific issue with the weighing platform (Figure 2).
In the first case, to determine whether the drift was due to a change in the herd or not, a changepoint analysis was run on the liveweight and also on the number of cows in the herd, the average days in milk, and the average number of lactations. The analysis was performed with the changepoint package, version 2.2.2 (Killick, 2013). The Pruned Exact Linear Time (PELT) algorithm with manual penalty was used for the four series. Liveweight and number of cows only

showed changes in mean. For average days in milk and average numbers of lactations, a better fit was obtained by detecting both change in mean and variance. An example of detected changes in liveweight over time is shown in Figure 3.

When a change occurred on the average liveweight curve, it was considered normal if another change was observed at the same time (the previous week, the same week and the next week): for example an increase in the number of cows; otherwise an alert was generated and the rest of the series (after the change) was discarded for all cows in the herd. To detect the second kind of anomalies, the averaged liveweight variation from one week to another was calculated and the data for all the cows were removed if this variation exceeded 5%.

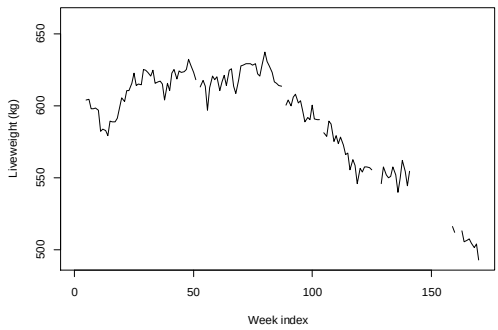


Figure 1: Example of drift over time weighing

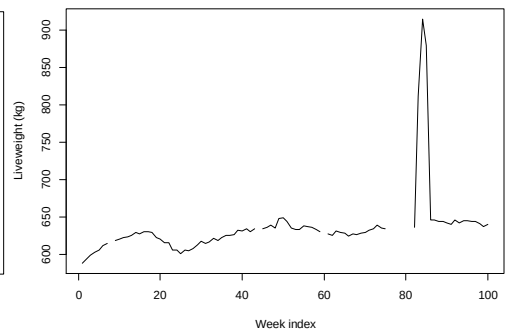


Figure 2: Example of a specific platform issue

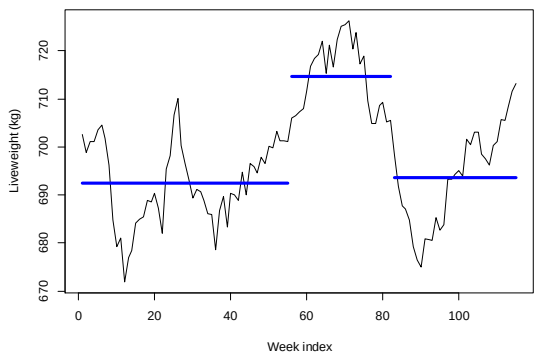


Figure 3: Example of changes detected by changepoint method

Qualification of artificial insemination

To assess the artificial insemination outcome, the following rules were applied:

- If the AI was the last one of the current lactation and calving was observed in the interval of [220;310 days] following artificial

insemination, the AI was considered successful. The same assessment was assigned if a positive pregnancy diagnosis matched with the AI.

- If the AI was the last one of the current lactation but no re-calving was observed for the moment (Interval AI – date of the day lower than 280 days), the success of the AI was considered as probable.
- If the AI was not the last one or no re-calving was observed after 310 days, the AI was considered unsuccessful.
-

Only successful AI (first rule) were processed to create the BoB indicator.
The AI we investigated came directly from the database without distinction as to whether it was carried out by the farmer or the commercial operator. Moreover, we did not know whether the dairy farmers deliberately waited for AI at the beginning of lactation or whether they inseminated cows at each oestrus detection. Furthermore, the time lapse between oestrus detection and insemination or presentation to the bull was not recorded. This lack of information restricted the ability to explain the variability of successful fertilisation.

Formatting of the dataset
To obtain the final dataset, liveweights cleaned of weighing platform drift were merged with milk yields and information about artificial inseminations. Daily milk yield and liveweight were averaged by ten-day lactation period for each cow. The average daily milk yield sums milk production during the ten-day period and divides it by the number of milk recording days during the ten-day period. The weight average was calculated only if at least five days of data were recorded over the ten-day period. Aggregated data by ten-day period smoothed information from daily variability: rumen content can be cited for the weight and the number of milkings a day for milk yield.
Only Prim'Holstein cows were used for model processing. It will be possible to assess Normande and Montbeliarde breeds as more data becomes available.

<u>Establishing the indicator BoB</u>
This study made it possible to explain the interval postpartum to return pregnant (IPP). IPP values above 250 were deleted, assuming that breeders will not use this indicator after 250 DIM. They will mate their cows as soon as the cows are in oestrus.
We created two classes for the first lactating cows: calving before and after 28 months. We distinguished the first lactation from the second lactation and from cows in the third or higher lactation. In each of these four classes, IPP were discretised by ascending hierarchical classification. Classes were cut to

maximise heterogeneity between groups and maximise homogeneity inside each group.
The second step was to match cows with one of the IPP groups, by recursive partitioning. The tree was built using the following variables. These variables were selected by covariance analysis for their ability to explain IPP variability.
P1: average weight during the first ten-day period of the lactation (1 to 10 days in milk): to evaluate the weight at calving
P4: average weight during the fourth ten-day period of the lactation (31 to 40 days in milk). P4 was selected rather than P3, P5 and P6 by maximising the covariance explanation.
P4P1: Difference between P4 and P1: to evaluate the kinetics of the weight
P1P4P1: Interaction between P1 and P4P1: the heavier the cow at calving, the more weight it can lose.
L1: average daily milk production during the first ten-day period of lactation
L4: average daily milk production during the fourth ten-day period of lactation
L4L1: Difference between P4 and P1: to evaluate the kinetics of the weight
L1L4L1: Interaction between L1 and L4L1
MonthCalving: Month of calving
MonthPAI: Month of successful AI

Initially, we wanted to process liveweights using curves where data were smoothed by BSplines, but this method cannot take account of missing data between calving and the fourth decade of lactation, and a lot of cows were missed.
We currently lack measurements by herd which can be used to take account of its effect. This should be possible with time.
The number of AI in a same lactation was not significant to explain the IPP variability, which confirms that all AI can be considered as independent during lactation. Moreover it would be easy to calculate *a posteriori* how many AI events had occurred during the lactation, but in real time we are not able to do this.
The trees were automatically pruned by cross validation to avoid overfitting of the rules. This step was made necessary by the lack of data, which did not allow one learning database and one testing database.
Finally, the cumulated percentage of pregnant cows was calculated over the first 250 days in milk, by group. The BoB is based on this cumulative percentage. The prediction is inferred by the choice of a threshold in the cumulative percentage.

Results and discussion

This study was handicapped by manual data extractions (information about cows) which limited the potential of this paper because of the delay in receiving them.

A lot of data were lost when all the quality rules were applied. The data available were therefore very restricted, but for research and development studies, it is better to gather a small amount of well-qualified data than a lot of poor data. Table 1 shows the available data and studied data by French department (county).

Table 1 : Summary of available and processed data

County	Available data		Processed data		
	Herds	Dairy cows	Herds	Dairy cows	Lactations
14	13	2066	4	49	49
22	80	9032	34	595	627
27	2	155			
29	42	5501	13	234	255
50	38	5136	7	91	95
53	12	1461			
54	21	2501	2	23	23
55	20	2906	2	33	33
56	32	4328	4	94	103
57	11	1702			
67	23	2778			
68	7	656			
72	3	193			
76	6	532			
88	26	3066	2	10	10

The second problem with the data arose from the merge step. In AMS data, cows are sometimes identified by just 4 digits (the working number) but in official data (date of birth, etc.) cows are nationally identified by a 10-digit number. Database matching failed for these cows.

The results presented relate to first lactation Friesian cows which calved before 28 months old. Figure 3 compares, on the left, the variability of IPP after discretisation (by classification) and, on the right, IPP variability after prediction by recursive partitioning. Four groups were created by the discretisation but this would change with an increase in data.

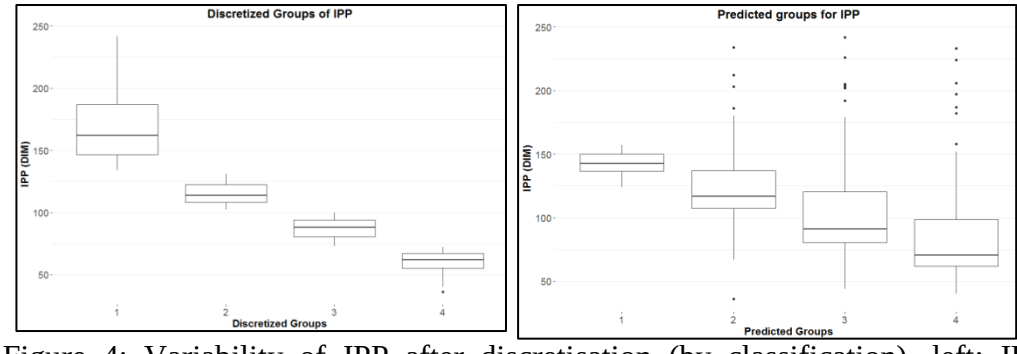


Figure 4: Variability of IPP after discretisation (by classification), left; IPP variability after prediction by recursive partitioning, right.

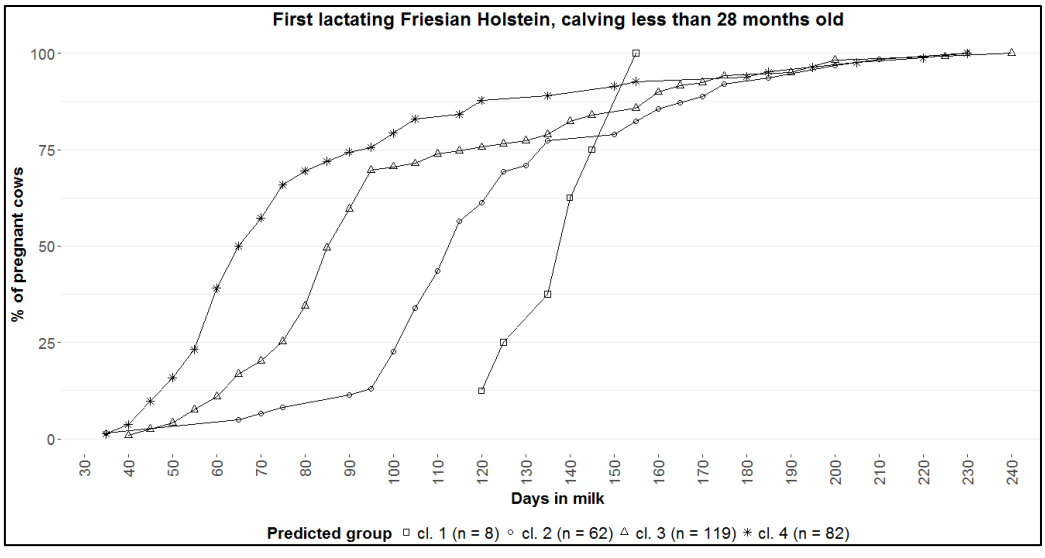
The extreme IPP values were the hardest to classify. The highest IPP severely handicapped the cross validation. Table 2 presents the results of the cross validation. The recursive partitioning included P1, P4P1, P1P4P1, L4L1, MonthPAI and MonthCalving to build the tree. Milk yield data was poorly represented given the correlation between milk production and liveweight (+0.30 between P1 and L1, +0.34 for P4 and L4).

		Discretised groups					
		1	2	3	4	Total	Misclassified
Predicted groups	1	6	18	28	10	62	90%
	2	2	36	8	10	56	36%
	3	0	5	63	18	86	27%
	4	0	3	20	44	67	34%
	Total	8	62	119	82	271	

Table 2: Summary of the recursive partitioning quality

We will improve the model and database in a second step in order to understand whether the highest of IPP values come from dairy manager actions or whether we lacked knowledge about cows in the model.

Figure 5 outlines BoB for the four predicted groups.



The distinction between the four groups is clear: more than 20 days in milk between each rank of groups. The objective of predicting a cow's membership of a group rather than directly predicting IPP is to maintain variability in the prediction. The variability in each class enables the manager to start the breeding period according to the economic value of the straw. If the straw is cheap or if the cow is presented to the bull, the manager can chose a low threshold (30%). A 70% threshold is more advisable with sexed AI. The difference in DIM relates to a biological cycle (20 days). Testing of this work on the farm from May 2017 will make it possible to refine these thresholds.

Conclusions

This paper confirms the importance of liveweight kinetics in explaining the variability in fertility. The quality of recursive partitioning is very hopeful except for the highest IPP. A new phase of study of data will now be launched.
Concentrate intake could be tested to improve the understanding of energy balance. This could enhance prediction of BoB. De Vries et al. have also shown the importance of fat kinetics in predicting the onset of fertility.
The methodology used, based on machine learning, will be able to fit models with changes in liveweight measures and the new explanatory variables, and enhance prediction quality with time. This opens up opportunities for improved reproductive management and is particularly relevant to precision dairy farming.

Acknowledgements

The authors thank the 11 members of the FCEL groups of statisticians and zootechnicians who helped them in their work.

References

de Vries, M. J. and Veerkamp, R. F. 2000. Energy balance of dairy cattle in relation to milk production variables and fertility. *Journal of Dairy Science* 83, 62-69.

Killick, R. and Eckley A, I. 2013. Changepoint: An R Package for Changepoint Analysis. *Lancaster University*, 2013/05/06.

Thorup, V. M., Edwards, D., and Friggens, N. C. 2012. On-farm estimation of energy balance in dairy cows using only frequent body weight measurements and body condition score. *Journal of Dairy Science* 95, 1784–1793.

Thorup, V. M., Højsgaard, S., Weisbjerg, M. R. and Friggens, N. C. 2013. Energy balance of individual cows can be estimated in real-time on farm using frequent liveweight measures even in the absence of body condition score. *Animal* 7:10, 1631–1639.

Session 12

Feed and Cattle

Effect of restricted feeding conditions on cow's feeding behaviour and activity on pasture-based milk production systems

J. Werner[1,2], L. Leso[1], C. Umstätter[3], E. Kennedy[1], N. O'Leary[1], M. Schick[2,4], B. O' Brien[1]
[1]*Teagasc, Animal & Grassland Research and Innovation Centre, Moorepark, Fermoy, Co. Cork, Ireland*
[2]*University of Hohenheim, Institute for Agricultural Engineering, 70599 Stuttgart, Germany*
[3]*Agroscope, 8356 Ettenhausen, Switzerland*
[4]*Strickhof, 8315 Lindau, Switzerland*
jessicaanna.werner@teagasc.ie

Abstract

In pasture-based milk production systems grass utilization is a key factor in driving economic performance. Grass is currently allocated based on a combined calculation of either grass height measurements or estimates and grass quality estimations. However, the recommended measurement procedures are time and labour demanding and estimates are subjective. The aim of this study was to evaluate if cow feeding and activity behaviour, measured by an automated noseband sensor and pedometer, could be used to identify different levels of feed availability in a pasture-based system. Control cows were offered 100 % of their intake capacity as herbage allowance (Control) throughout a 10-week experimental period, while treatment cows were offered 60 % of the herbage allowance of the control cows (Treatment) for a 2-week or 6-week period in spring-time. Rumination behaviour (rumination time/day and chews/bolus) as well as bite frequency were significantly affected by the restricted feeding regimen. Thus, a change in feeding behaviour was observed when the herbage allowance was restricted. This indicated that feeding behaviour may represent a suitable indicator of insufficient grass allocation. Decision support based on monitoring cow behaviour can be indicative of insufficient grass allocation and may allow improved management of pasture based milk production systems.

Keywords: activity behaviour, restricted feeding, decision support tool, rumination time, pedometer, noseband sensor

Introduction

Intensively grazed grass is the cheapest home produced feedstuff on dairy farms (Finneran *et al.*, 2010). Fulkerson *et al.* (2005) found that the correct allocation of appropriate pasture on a constant daily basis would result in ~ 10 % higher

milk yield. Pasture-based milk production systems should thus aim to maximize the utilization of grazed grass to increase farm profitability. Accurate and timely assessment of pasture biomass is however required to achieve this (French *et al.* 2015). This assessment of pasture biomass and appropriate grass allocation to the herd is generally based on a combination of grass height measurements/estimations and grass quality estimations. Methods of assessment of grass height vary from experience-based eye estimation to automated measurement using precision tools such as the Grasshopper device (McSweeney *et al.* 2015). However, the determination of the correct allocation of feed to the herd is mostly subjective and quantitative measurement tools are not routinely used on a widespread basis. Reasons for this may include low confidence in accuracy of tools to measure grass quality or the high labour demand (French *et al.* 2015). Evaluating the correct feed allowance based on automatically collected measures of animal behaviour is a relatively novel concept and in tandem with appropriate decision support infrastructure, may be a useful approach to improving pasture based production.

In this study, cows were assigned to two different treatments with either a 100 % or 60 % herbage allowance to determine any potential impact on their feeding behaviour or activity as a consequence of the restricted herbage allowance.

Material and Methods

The experiment was conducted at the Teagasc Moorepark Dairy Research Farm, Fermoy, Co. Cork, Ireland from 16 March to 22 May 2016 with a spring calving pasture-based dairy farm. Pre-experimental milk production averaged 24.1 ± 3.6 kg/cow/day, body weight was 503 ± 72 kg, and days in milking were 34 ± 11. Twenty one Holstein Friesians and 19 Jersey crossbreds were included and stratified across groups. Cows were balanced across the treatments based on genotype, calving date and pre-experimental milk production and were assigned to treatments where they were offered a herbage allowance of either 100 % of their intake capacity (IC; Faverdin *et al.* 2011) (CTRL) or 60 % IC (TRTM). In total, there were seven individual herds of 15 cows per herd; six of these herds were assigned to TRTM during early lactation, whereas one of these seven herds functioned as a control group (CTRL) with 100 % IC. Within the CTRL herd there were ten of fifteen cows selected for behaviour recordings. While within each of the six TRTM herds, there were five cows selected, resulting in forty cows in total. The six treatment groups had different durations of feed restriction. Corresponding to three different start times during the spring, three of the treatment groups experienced 2 weeks of restricted herbage allowance in total, whereas three groups experienced 6 weeks of restricted herbage allowance. The experimental grazing areas represented permanent grassland with 80 % perennial

ryegrass and 20 % annual meadow grass. Fresh grass was allocated twice daily after each milking.

The RumiWatch noseband sensor and the RumiWatch pedometer (Itin+Hoch GmbH, Liestal, Switzerland) were used for measuring feeding behaviour and activity of the cows. The RumiWatch noseband sensor was validated in a pasture based milking system against visual observation. The accuracy was very high with r = 0.96 and r = 0.98 for grazing and ruminating behaviour, respectively (Werner *et al.* 2017). The behaviour of the CTRL herd was monitored over a 10-week period, whereas five of the TRTM herds were monitored for two weeks and one TRTM herd was monitored for six weeks. After two weeks of continuous recording the data was downloaded. Further technical information about the RumiWatchSystem is reported by Alsaaod *et al.* (2015) and Zehner *et al.* (2017). The RumiWatch noseband sensor has the ability to identify feeding time with head position up and head position down. In this study, grazing time was defined as feeding time with head position down ("EAT1TIME"). Only complete daily records were included in the analysis. The RumiWatch Manager 2 (V.2.1.0.0) and the RumiWatch Converter (V.0.7.3.36) were used to record and analyse behavioural data at a daily resolution level. In total, there were 1,120 daily summaries recorded, 635 and 485 for the CTRL and TRTM groups respectively.

Statistical analysis was performed using R (R Core Team, 2016). Outcome variables investigated were daily grazing time, number of grazing bites, biting rate, grazing bouts, rumination time, number of rumination chews, rumination chews per bolus, rumination bouts, lying time, standing time and walking time. Bite frequency was calculated as number of grazing bites (RumiWatch output "EATBITE") divided by grazing time (RumiWatch output "EAT1TIME"). A linear mixed model for repeated measures was developed for every response variable to evaluate the effects of herbage allowance on the behaviour of cows. Herbage allowances (60 % or 100 %) were included as fixed explanatory factors in the models. In all models, the random effects of individual cow and recording day were included. Normality and homoscedasticity of variance for all models were visually inspected using residual plots. Least square means (LSmeans) and standard error of the mean (SEM) were analysed. Tukey's method was used for pairwise comparisons of LSmeans. The level of significant differences was declared at $p < 0.05$.

Results and Discussion

The results in Table 1 indicate that cow feeding behaviour was significantly influenced by restricted herbage allowance. In contrast, there were no significant effects on daily activity detected. Time spent walking, standing and lying were

similar for TRTM and CTRL groups. These findings concur with those of O'Driscoll *et al.* (2015) who found that daily herbage allowance had no effect on daily lying time.

Table 1: Effect of herbage allowance (100 % and 60 %) on cow feeding behaviour and activity parameters

Parameter	60 % herbage allowance (TRTM)	100 % herbage allowance (CTRL)	SEM	Significance
Grazing time (min/day)	488.2	502.0	16.20	0.396
Number of grazing bites (n/day)	32246	31952	1316	0.8241
Bite frequency (n/min)	65.85	63.43	1.20	0.0457
Grazing bouts (n/day)	7.95	8.15	0.31	0.5273
Ruminating time (min/day)	403.4	468.5	13.26	<0.0001
Number of rumination chews (n/day)	25402	30495	1039	<0.0001
Rumination chews per bolus (n/bolus)	33.99	38.81	1.16	0.0001
Ruminating bouts (n/day)	13.49	13.17	0.55	0.5549
Walking time (min/day)	87.8	85.0	4.37	0.512
Standing time (min/day)	829.4	837.9	14.91	0.5699
Lying time (min/day)	523.1	517.6	15.31	0.7173

SEM = Standard error of means

Regarding feeding behaviour, the 100 % herbage allowance group spent significantly longer time ruminating per day and exhibited a higher number of rumination chews/bolus than the 60 % herbage allowance group. These effects are observed for the parameters of total rumination time/day and rumination chews/bolus in Table 1 and Figure 1, respectively. CTRL cows had significantly longer rumination time at 468.5 min/day compared to the TRTM cows at 403.4 min/day ($p < 0.0001$). A reduced rumination time observed by Kennedy *et al*. (2009) in their study was interpreted as being due to there being less material in the rumen to digest. The number of rumination chews/day was 30495 and 25402 ($p < 0.0001$), while the rumination chews/bolus recorded were 38.81 and 33.99 for the respective groups. However, no significant difference in rumination bouts was detected.

The effect of restricted herbage allowance was more distinctive in rumination behaviour than in grazing behaviour. There were no significant differences detected in grazing time, number of grazing bites and grazing bouts/day between CTRL and TRTM groups. The grazing time ranged from 239 to 654 min and 102 to 724 min for the CTRL and TRMT groups respectively. The LSmean of 502 min/day and 488 min/day for the CTRL and TRTM groups concurred with results of Kennedy *et al.* (2009) where grazing time was reported as 481 min/day with 22-hours access to pasture per day. In that study, the restriction in herbage allowance was achieved by decreasing the time cows had access to pasture, but the same pasture allowance was offered. A main finding in that study was that grazing efficiency increased as pasture access time was reduced. However, grazing time was similar for CTRL and TRTM groups in the current study, even though the TRTM group had less grass allocated to them (60% compared to 100%). But the higher bite frequency observed with the TRTM group may account for this. Bite frequency was significantly higher for TRTM cows (65.85 bites/min) than CTRL cows (63.43 bites/min; $p = 0.0457$). The TRTM and CTRL cows spent similar time grazing but the CTRL cows had a higher bite frequency resulting in higher intake per minute. This effect was also observed by Patterson *et al.* (1998) when dairy cows grazing good swards were capable of compensating for an increased degree of hunger by increasing bite rate. Taking grass residuals and post-grazing height into account might show that the TRTM group had lower residuals and less post-grazing height than the CTRL group. This analysis may be performed and reported in future publications.

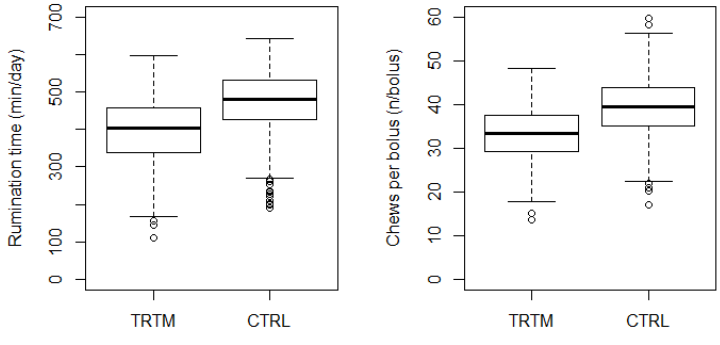


Figure 1: Effect of treatment (60 % herbage allowance) versus control group (100 %) in rumination time per day and rumination chews per bolus. Data are presented as box plots indicating observed median, first and third quartiles and absolute range of data with outliers, displayed as circles.

Although most studies have focused on the effects of restricted feeding on grazing behaviour (Pérez-Ramírez *et al.* 2009), this current study demonstrated that the effects are more significant with regard to rumination behaviour. This distinction is underlined by the findings of Patterson *et al.* (1998) and Kennedy *et al.* (2009) which indicated that cows can cope with a restriction in herbage allowance through a higher bite frequency but they cannot maintain normal rumination duration when there is less material in the rumen to digest. The decline in rumination time may thus be a more suitable indicator than grazing time for assessing appropriate grass allocation. Overall this study has demonstrated that restricted grass allowances have an effect on feeding behaviour in general and on rumination in particular. With the application of automated sensor technologies, such as the RumiWatch noseband sensor, it is now possible to monitor those parameters on a continuous basis. Rumination time/day or chews/bolus, may contribute to decision support provision to farmers potentially highlighting detrimental changes in pasture availability or insufficient grass allocation. As rumination time is already a well acknowledged parameter with regard to heat detection or calving prediction (Pahl *et al*. 2015), it may be easily adapted to use as an indicator of starvation or insufficient herbage allowance. With a monitoring system providing decision support for more than one application, the automated measurement of rumination time might become even more useful for farmers improving the return on investment attainable from rumination observation sensors.

Conclusions

In conclusion, grazing behaviour in terms of bite frequency was significantly increased for the treatment (60 % herbage allowance) over the control (100 % herbage allowance) group. Alternatively, rumination behaviour in terms of rumination time/day and chews/bolus were significantly decreased for the treatment groups. There was no significant effect detected in activity such as walking time or standing time between the treatment and control groups. These results demonstrate that rumination behaviour in particular may be a good indicator of appropriate grass allocation per cow and could be investigated further with a view to developing a decision support tool taking these parameters into account.

Acknowledgements

The authors would like to thank Science Foundation Ireland for funding the project “Precision Dairy” and the farm staff at the Moorepark research farm for the handling of the animals and grass management to accomplish the experimental requirements.

References

Alsaaod, M., Niederhauser, J. J., Beer, G., Zehner, N., Schuepbach-Regula, G., and Steiner, A. 2015. Development and validation of a novel pedometer algorithm to quantify extended characteristics of the locomotor behavior of dairy cows. *Journal of Dairy Science*, **98**(9) 6236-6242.

Faverdin, P., Baratte, C., Delagarde, R., and Peyraud, J. L. 2011. GrazeIn: a model of herbage intake and milk production for grazing dairy cows. 1. Prediction of intake capacity, voluntary intake and milk production during lactation. *Grass and Forage Science*, **66**(1) 29-44.

Finneran, E., Crosson, P., O'Kiely, P., Shalloo, L., Forristal, D., and Wallace, M. 2012. Stochastic simulation of the cost of home-produced feeds for ruminant livestock systems. *The Journal of Agricultural Science*, **150**(01) 123-139.

French, P., O’Brien, B., and Shalloo, L. 2015. Development and adoption of new technologies to increase the efficiency and sustainability of pasture-based systems. *Animal Production Science*, ***55***(7) 931-935.

Fulkerson, W. J., McKean, K., Nandra, K. S., and Barchia, I. M. 2005. Benefits of accurately allocating feed on a daily basis to dairy cows grazing pasture. *Animal Production Science*, **45**(4) 331-336.

Kennedy, E., McEvoy, M., Murphy, J. P., and O’Donovan, M. 2009. Effect of restricted access time to pasture on dairy cow milk production, grazing behavior, and dry matter intake. *Journal of Dairy Science*, **92**(1) 168-176.

McSweeney, D., Foley, C., Halton, P. and O’Brien, B., 2015. Calibration of an automated grass height measurement tool equipped with global positioning system to enhance the precision of grass measurement in pasture-based farming systems. In: A. van den Pol-van Dasselaar, H.F.M. Aarts, A. De Vliegher, A. Elgersma, D. Reheul, J.A. Reijneveld, J. Verloop, A. Hopkins (eds.) *Proc. of the 18th Symposium of the European Grassland Federation* Wageningen Publisher, The Netherlands, 265-267.

O’Driscoll, K., Lewis, E., and Kennedy, E. 2015. Effect of feed allowance at pasture on lying behaviour and locomotory ability of dairy cows. *Applied Animal Behaviour Science*, **166** 25-34.

Pahl, C., Hartung, E., Grothmann, A., Mahlkow-Nerge, K., and Haeussermann, A. 2014. Rumination activity of dairy cows in the 24 hours before and after calving. *Journal of Dairy Science*, **97**(11) 6935-6941.

Patterson, D. M., McGilloway, D. A., Cushnahan, A., Mayne, C. S., and Laidlaw, A. S. 1998. Effect of duration of fasting period on short-term intake rates of lactating dairy cows. *Animal Science*, **66**(02) 299-305.

Pérez-Ramírez, E., Peyraud, J. L., and Delagarde, R. 2009. Restricting daily time at pasture at low and high pasture allowance: effects on pasture intake and behavioral adaptation of lactating dairy cows. *Journal of Dairy Science*, **92**(7) 3331-3340.

Werner, J., Leso., L., Umstatter, C., Schick, M. and O'Brien, B. 2017. Evaluation of precision technologies for measuring cow's grazing behaviour. In: C. Porqueddu, A. Franca, G. Lombardi, G. Molle, G. Peratoner, A. Hopkins (eds.) *Proc. of the 19th EGF Symposium of the European Grassland Federation* Wageningen Publisher, Alghero, Sardinia (Italy), 82-84.

Zehner, N., Umstätter, C., Niederhauser, J. J., and Schick, M. 2017. System specification and validation of a noseband pressure sensor for measurement of ruminating and eating behavior in stable-fed cows. *Computers and Electronics in Agriculture*, **136** 31-41.

Dairy cow response in water intake to short-term fluctuations of silage K and Na concentration and its implications for estimation of dry matter intake

T. Eriksson and B.-O. Rustas
Department of Animal Nutrition and Management, SLU, Box 7024, 750 07 Uppsala, Sweden
Torsten.Eriksson@slu.se

Abstract

The ad libitum intake in dairy cows of silage or of a mixed ration is fundamental to performance, but the intake of individual cows is commonly not known. Drinking water intake is correlated to dry matter intake and to the intake of K and Na. If there is a consistent individual response of drinking water intake to feed factors, it would in theory allow for estimating individual feed intake once the response is known. This issue was addressed in an experiment with 57 mid-lactation cows (30 kg milk/d) in a VMS barn equipped with water bowls for automated recording. The cows were subjected to a treatment sequence with 7 periods of 4-8 d where the ad libitum fed grass silage was fortified with two equimolar levels (0.2 and 0.4 mol/kg DM) of K and Na, respectively, with control periods in between. Daily fluctuations in the herd mean intake of (K+Na) (13.2 – 25.7 mol/d), whether caused by silage fortification or by fluctuating silage intake, were well correlated to drinking water intake (113 – 153 kg/d; r = 0.86). The period means for drinking water intake of individual cows (55-209 kg/d) increased with 3.64 kg/mol (K + Na) (R2 = 0.83) during K fortification and with 1.95 kg/mol (K + Na) (R2 = 0.61) during Na fortification. Individual cows had slopes of 1.5 – 7.6 kg/mol during K fortification and -4.1 – 4.2 kg during Na fortification. The rankings of the responses among individuals to K and Na, respectively, were not correlated.

Keywords: Dairy cows, water intake, dry matter intake, automatic recording, potassium, sodium

Introduction

Knowledge about the individual dairy cow's ad libitum intake of silage or of a mixed ration is of great value for allocating concentrate supplementation and for the ranking of animals for feed efficiency. Drinking water intake in dairy cows is correlated to dry matter intake (Kramer et al., 2008; Khelil-Arfa et al., 2012) and even stronger to the intake of Na (Spek et al., 2012) and K (Eriksson & Rustas,

2014) if they are the only factors altered in the ration. This suggests a possibility to utilize drinking water registrations as a tool for estimations of dry matter intake and especially to monitor relative changes in the individual animal´s dry matter intake level. There is considerable individual variation in the drinking water consumption (Cardot et al., 2008), but if an individual has a consistent response to feed factors affecting water intake, feed intake should be possible to estimate once this individual response has been established. The objective of the experiment reported here was to evaluate the response to a treatment sequence where the silage concentration of either K or Na fluctuated.

Material and methods

Barn and registration equipment

The experiment was performed in a section of the dairy barn at the The Swedish Livestock Research Centre, Uppsala. The barn section was equipped with a DeLaval voluntary milking system (VMS) and designed for 60 cows. There was existing equipment for registration on animal level of the intakes of concentrates (Delpro system, Delaval International, Tumba, Sweden) and silage (BioControl AS, Rakkestad, Norway). For registration of drinking water intake, custom water bowls were developed by BioControl AS, where signals from flow meters were logged by the same technique that was used for logging weights from the silage feeders. The development of the water bowls included modification of antenna placement for reliable necklace transponder identification (Figure 1) and, preceding the experiment reported here, adaptation to ear tag transponders. Temperature and relative humidity of the barn section was recorded hourly with a logger system (Hobo, Onset, Bourne, MA, USA).

Material and methods

Experimental data

The data, both pathologic and healthy coughs, used for the analysis are cough sounds recorded in laboratory conditions. The healthy coughs were induced in an inhalation chamber by injecting an irritating substance namely 0.8 moles per litre of citric acid…

Signal analysis

The frequency characteristics of the signal on which the identification process is based, **Figure 1.** Stepwise modification of water bowls for automated recording of drinking water intake. Antennae are indicated by red arrows. Horizontal antenna for necklace transponder (left and middle) was moved out and the water bowl was fenced of for reliable identification. At switch to ear tag transponders (right) preceding this experiment, the antenna was mounted under the vertical cover of the right hand side.

Experiment and basal feeding

The experiment was performed from September 16 until October 22, when a group of dairy cows were fed silage with different concentrations of K and Na, respectively, in periods lasting for 4-8 days (Figure 2). A total of 57 lactating cows of the Swedish Red and Swedish Holstein breeds were used, whereof 31 primiparous and 26 multiparous. The cows were 187 days in milk at experimental onset. The cows were fed grass silage ad libitum and concentrates (Komplett Fiber 170 and Konkret Mega 28, Lantmännen, Stockholm) at pre-experimentally set individual levels according to yield and Swedish feeding standards.

K and Na fortification of silage

The silage contained per kg DM: 159 g CP, 29 g K and 1.5 g Na. Different levels of K and Na were created in the silage by addition of KCl (Product 1003259, Univar Europe, Malmö) and NaCl (Feed salt 26252A, Hanson & Möhring, Göteborg). The salts were dissolved in 75 liters of tap water and sprinkled on 925 kg (fresh weight) silage in a TMR mixer (DeLaval DSM 10). The salt amounts (8.0 and 16.0 kg KCl and 6.25 and 12.5 kg NaCl) were intended to provide two equimolar concentrations (0.2 and 0.4 moles/kg DM) of K and Na, respectively. In periods without salt addition, 75 liters of tap water only was sprinkled onto each silage batch in the same manner.

Recordings, sampling and analyses

All intake of feed and water was recorded and feeds were sampled daily. Standard wet chemistry methods were used for the analysis of crude protein and minerals in the feeds. Milk yield was recorded at every milking in the VMS

system, and the hourly production from each cow during the last 48 h in each period was multiplied by 24 to obtain a mean for milk production per day.

Statistical analysis

Daily intake means were calculated for the entire group of cows, but the main calculations were on period means from each cow, including all 4-8 days in each period. Treatment effects were evaluated with PROC MIXED of SAS 9.3 with period as fixed effect and cow as random variable. Simple linear regressions and regressions with a random intercept (St-Pierre, 2001) were calculated with PROC REG and PROC MIXED, respectively in SAS. Regressions were done both with the added cation (K or Na) and with the sum K+Na, also taking the ration's basal level into account. Individual regressions for each cow were also performed on the three period means for K and Na addition, respectively, where the preceding 0-period constitued one of the observations. The relationship in response to K and Na addition, respectively, among individual cows was then tested with the correlation between how the slopes ranked for K and Na.

Results and Discussion

The daily group means for intake of K+Na varied by the addition, but also by variations in silage intake (Figure 2). The correlation between daily group means of drinking water intake and the intake of K+Na was 0.86. There was a treatment effect on silage intake (Table 1) where the highest K addition level resulted in a lower intake than in other periods with addition ($P < 0.001$), although not different from the 0-periods ($P > 0.05$). The drinking water intake increased with addition of KCl and NaCl (Figure 3), but there was a higher slope with K addition, 3.64 kg water/mol K compared to 1.95 kg water/mol Na (Table 2). The lesser response to Na than to K is surprising and divergent from previous findings (Murphy et al., 1983; Spek et al., 2012). It is possible that longer experimental periods would have resulted in a different outcome, because most previous studies are either change-over trials with period lengths of 2-4 weeks or data registrations collected continuously for several months. The slopes for the response of individual cows to K and Na addition were not correlated ($r = -0.03$). There was a larger variation in regressions for individual cows with Na addition than with K addition in that fewer cows had regressions with $P < 0.25$ (Table 3). A more narrow range in water intake with Na may be the reason.

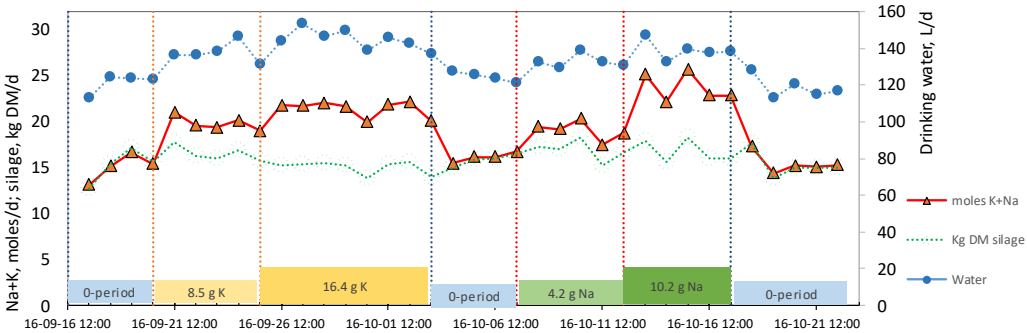


Figure 2. Daily means for intake of silage, Na + K and drinking water in 57 cows. Vertical bars indicate when addition of KCl and NaCl to the silage was changed. 0-period means that only water was added. The amounts of added K and Na (g/kg DM silage) are indicated for periods with salt addition.

Table 1. Barn climate, milk yield and intake of feed and water in 57 cows

	0-per. 1	K low	K high	0-per. 2	Na low	Na high	0-per. 3	SEM	P
Barn temp. °C	16.8	16.2	16.0	13.7	13.5	13.3	13.1	-	-
Rel. hum.,%	69	74	71	64	68	63	65	-	-
Milk, kg/d	30.7	31.1	30.2	29.4	30.2	30.1	30.0	0.75	0.76
Daily intake									
Silage, kg DM	15.3	16.6	15.1	15.9	17.0	16.8	15.4	0.31	<.0001
Conc., kg DM	8.5	8.5	8.5	8.4	8.5	8.5	8.6	0.33	1.00
Total DM, kg	23.8	25.1	23.6	24.4	25.5	25.3	24.0	0.47	0.02
CP, g	3991	4150	3837	4037	4052	4109	4007	81	0.17
Ash, g	1871	2236	2385	1962	2144	2386	1919	38	<.0001
K, g	519	697	766	548	546	564	531	11	<.0001
Na, g	43	48	44	50	119	218	45	1.9	<.0001
K+Na, moles	15.2	19.9	21.5	16.2	19.1	23.9	15.5	0.3	<.0001
Drink. w[1]., kg	121.6	138.4	145.3	125.0	133.3	139.5	119.1	3.1	<.0001
Tot. w[2]., kg	144.4	161.1	169.0	149.0	156.7	163.7	143.8	3.4	<.0001

[1]Drinking water

[2]Total water including water content in feed

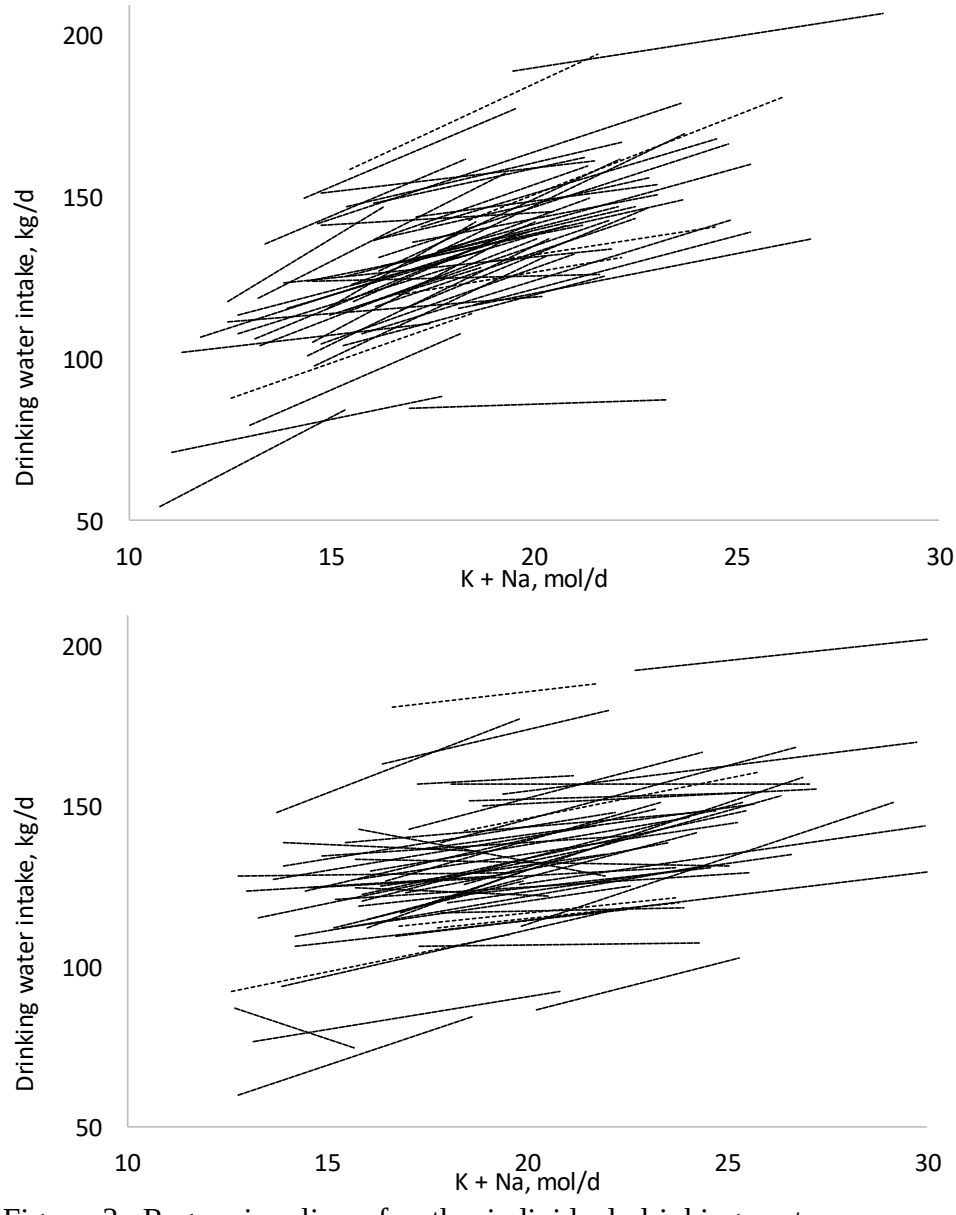


Figure 3. Regression lines for the individual drinking water response in 57 lactating cows to total daily intake of K+Na. Top chart: Three periods of KCl supplementation (0, low and high). Bottom chart: Three periods of NaCl supplementation (0, low and high).

Table 2. Regressions for drinking water intake on the intakes of K and Na

	Linear regression				Mixed model, random intercept			
	Interc	Slope	R^2	RMSE	Interc.	Slope	R^2	RMSE
K addition (Period 1-3)								
K, g/d	59	0.115	0.374	20.0	72	0.094	0.825	5.9
K + Na, moles/d	51	4.43	0.405	19.5	66	3.64	0.834	5.9
Added K+Na, moles/d	121	4.16	0.198	22.6	122	3.71	0.733	6.0
Na addition (Period 4-6)								
Na, g/d	117	0.120	0.123	22.9	121	0.089	0.488	6.6
K + Na, mol/d	77	2.82	0.228	21.5	94	1.95	0.606	6.5
Added K + Na, moles/d	124	2.31	0.086	23.4	125	2.00	0.472	6.6
Entire experiment								
K + Na, moles/d	64	3.58	0.318	20.7	80	2.75	0.621	8.5
Added K + Na, moles/d	122	3.30	0.150	23.0	122	2.97	0.515	8.5

Table 3. Mean value, maximum and minimum for statistical parameters and measurements of fit in regressions of drinking water intake in individual cows (kg/d) on incremental intake of K and Na (moles/d). Based upon three period means per cow. Only regressions with $P < 0.25$ are included

	K addition, 38 cows of 57				Na addition, 24 cows of 57			
	Intercept	Slope	RMSE	R^2	Intercept	Slope	RMSE	R^2
Mean	50	4.6	3.9	0.95	86	2.3	2.6	0.96
Min	-16	1.5	0.1	0.86	30	-4.1	0.0	0.88
Max	102	7.6	10.6	1.00	163	4.2	7.0	1.00

Conclusions

On a group level, changes in the intake of dry matter and K+Na were well mirrored by changes in drinking water intake. This suggests that use of drinking water registrations for estimating intake in groups of cows is possible. The lack of correlation in the response of individuals to K and Na intake does not support that dry matter intake in individual cows can be estimated from drinking water intake and a once-for-all measurement of the animal´s response in drinking water intake to feed factors.

Acknowledgements

This project was funded by the The Swedish Farmers' Foundation for Agricultural Research.

References

Cardot, V., Le Roux, Y. & Jurjanz, S. 2008. Drinking behavior of lactating dairy cows and prediction of their water intake. J. Dairy Sci. 91:2257–2264.

Eriksson, T. and Rustas, B.- O. 2014. Effects on milk urea concentration, urine output and drinking water intake from incremental doses of potassium bicarbonate fed to midlactating dairy cows. J. Dairy Sci. 97: 4471–4484.

Khelil-Arfa, H., Boudon, A., Maxin, G. & Faverdin, P. 2012. Prediction of water intake and excretion flows in Holstein dairy cows under thermoneutral conditions. Animal 6, 1662-1667.

Kramer, E., Stamer, E., Mahlkow, K., Lüpping, W. & Krieter, J. 2008. Relationship between water intake, dry matter intake and daily milk yield on a German research farm. Livest. Sci. 115:99–104.

Murphy, M. R., Davis, C. L. & McCoy, G. C. 1983. Factors affecting water consumption by Holstein cows in early lactation. J. Dairy Sci., 66, 35–38.

Spek, J. W., A. Bannink, G. Gort, W. H. Hendriks, & J. Dijkstra. 2012. Effect of sodium chloride intake on urine volume, urinary urea excretion, and milk urea concentration in lactating dairy cattle. J. Dairy Sci. 95:7288–7298.

St-Pierre, N. R. 2001. Integrating quantitative findings from multiple studies using mixed model methodology. J. Dairy Sci. 84:741-755.

Effects of frequent feed pushes of mixed feed on feeding behaviour, feed intake, and milk production in an AMS herd

K. H. Sloth[1], C. Coletti[2], A. Peña Fernández[3], D. Bossen[4], E. Tullo[2], I. Fontana[2], M. Guarino[2]
[1]GEA Farm Technologies GmbH, Nørskovvej 1B, DK-8660 Skanderborg, Denmark.
[2]Department of Environmental Science and Policy, Università degli Studi di Milano, Via Celoria 2, 20133 Milan, Italy
[3]Department of Biosystems, Division M3-BIORES: Measure, Model & Manage Bioresponses, KU Leuven, Kasteelpark Arenberg 30, 3001 Heverlee, Belgium
[4]Agri Nord, Markedsvej 6, DK-9600 Aars, Denmark
KarenHelle.Sloth@gea.com

Abstract

Precision Livestock Farming offers new technologies to substitute man hours spent on feeding management in intensive dairy farming, including automated feed pusher robots. Value of the technology may be more than just labour replacing if it creates increased feeding activity leading to higher feed intake and milk production. A trial was set up in a commercial dairy herd with an automatic milking system (AMS). The experimental treatments in terms of three versus ten feed pushes per day were performed twice in one large group of lactating dairy cows during July-August 2015. Mixed models were used to evaluate the effect of the applied feed pushing frequencies on three feed event-based feeding behaviours and three meal-based feeding behaviours, dry matter and energy intake, daily milk yield and milking attendance. Results from this study could not support increasing number of feed pushes in this herd in order to improve production as ten feed pushes did not as expected increase feeding activity of the cows. Instead it resulted in significantly longer duration of feed events, fewer meals and less total meal time compared to three feed pushes per day. Furthermore, feed intake and daily milk yield were significantly lower during experimental periods with ten feed pushes. Parity, days in milk and repetition included as fixed effects in the mixed models all proved to be important factors for the response variables.

Keywords: Automatic feed pushing, Real-Time-Location-System, feeding behaviour, feed intake, milk yield, milk attendance

Introduction

With Precision Livestock Farming several solutions for automation of manual work routines in feed management have been marching in the dairy farms during the later decades including automated feed pusher robots. Every one of these solutions and the way they are managed on specific farms influence cow behaviour and affect feed intake in free stall housing systems. Pushing of mixed feed is a feed manipulating action along with delivery of fresh feed to secure cows having access to feed. DeVries et al. (2003) found that fresh feed delivery and milking were much stronger drivers than feed pushing in stimulating feeding activity of group-housed cows and had greater effect on the diurnal pattern of feed alley attendance. In a study comparing three with five feed pushes per day in a tie-stall environment, Miller-Cushon & DeVries (2017) did not find any effect on dry matter intake, feed sorting, milk production, and standing and lying patterns of the cows. In AMS herds milking is distributed round the clock, thus effect of pushing feed in this type of production may be different. Having a Real-Time-Positioning-System (RTLS) available which offers the possibility to quantify cows' whereabouts 24-7 (Sloth et al., 2015; Tullo et al., 2016), we would like to evaluate the possibilities to estimate changes in feed behavioural activities when changing feeding management, e.g. apply high frequency feed pushing. Therefore, the purpose of this study was to investigate the effect of frequent automated feed pushing of the partially mixed ration (PMR) on RTLS based feeding behaviour, feed intake, daily milk yield and milking attendance in an AMS herd.

Materials & Methods

Experimental design

The trial was performed in a commercial AMS herd with 220 Holstein Frisian cows. The dataset was collected over four experimental periods of seven days duration in Summer 2015 (see Table 1), and included one large group of lactating dairy cows housed in a free stall environment with slatted floors, deep straw cubicles, post-and-rail system along the feed bunk and free cow traffic with pre-selection for accessing the milking waiting area in front of the AMS.

Table 1. Trial design in terms of repetition, experimental periods and treatments as in number of feed pushes applied and average number of experimental animals included.

Repetition	Experimental period	Experimental treatments	Number of cows
1	July 1st – 7th July 2015	3 feed pushes	181
	July 15th – July 21st 2015	10 feed pushes	186
2	July 29th – August 4th 2015	3 feed pushes	190
	August 12th – August 18th 2015	10 feed pushes	193

The experimental treatments were applied twice each (two repetitions), namely (1) one feed delivery of PMR in the morning plus three feed pushes per day at 5:30, 13:30, and 21:30 and (2) one feed delivery of the PMR in the morning plus ten feed pushes per day at 01:30, 03:30, 05:30, 06:30, 13:30, 15:30, 17:30, 19:30, 21:30, and 23:30. Every experimental period was preceded by a seven day transition period in which the new feed pushing frequency was applied. The feed pusher robot used in the barn facility was a Moov feed pusher robot (JOZ B.V., Westwoud, The Netherlands). Parity and days in milk (mean ± standard deviation) were 2.6 ± 1.5 and 176 ± 102 in the first repetition and 2.6 ± 1.5 and 177 ± 105 days in the second repetition, respectively. Animal densities cubicle- and feed-bunk-wise (mean ± standard deviation) were 0.95 ± 0.01 animals per cubicle and 47.7 ± 0.3 cm feed bunk space per animal in the first repetition and 0.96 ± 0.01 animals per cubicle and 47.6 ± 0.4 cm feed bunk space per animal in the second repetition, respectively.

Feeding behaviour

Feeding behaviour variables were derived from data provided by the GEA CowView system based on the classification of cow positions within activity zones, e.g. feed event equal to cow being positioned at the feeding table. Overall, six feeding behaviour variables were investigated: Average number of feed events, average duration of feed events, average total daily time spent at the feeding table (= total feed event time), average number of meals, average meal duration, and average total daily meal time. The mixed density approach by Tolkamp et al. (1998) was used to create the meal variables based on the feed event data. It implies the need for a herd level meal criterion, which was estimated to 3.06 $\log_{10}$ seconds (=19.1 minutes) using a three-component mixture model (FMM procedure, SAS) with two normal and one Weibull distributions. At animal level, a new meal was generated every time an interval between two feeding events exceeded the duration of the herd level meal criterion. Before summarizing the feeding variables to individual animal average

values per experimental period, outliers in meal-based feeding variables were filtered out using the median absolute deviation (MAD) method according to Leys et al. (2013) on $\log_{10}$ transformed meal durations within animal. The level of two times MAD (95 % level) was chosen to remove extremely short and long meal durations.

Feed ration and feed intake

The full ration fed to the lactating dairy cows included a PMR and three individually adjusted concentrate types. One batch of the PMR was prepared in a Trioliet Solomix 2-3200 mixer wagon (Trioliet B.V., Oldenzaal, The Netherlands) and fed out once daily in the morning. The PMR consisted of: wheat, minerals, different cut grass silages, sugar beet pulp, potato pulp, corn silage and a distiller by-product named ProtiWanze®. A change in the mixed feed was performed between the first and second repetition, substituting 3rd cut grass 2014 with 4th cut grass 2014 and 1st cut grass 2015. Feed intake of the PMR was monitored at group level. Weights of all feed ingredients were recorded daily at mixing. Furthermore, feed residuals were weighed on removal once daily before feeding out the new ration. Amounts of feed residuals weighed during the first repetition was 10.7 ± 4.5 % (mean ± standard deviation) and during the second repetition 7.2 ± 4.8 %. Dry matter and net energy for lactation of the PMR was calculated using feed batch analyses or table values for delivered feed minus feed residuals, assuming same relative composition. As the proportion of young and old cows were unbalanced between experimental periods and repetitions, we chose to factor the feed intake capacity of cows in 1st lactation to 0.81 of older cows when estimating individual daily intake of the PMR (Østergaard et al., 2003). Production concentrate was fed in both milking robots and concentrate boxes, while starter concentrate and soya was fed only in the milking robots. Concentrate allowance followed a plan based on milk yield, parity and stage of lactation. Amounts of the concentrate types supplied were recorded at individual animal level via the dairy herd management program. Dry matter and net energy for lactation were calculated using feed information given by the feed supplier. For statistical evaluation, daily records of total kilograms (kg) dry matter and Mega Joules (MJ) net energy intake (PMR + concentrate) were averaged to single animal-level values per experimental period.

Milking attendance and milk yield

Number of milking and kg milk yield were recorded at animal level via the AMS (one 5-box MiOne robot, GEA Farm Technologies GmbH, Bönen, Germany). Cows exhibiting more than 50 % overdue in milk allowance were collected and led to the milking robot twice daily. For statistical evaluation, daily records of

number of milking and daily milk yield were averaged to single animal-level values per experimental period.

Statistical evaluation

The general null hypothesis to be investigated was that changing the number of feed pushes would not affect the cows' feeding behaviour, feed intake, number of milking per day or daily milk yield. To examine this, a multivariable mixed model (MIXED procedure, SAS) was produced for each response variable including the following fixed effects: Parity (1, 2, 3+), days in milk (0-89 (early), 90-220 (mid), >220 (late)), repetition (1, 2), number of automatic feed pushes (3x, 10x), and the interaction term repetition*number of automatic feed pushes. Cow was fitted as random effect. Full model least-square-mean values (LSMEANS, SAS) with 95%-confidence intervals were generated as estimates of treatment effect levels.

Results & Discussion

Surprisingly in this trial, ten feed pushes resulted in less feeding activity and lower feed intake. Feeding activity changed to fewer and longer feeding events, fewer meals and shorter total meal time (see Table 2). No significant difference was found in average meal duration and total feed event time between the two feed pushing treatments. Feed intake was on average 0.9 kg dry matter and 6.3 MJ lower per day with ten feed pushes compared to three per day.

Table 2. Effect of three versus ten partial mixed feed pushes on cow feeding behaviour and total feed intake in an AMS herd. Estimated effects are main effect model least-square mean values; 95%-confidence intervals in brackets ([ ]).

Response variable	Feed pushing frequency		F-test,
	3x	10x	*P*-value
N feed events, count/day	67.7 [64.6-70.7]	65.6 [62.5-68.7]	0.0230
Feed event duration, seconds	380 [363-397]	394 [377-410]	0.0030
Total feed event time, hours/day	5.81 [5.68-5.93]	5.85 [5.72-5.97]	0.2690
N meals, count/day	6.33 [6.21-6.45]	6.08 [5.96-6.20]	<0.0001
Meal duration, minutes	79.3 [76.8-81.8]	80.9 [78.4-83.4]	0.0786
Total meal time, hours/day	7.86 [7.67-8.04]	7.73 [7.54-7.91]	0.0314
Dry matter intake, kg/day	20.4 [20.2-20.7]	19.5 [19.2-19.8]	<0.0001
NEL[1], MJ/day	134.0 [132.3-135.8]	127.8 [126.0-129.5]	<0.0001

[1]Net energy intake for lactation

The lower feeding activity and feed intake found at ten feed pushes per day were followed by a significantly lower milk yield as well as a tendency to lower milking attendance (*P*=0.0614, see Table 3).

Table 3. Effect of three versus ten partial mixed feed pushes on cow daily milk yield and milking attendance in an AMS herd. Estimated effects are main effect model least-square mean values; 95%-confidence intervals in brackets ([ ]).

Response variable	Feed pushing frequency		F-test,
	3x	10x	*P*-value
Milk yield, kg/day	28.5 [27.4-29.6]	27.2 [26.1-28.3]	<0.0001
Number of milking, count/day	2.70 [2.61-2.79]	2.66 [2.57-2.74]	0.0614

Output from modelling the different feeding behaviour response variables showed that younger cows had more feeding events of longer duration, longer meals and longer total feeding event time and total meal time than older cows. Furthermore, cows in early and mid-lactation had more feeding events and meals of shorter duration than cows in late lactation.

Feed intake-wise, younger cows had lower feed intake compared to older cows. Furthermore, feed intake was higher in early and mid-lactation than in late lactation. These effects are clearly related to the supplementation plan for concentrate and the estimation approach used for individual consumption of PMR in this trial. Effects of parity and days in milk on milk yield fulfilled expectations of lower daily milk yield in younger cows and higher daily milk yield for cows in early and mid-lactation compared to late lactation. Furthermore, younger cows had significantly lower milking attendance compared to older cows and cows in early, and mid-lactation had higher milking attendance than cows in late lactation. These effects may very well be related to motivation to be milked as well as AMS limitations in milking allowance.

Five out of the six feeding behaviour models, both feed intake models and the milk yield and milk attendance models showed significantly higher activity, intake, milk yield and number of milking in the first repetition. This may of course be due to the known change in the PMR when substituting the 3rd cut grass 2014 with 4th cut grass 2014 and 1st cut grass 2015 between the test rounds. However, there can be more reasons, like differences in environmental factors as for example occasional heat stress due to high ambient temperatures and high humidity which has well-known negative impacts on feed intake and milk yield (West et al., 2003). Furthermore, no surveillance of the feed value of either PMR or refusals was performed during the trial to control for day-to-day variation in especially roughage components.

Basically, not being able to run both treatments at the same time weakens the study design and complicates inference of results in general. Also the fact that the trial was performed with a minor imbalance towards a few more animals in the lactating cow group when applying ten feed pushes may have had an influence on the results. We included the interaction term repetition*treatment in the response models, which may have accounted for some time-related variation but we cannot be sure that the treatment effect found was not affected by some unknown important time-related factor. More repetitions should be performed in order to strengthen these findings in a controlled way where important factors like environmental temperature and humidity are monitored as well.
Our experience in general is that the combination of automation and the way it is operated is highly farm specific, and it is sometimes difficult for the individual farm manager to identify the optimal setting or usage in his specific system. We believe that RTLS with the possibility to quantify cows' whereabouts 24-7 has the potential to generate key performance indicators useful to the farmer, because it implies the opportunity to track variations over time, between groups of cows, and illustrate how automation as well as the daily manual management routines influences the behaviour of the cows.

Conclusion

Results from this study could not support high feed pushing frequency to improve production. Ten feed pushes resulted in significantly lower feeding activity, feed intake and daily milk yield when compared to three feed pushes per day. Parity, days in milk and repetition included in the statistical models all proved to be important factors for the different feeding behaviour variables, feed intake, milk yield and number of milking per day.

Acknowledgement

This project has received funding from the European Union's Seventh Programme for Research, Technological Development and Demonstration under Grant Agreement No 311825.

References

DeVries, T. J., M. A. G. von Keyserlingk, and K. A. Beauchemin. 2003. Short communication: Diurnal feeding pattern of lactating dairy cows. J. Dairy Sci. 86, 4079-4082.

Leys, C., C. Ley, O. Klein, P. Bernard and L. Licata, 2013. Detecting outliers: Do not use standard deviation around the mean, use absolute deviation around the median. Journal of Experimental Social Psychology (2013), http://dx.doi.org/10.1016/j.jesp.2013.03.013T

Miller-Cushon, E. K., and T.J. DeVries. 2017. Short communication: Associations between feed push-up frequency, feeding and lying behaviour, and milk yield and composition of dairy cows. J. Dairy Sci. 100, 2213-2218.

Tolkamp, B. J., D. J. Allcroft, E. J. Austin, B. L. Nielsen, and I. Kyriazakis. 1998. Satiety splits feeding behavior into bouts. J. theor. Biol. 194, 235-250.

SAS Institute Inc., SAS® 9.4.

Sloth, K. H., D. Frederiksen, and S. Klimpel. 2015. Estimated cow time-budgets using a Real Time Location System. Pages 740-748 in: Proc. Precision Livestock Farming 2015, Posters, 7th European conference on Precision Livestock Farming, September 15-18 2015, Milan, Italy.

Tullo, E., I. Fontana, D. Gottardo, K. H. Sloth, and M. Guarino. 2016. Technical note: Validation of a commercial system for the continuous and automated monitoring of dairy cow activity. J. Dairy Sci. 99, 7489-7494.

West, J. W., B. G. Mullinix, and J. K. Bernard. 2003. Effects of hot, humid weather on milk temperature, dry matter intake, and milk yield of lactating dairy cows. J. Dairy Sci 86, 232-242.

Østergaard, S., T. Kristensen, O. Aaes, V. F. Kristensen, M. Jensen, S. Clausen. 2003. 16. Planlægning af økonomisk optimal fodring af malkekøer. In: DJF rapport Husdyrbrug nr. 54. Kvægets ernæring and fysiologi. Bind 2. Fodring og produktion. Edited by F. Strudsholm and K. Sejersen. Publisher: Danmarks JordbrugsForsking, Ministeriet for Fødevarer, Landbrug og Fiskeri. P. 371-405.

Session 13

Tracking and body measurements

Bluetooth Low Energy Based Location Tracking for Livestock Monitoring

J. Trogh[1], D. Plets[1], L. Martens[1] and W. Joseph[1]
[1]*Department of Information Technology, IMEC - Ghent University, Belgium*
Jens.Trogh@UGent.be

Abstract

This paper proposes a location tracking system to monitor livestock behaviour which provides useful information about their health and welfare. In the proposed approach, Bluetooth Low Energy (BLE) nodes are used to track dairy cows while a self-organizing multi-hop mesh network collects the data. This data is processed with an advanced tracking algorithm that copes with signal fading and body shadowing. The experimental validation is conducted in a barn with dairy cows over the course of three days and the presented results are verified with video data from a closed-circuit television (CCTV) system.

Keywords: Bluetooth Low Energy, Location Tracking, Health Monitoring, Received Signal Strength Indicator

Introduction

The automated analysis of animal behaviour has gained a huge interest over the last decade while farms got larger and were managed by fewer farmers. Knowing the location of all cows in a herd can provide real-time updates about an animal's health or welfare, by looking for anomalies. Most location tracking systems use a wired backbone network to report and transfer all measurements to a central location. This increases the installation cost and is not always feasible in harsh environments like a barn or stable. In this work a Bluetooth Low Energy (BLE) system that communicates over a wireless, self-organizing, multi-hop mesh network, is used to localize, track and monitor livestock.

Bluetooth Low Energy

The nRF51822 Bluetooth Smart SoC from Nordic Semiconductor were used for the BLE setup (Nordic Semiconductor, 2016). The setup consists of two sink nodes, nine anchors and four mobile nodes. The programmable development kits were used as sink and anchor, and the dongles are used as mobile node (Figure 1).

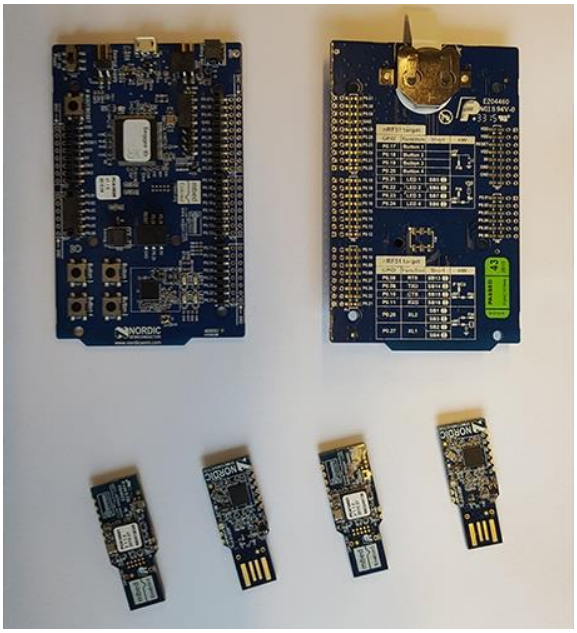


Figure 1: Two nRF51822 development kits and four dongles

The sinks and anchors work in a plug and play fashion and organize themselves in a multi-hop mesh network with the FruityMesh protocol (M-Way Solutions, 2016). FruityMesh is an open source implementation of a mesh network that is based on standard Bluetooth Low Energy 4.1 connections. In contrast to meshes that use advertising and scanning, this allows for a network run with battery-powered devices. It uses time multiplexing to allow simultaneous connections to different nodes. The two sinks both form a cluster with 5 or 6 nodes and the mobile nodes broadcast packets at a sending rate of 1 Hz. All anchors and sinks receive the packets, and log the measured received signal strength indicator (RSSI) with a sequence number. The messages are forwarded to the sink nodes where they are annotated with a timestamp and merged into one log file. Outdated measurements are filtered out by making use of the sequence number.

Tracking algorithm

The tracking algorithm is based on a Viterbi-like technique (Trogh *et al*., 2015), (Trogh *et al*., 2016). It uses a motion model and floor plan information to determine the most likely path (i.e., sequence of locations) instead of only the most likely current position (Viterbi principle). These constraints ensure that no unrealistically large distances are travelled within a given time frame and no fences or enclosures are crossed. A moving average of the measured RSSI values are used as input to calculate a location update. The tracking algorithm uses a cost function where the measurements are compared to reference RSSI values.

These reference values are calculated with a theoretical pathloss model and are stored in a fingerprint database (Plets *et al*., 2012). The theoretical model takes into account the pathloss due to the travelled distance, the cumulated wall loss (when a signal propagates through a wall) and the interaction loss caused by direction changes of the propagation path from transmitter to receiver. The only prerequisite to generate the fingerprint database is to provide a floor plan of the environment; no additional measurements are needed. The pathloss due to the travelled distance is based on an experimental characterization of the off-body wireless channel at 2.4 GHz for dairy cows in barns and pastures (Benaissa *et al*., 2016).

Experiment configuration

The measurements were conducted in a state-of-the-art research barn at the Institute for Agricultural and Fisheries Research (ILVO) in Melle, Belgium. The barn measures 114 by 36 meters and is divided in several zones. A zone of 30 by 13 meters, housing 31 dairy cows, was used in the experiment. The zone consists of a concrete slatted floor and 32 individual cubicles, that were bedded with a lime-straw-water mixture (Figure 2).

Figure 2: Experiment zone

The cows had access to drinking water, a rotating cow brush and a milking robot via the feeding area and a smart selection gate (feed-first cow traffic system). The cows were fed roughage ad libitum. The concentrates were supplied both in the milking robot and by computerized concentrate feeders. Four different

second parity Holstein cows were equipped with a BLE mobile node, attached to their collar in a plastic housing case along with a 2000mAh battery (Figure 3).

Figure 3: BLE node with housing case attached to collar

A closed-circuit television (CCTV) system with three cameras aimed at the experiment zone was used as ground truth verification (Figure 4).

Figure 4: CCTV configuration

Results

Data was collected over the course of three days. Because cows spend most of their time lying down in the cubicles, a more active period was searched for in the CCTV video feed. A time interval of two hours (14h30 - 16h30), where a tracked cow passes by the feeding trough, walks around and ends at the drinking trough, was used to verify the location algorithm. The real position of the cow was marked on the floor plan based on the video data.

Figure 5 shows the ground truth and reconstructed trajectory from the measured BLE system with the location tracking algorithm. The start and end point, feeding and drinking trough, cubicles, milking robot, and locations of the BLE anchors are also indicated. At 14h30 the cow is located in right bottom corner,

eating at the feeding trough. Next, she moves to the left bottom corner where she moves around and eats again. Then, she goes to the drinking trough on the right where the trajectory stops at 16h30. The proposed location tracking system has a median accuracy of 3.3 meter, the mean and standard deviation of the accuracy are 4.2 and 2.7 meter, respectively. The largest differences between prediction and ground truth occur in left bottom corner while the cow is eating. While she stands still for the almost 45 minutes, the prediction shows outliers up to 6 meters around the actual location. This is partly because of the metal surroundings of the feeding trough which cause reflections, shadowing and interference (Figure 3).

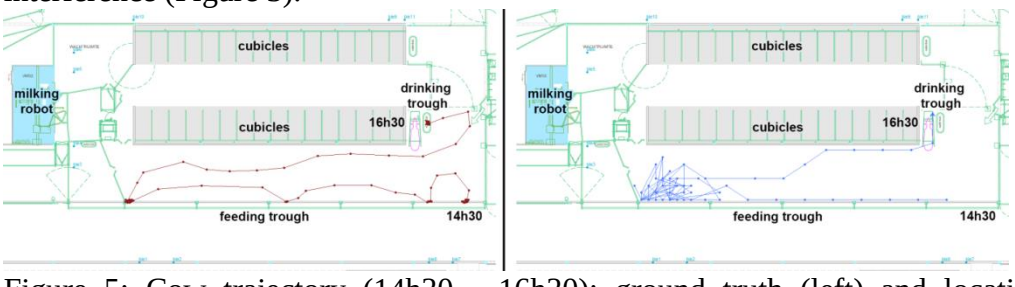


Figure 5: Cow trajectory (14h30 - 16h30): ground truth (left) and location tracking algorithm (right)

Figure 6 shows a five minute plot of the measured RSSI values with and without averaging, while the cow stood still. Signal variations of up to 12dB occur during the experiment, an averaging interval of 10 seconds diminishes the variations but they remain present.

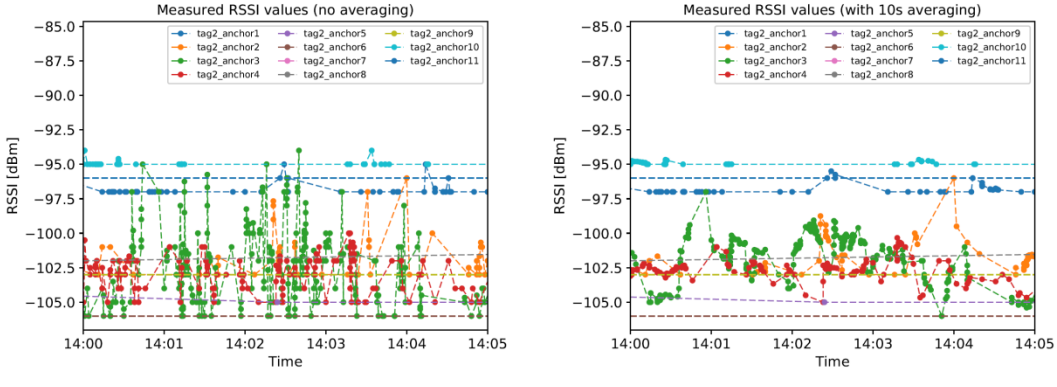


Figure 6: Five minutes of measured RSSI data with and without averaging

The deviations around the actual location also results in an overestimated travelled distance. According to the estimated locations with the BLE data, the cow walks over a total distance of 101 meters. Based on the CCTV data this is only 58 meters. Another problem is the packet loss. Although the mobile nodes are broadcasting at a sending rate of 1 Hz, only 16% of the measurements arrive

at the sink nodes (all communication is wireless and outdated measurements are discarded). This is partly caused by the housing case where the mobile node with integrated antenna is closely packed with the battery. Future work includes a new design to avoid shielding by the battery.

Conclusions

In this work a Bluetooth Low Energy (BLE) location tracking system to track and analyse cow behaviour, was proposed. Four cows were tracked over a period of three days while a CCTV system recorded all their movement with three video cameras. An active period of two hours was annotated manually to calculate the accuracy. During these two hours the median precision was 3.3 meter. This allows to find a cow but does not suffice to accurately calculate the travelled distance or analyse a cow's drinking and eating behaviour. Future work will include more accurate location tracking with ultra-wideband (UWB), and the collection and analysis of location data over longer periods of time.

Acknowledgements

This work was executed within MoniCow, a research project bringing together academic researchers and industry partners. The MoniCow project was co-financed by imec (iMinds) and received project support from Flanders Innovation & Entrepreneurship. The authors would like to thank Thijs Decroos and Sara Van Lembergen for their help during the measurements.

References

Trogh, J., Plets, D., Martens, L. and Joseph, W., 2015. Advanced real-time indoor tracking based on the viterbi algorithm and semantic data. *International Journal of Distributed Sensor Networks.*

Trogh, J., Plets, D., Thielens, A., Martens, L. and Joseph, W., 2016. Enhanced indoor location tracking through body shadowing compensation. *IEEE Sensors Journal*, 16(7), pp.2105-2114.

Plets, D., Joseph, W., Vanhecke, K., Tanghe, E. and Martens, L., 2012. Coverage prediction and optimization algorithms for indoor environments. *EURASIP Journal on Wireless Communications and Networking*, 2012(1), p.123.

Benaissa, S., Plets, D., Tanghe, E., Verloock, L., Martens, L., Hoebeke, J., Sonck, B., Tuyttens, F.A.M., Vandaele, L., Stevens, N. and Joseph, W., 2016. Experimental characterisation of the off-body wireless channel at 2.4 GHz for dairy cows in barns and pastures. *Computers and Electronics in Agriculture*, 127, pp.593-605.

Benaissa, S., Plets, D., Tanghe, E., Vermeeren, G., Martens, L., Sonck, B., Tuyttens, F.A.M., Vandaele, L., Hoebeke, J., Stevens, N. and Joseph, W., 2016. Characterization of the On-Body Path Loss at 2.45 GHz and Energy Efficient WBAN Design for Dairy Cows. *IEEE Transactions on Antennas and Propagation*, 64(11), pp.4848-4858.

Nordic Semiconductor, nrf51822, online at https://github.com/mwaylabs/fruitymesh/wiki, visited Nov, 2016

M-Way Solutions, FruityMesh, online at http://www.nordicsemi.com/eng/Products/Blue-tooth-R-low-energy/nRF51822, visited Nov, 2016

Tracking animals and predictive healthcare using new low power radio standard LoRa.

D. Frueh[1], M. Schick[2] and C. Umstaetter[2]
[1]*Centre for Signal Processing/ Communications Engineering, ZHAW, 8401 Winterthur, Switzerland*
[2]*Competitiveness and System Evaluation Research Division, Agroscope, 8356 Ettenhausen, Switzerland*
Christina.Umstaetter@agroscope.admin.ch

Abstract

In rangeland and mountain areas it can be difficult and labour intensive to find livestock in order to check health and welfare. In addition, wild predators can be counted as substantial thread to the livelihood of farmers and to animal welfare. Modern technology can support stock personnel by tracking animals to decrease labour costs and ensure animal welfare. However, one major limitation is the energy demand of these systems.

In a pilot study, we were testing a new low cost radio technology with minimal energy requirements and large range. A GPS tracking device was integrated into collar. Every 30 min the position of the animal can be send through “LoRa” (Long Range, Chirp Spread Spectrum Technology from Semtech Cooperation)

Ten collars were deployed in a first pilot study in the Alps on eight sheep, one donkey and a livestock guardian dog. A reception sensitivity above -144 dBm could be reached with the chosen modulation parameters. The propagation simulation, including the mountainous topography in the area of the animals’ home range, predicted an adequate coverage. Therefore, 90% of the position massages were transmitted successfully.

In future, data of the integrated 3-D-accelerometers can be used to identify unusual behaviour of the animals for predictive healthcare, estrous detection or alert stock personnel in case a wild predator attack is taking place.

Keywords: sheep, mountainous area, signal simulation

Introduction

Finding and monitoring flocks of sheep and herds of cattle in remote, extensive and mountainous areas can be difficult and labour-intensive. Furthermore, wild predators such as wolves or stray dogs, can pose a significant threat to livestock,

and hence to farmers' livelihoods. Although modern technologies can support farmers in locating and monitoring the animals, thereby reducing labour costs and improving animal welfare, the use of these systems is limited by the two main factors of energy requirement and cost. For this reason, "LoRa" (Long Range) – a new, competitively priced radio technology from the Semtech Corporation with a minimal energy requirement and the long range alluded to in its name – was tested in a pilot study. Unlike the mobile radio network, this technology allows the transmission of data at low cost and with low power consumption. The aim of the pilot study was to analyse the quality and reliability of data transmission in a mountainous region.

Materials and methods

In a first pilot study, ten collars were tested on eight sheep, one donkey and one livestock guard dog on a mountain pasture in the vicinity of Andermatt (Switzerland) in the mountainous "Unteralp" plateau (Figures 1a & b). The pilot study lasted from 9 Sept. 2016 until the return from the hills on 6 Oct. 2016. A hut, the *Vermigelhütte*, was chosen as the location of the receiver station, since a power supply was available there. The electronics, consisting mainly of a GPS receiver and a new radio transmitter with LoRa technology. The electronics were incorporated into a collar for the purpose of tracking the animals and transmitting the data so that stock personnel could reduce the time to find the animals.

Figures 1a & b: GPS collars with new, integrated radio transmitter (© Früh)

For our study, the location of the animal was transmitted every 30 min via LoRa, and received by its own base station. The receiver station consisted of a LoRa and a GPS receiver as well as a GSM modem for transmitting the positional data via the internet to the web server. The incoming coordinates allowed for live tracking of the animals. Continuous data storage and visualisation of the positional information took place via a web server. Besides the position, the reception level of the respective radio message and the quality of the GPS reception on the animal were also recorded on the web server (Figure 2). In addition to tracking the animals, a dispersion simulation was carried out beforehand, taking the topography into account. A link budget of 144 dB was available for the field test.

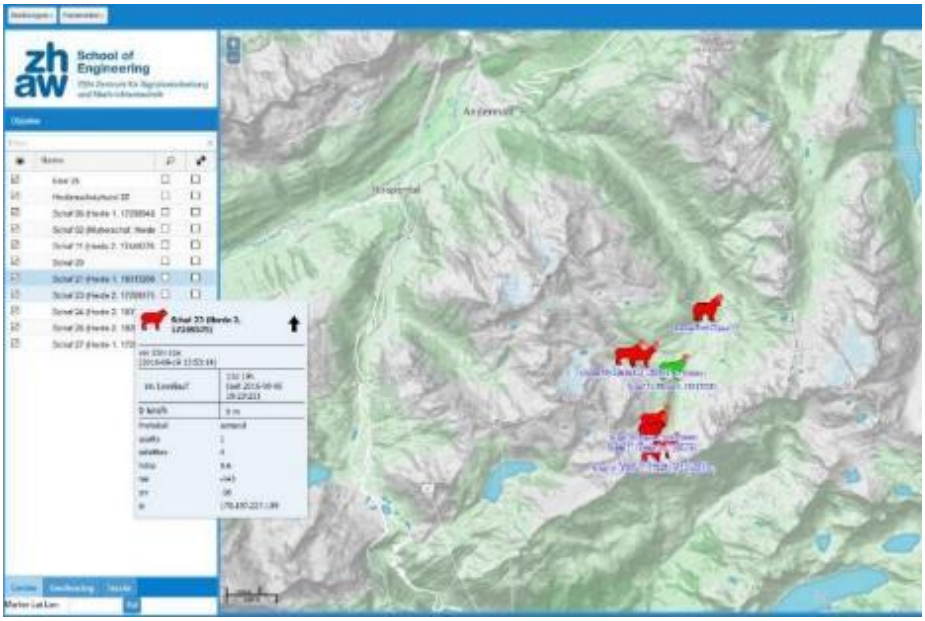


Figure 2: Web interface with topographic map for showing animals' location (© Früh)

Results

The RF propagation simulation at 169 MHz is illustrated in Figure 3. It was shown that the frequency of 169 MHz is clearly superior in the mountainous environment, owing to the diffraction effects of the second possible LoRa frequency at 868 MHz (Figure 4). The figure provides a colour coding of the reception level to be expected at the respective transmission location. In radio terms, the location of the base station in the valley basin is not entirely ideal; an even better illumination of the valley would be possible from a higher location. The location was chosen owing to the presence there of a hut with a power

supply. Red indicates the best reception level (near the hut); yellow and green, reception levels that are still satisfactory; light-blue, barely adequate reception levels; and violet, inadequate reception levels. With a spreading factor of 12 and a bandwidth of 20.8 kHz, the system possessed a reception sensitivity of -144 dBm, i.e. signals above this could still be received, but not those below -144 dBm. Broadcasting was carried out at 0 dBm effective radiated power (ERP).

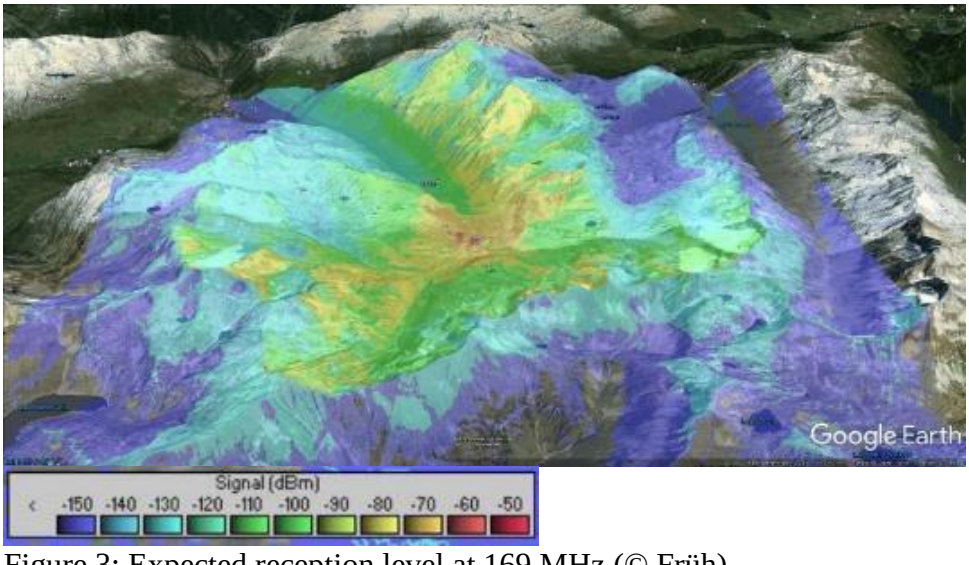


Figure 3: Expected reception level at 169 MHz (© Früh)

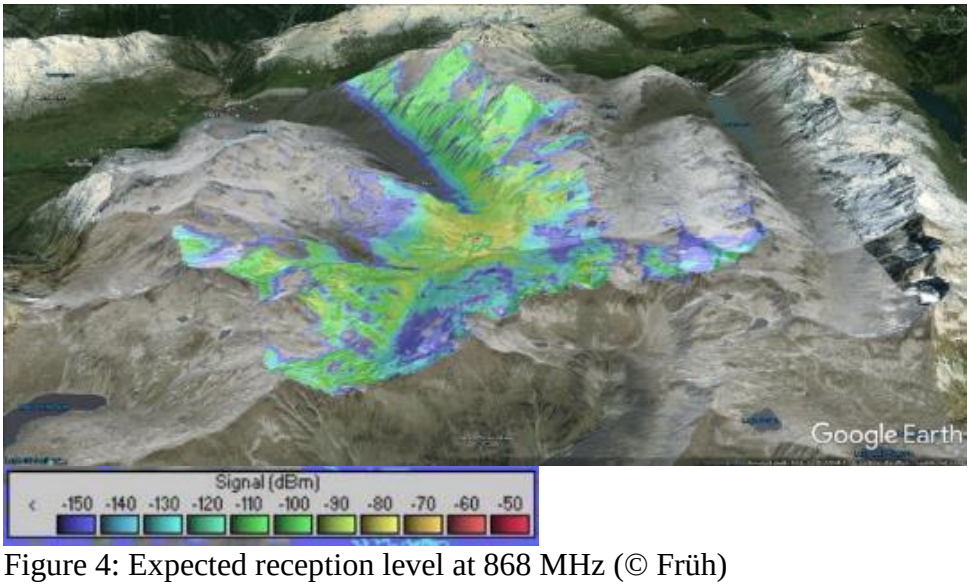


Figure 4: Expected reception level at 868 MHz (© Früh)

Figure 5 gives an example of the progression of the position of a sheep over the entire time period, projected onto the simulation data for reception. All in all, around 90% of the position reports were successfully transmitted. The 144 dB link budget and the 169-MHz frequency allowed for good coverage, even in a topographically very difficult environment. The levels of the transmitted position reports were well in line with the expected radio coverage.

A LiPo battery with a capacity of 1200 mAh was used as a battery, and easily bridged the 27-day time period. With optimisation of the GPS receiver and with two AA alkaline batteries, we expect that it will be possible to achieve a useful life of 5–6 months.

Discussion

Initial results have shown that data can be successfully transmitted in the mountain region. Particularly in agriculture, this data-transmission solution opens up the possibility of new applications which until now were not possible, owing to the costs, battery life, and battery weight. Apart from pinpointing the location of animals, there is also the possibility of using this cost- and energy-efficient means of data transmission in future for other sensors.

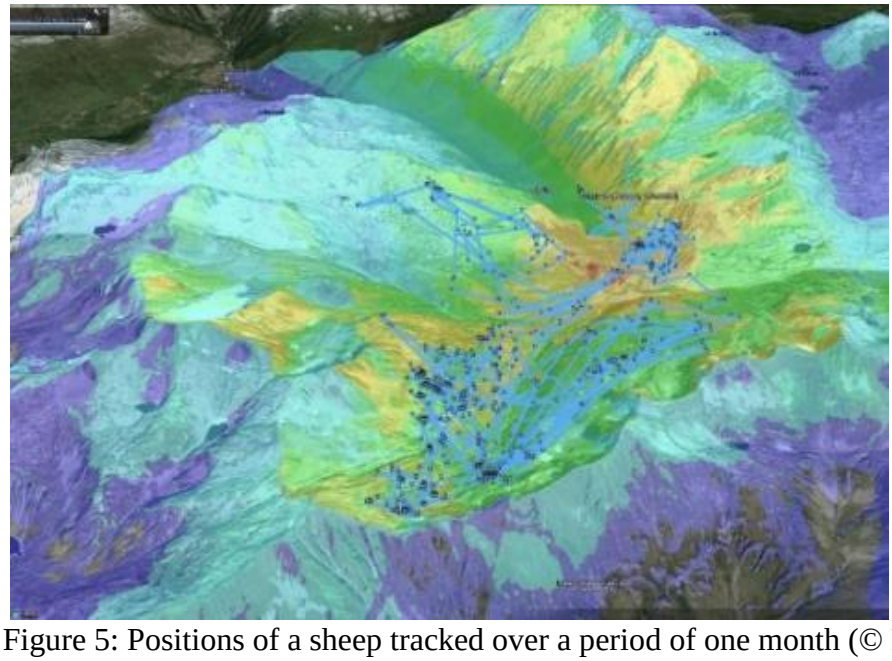


Figure 5: Positions of a sheep tracked over a period of one month (© Früh)

Vegetation sensors, environmental sensors (Misselbrook *et al.*, 2016) and virtual fences (Anderson, 2007), for example, would allow for active pasture management. Monitoring the feeding behaviour, e.g. using the RumiWatch system (Zehner *et al.*, 2017), could be a good monitoring tool to improve animal and pasture management. In addition, incorporating activity sensors in order to detect unusual behaviour in the animals is another way of supporting herd monitoring (Umstätter *et al.*, 2008). The changes in behaviour can be used for the early detection of health issues, for oestrus detection, or for assessing animal welfare. Furthermore, there is also the possibility of alerting the herd or flock owners in the event of e.g. an attack by a wolf, or a stray dog. It is also possible to reduce working-time requirement both for animal and for farm management.

Along the lines of Farming 4.0, in future, besides using LoRa for animal tracking, machines such as feeding or milking robots could also be linked with LoRa, so that animal management could be optimised even when grazing. In a next step, data transfer of monitoring data will be tested. Although LoRa is capable of transmitting data over a long distance, the capacity of data transmission is limited. Therefore, the amount of processing before transmission needs to be assessed. The deployed technologies need to be seen as a system which needs to be matched up.

Conclusions

The pilot test demonstrated that the new LoRa radio technology is suitable for the real-time monitoring of animals at reasonable cost and over a fairly long period, even in a topographically difficult environment. The communication of further data in addition to position is feasible.

Acknowledgements

The authors would like to thank TECSAG Innovation AG for their financial support of the pilot study.

References

Anderson, D.M. 2007. Virtual fencing – past, present and future. The Rangeland Journal **29** 65-78.

Misselbrook, T., Fleming, H., Camp, V., Umstatter, C., Duthie, C.-A., Nicoll, L. and Waterhouse, T. 2016. *Automated monitoring of urination events from grazing cattle.* Agriculture, Ecosystems & Environment **230** 191-198.

Umstätter, C., Waterhouse, A. and Holland, J.P. 2008. *An automated sensor-based method of simple behavioural classification of sheep in extensive systems*. Computers and Electronics in Agriculture **64** 19-26.

Zehner, N., Umstätter, C., Niederhauser, J.J. and Schick, M. 2017. *System specification and validation of a noseband pressure sensor for measurement of ruminating and eating behavior in stable-fed cows.* Computers & Electronics in Agriculture **136** 31-41.

Body measurements of dairy cows using a structure from motion (SfM) photogrammetry approach

A. Pezzuolo[1], L.A. González[2], D. Giora[1], L. Sartori[1], D. Cillis[1], and F. Marinello[1]
[1]*Department of Land, Environment, Agriculture, and Forestry, University of Padova, Viale dell'Università 16, 35020 Legnaro (PD), Italy*
[2]*Centre for Carbon Water and Food, School of Life and Environmental Sciences, Faculty of Science, University of Sydney, Camden, NSW, Australia.*
andrea.pezzuolo@unipd.it

Abstract

The possibility of frequently monitoring calf body growth allows early recognition of health anomalies, and accordingly can reduce the occurrence of problems connected to infertility or other diseases.
In the last fifty years, manual measurement has been the most straightforward way of evaluating animal body parameters. However, this approach is laborious and may be stressful for both the cows and the stockman.
In the present work, Structure from Motion (SfM) was studied and proposed as a low-cost and non-invasive technique for three-dimensional reconstruction of the cow body. Analyses carried out on a fibreglass model clearly show how SfM has the potential to provide a high-resolution three-dimensional reconstruction, which can be used for quantitative extraction of body parameters. The approach was implemented to get rid of cow movements, based on a segmented approach where different portions of the body were imaged during different frame acquisition tasks, focused firstly on the top and secondly on the sides.
Experimental tests demonstrated how body portions ranging between 20 and 40% of the whole cow area could be properly reconstructed, thus providing an adequate data set for extraction of body indices.

Keywords: body measurement, calf growth, low-cost sensor, 3D modelling, structure from motion.

Introduction

Data about the health and development of animals are still mainly collected through manual measurements or visual observations but these kinds of data collection method cause several problems (Halachmi *et al.*, 2013; Nilsson *et al.*, 2015; Salau *et al.*, 2016).

Manual measurements in fact require large amounts of time. They are also a potential cause of injuries to the stockman and are also very expensive in terms of labour (Van Hertem *et al.*, 2014). Visual observations might not very accurate because they are subjective and their accuracy depends on the stockman's skills. One of the biggest problems of manual measurements is that they cannot be continuous over time, and this is a problem, for example in the detection of symptoms (Rorie *et al.*, 2002).

Finally, manual measurements are causes of stress, especially for young animals (Grandin, 1997).

Improved sensors and techniques that could monitor cows throughout the day are a solution to this important problem, because they allow early detection of diseases and injuries, making it possible to solve problems before they become too serious. Early detection of injuries and diseases is very important in terms of productivity (Fournel and Rousseau, 2017).

Optical systems are often used for agricultural and livestock study and applications. Different studies have used different types of optical sensor, such as 2D cameras, but there is a potentially greater benefit in using 3D sensors, such as TOF (Time-Of-Flight) cameras or CTS (Consumer Triangulation Sensor) systems (Vázquez-Arellano *et al.* 2016). Indeed, 3D sensors can solve some of the problems of 2D sensors (Viazzi *et al.* 2014); however, these sensors are expensive. Another type of sensor that could be used in livestock applications is the Microsoft Kinect, which works with a depth IR-camera, and has also been used in agricultural and livestock applications (Konsgro, 2014; Marinello *et al.* 2015). However, Structure from Motion (SfM) is a revolutionary method of 3D reconstruction based on photogrammetry. SfM involves taking photographs of the object from all possible angles and points of view all around the object. Several studies have used this technique to collect data about plant phenology (Jay *et al.* 2015) or soil topography and roughness (Javernick *et al.* 2014), but SfM could also be used in livestock applications.

In the present paper, we propose a possible livestock application of SfM in order to create a virtual reconstruction of a cow's body.

Materials and methods

Animal housing

For the present work, three different Holstein Friesian cows were analysed at two different times. The times were defined to coincide with milking: the first in the morning (9:00 a.m.) and the second in the late afternoon (7:00 p.m.). Morning frames were captured using both natural and artificial light; afternoon experiments were carried out with no assistance from artificial light.

Structure from motion and data processing

Structure-from-Motion is a method based on estimating the motions of a camera to allow reconstruction of three-dimensional point clouds, through the following steps: (i) image feature detection and description, (ii) feature descriptor matching between image pairs, (iii) robust pairwise geometry estimation, and (iv) 3D point triangulation and transformation of the relative camera poses to a common coordinate frame.

In the present work, a commercial camera was used to collect the images needed for cow SfM reconstruction. Specifically, a Nikon D5100 camera was used, featuring a 23.6×15.6 mm CMOS sensor with a 4928×3264 pixel resolution and a lens with a 35mm focal length.

For animal side reconstruction, data were collected at a distance between the camera and the animal ranging between 0.7 and 1.0 m; a total of 50 frames were taken, from withers to buttock and from the top of the back to ground.

Animal top 3D reconstruction was carried out on the basis of 50 frames taken from withers to buttock and from the two sides of the back, at an average height of 2.5 metres, with a relative distance ranging between 0.50 and 0.70 m from the animal.

Three-dimensional reconstruction was carried out using commercial software (AgiSoft PhotoScan, version 1.3.1), allowing reconstruction of three-dimensional point clouds using the Structure-From-Motion technique.

Results and discussion

Preliminary tests

The first part of the work involved a preliminary validation of the SfM technique. To this end, a fibreglass reference artefact (Fig. 1) resembling the actual shape, posture, colour and dimensions (Tab. 1) of a real cow was constructed. The fixed position and time stability (thermal distortions of the overall length were estimated to be lower than 0.1 mm/°C) made it possible to calibrate the imaging and reconstruction procedure using the substitution approach (Savio *et al.* 2007). The preliminary test therefore had a double aim: (i)

calibrate the 3D data set in order to allow extraction of animal quantitative data and (ii) optimise the definition of the image data collection procedure, in terms of number, dimensions and localisation of the camera poses.
100 photographs of the fibreglass cow were taken with a frequency of about 0.3 frames per second from different perspectives and distances and used to reconstruct a three-dimensional model. As is typical with optical instrumentation (Dubbini *et al*. 2017) diffused light conditions were used, with an average illuminance of about 400 lux.
Height at the wither position (Fig. 1, parameter 0) was chosen and used as a reference dimension for scaling of the model's overall dimensions. Indeed, as verified in previous work (Marinello *et al.*, 2015), this dimension presents good repeatability in quantitative analyses of cows. In order to verify the scaling process, a set of comparisons was scheduled, using manual measurements. Body parameters were defined (as reported in Fig.1) and estimated both from the 3D digital model and from manual measurements with a ruler (resolution 1 mm).

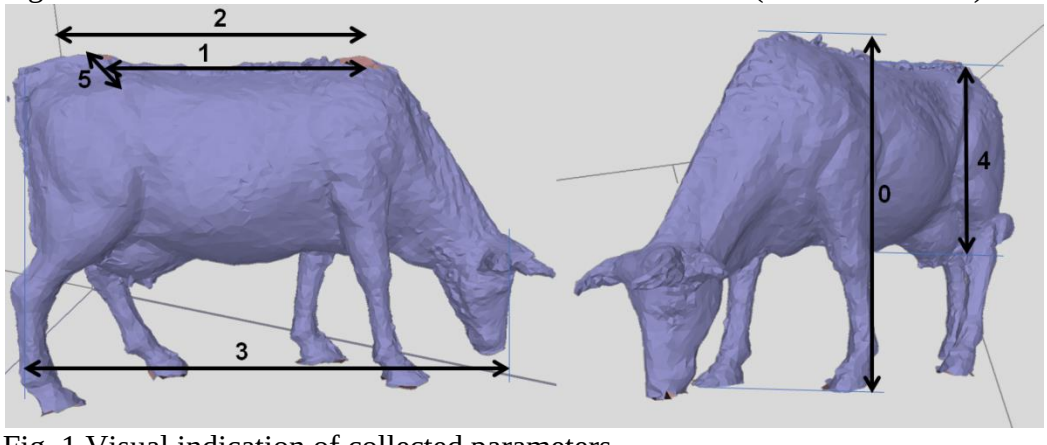


Fig. 1 Visual indication of collected parameters
Results of the comparison are reported in Tab. 1: Since the height at the withers was used for scaling purpose, it was not included in the comparison. A clear correspondence can be noted between different parameters, with a slightly higher deviation only in the case of the depth, mainly due to the difficulty in defining a reference position in the measurement process. Values estimated from the three-dimensional model were also correlated to manual measurement results: a relatively high coefficient of determination (R^2=0.997) was estimated, with an average deviation from linearity as low as 2.3%, indicating a high-quality 3D reconstruction.

Table 1. Manual measurement vs non-contact measurement: values in brackets represent standard deviations on three repeated tests; ID refers to Fig. 1 numbering.

ID	Parameter	Manual measurement [mm]	Non-contact measurement [mm]
1	Hips-withers length	810 (0.03)	725 (0.02)
2	Distance between withers and tail base	1183 (0.03)	1132 (0.03)
2	Total length	2120 (0.02)	2031 (0.02)
4	Depth	704 (0.02)	836 (0.04)
5	Distance between hips	452 (0.02)	404 (0.02)

The quality of a 3D reconstruction can be estimated by reference to the amount of reconstructed surface relative to the total object surface. Accordingly, the total area of the reconstructed cow model is an interesting parameter to be considered for optimisation of the reconstruction process. For this reason the total reconstructed area was monitored as a function of the number of frames used by the software tool. Reconstruction processes were thus repeated with a number of frames ranging between 10 and 100. The resulting area, expressed as a percentage of the maximum reconstructed area, is reported in Fig. 2, where error bars indicate standard deviation for three repeated reconstructed processes. The graph shows how the ideal trade-off between number of frames and quality of the reconstruction ranges between 40 and 60 frames: for this reason, 50 frames were defined as the reference number for live animal tests.

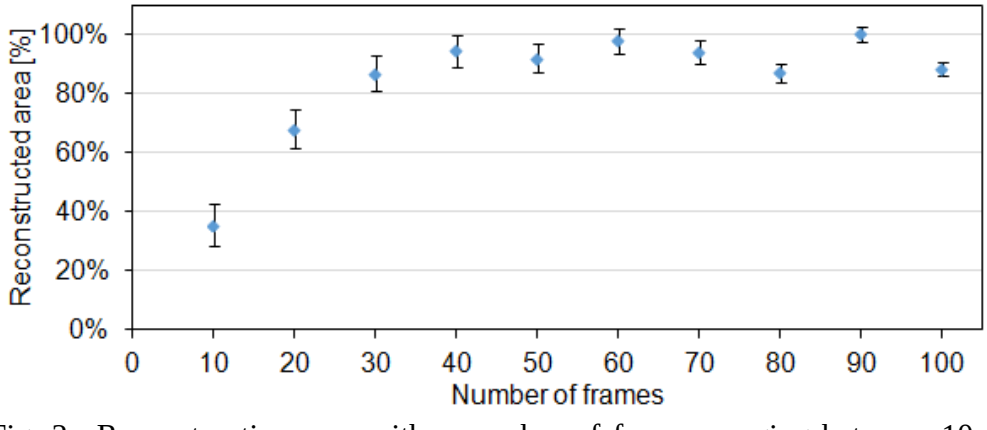


Fig. 2.: Reconstruction area with a number of frames ranging between 10 and 100

Live animal tests

In the second part of the work a total of 50 images per animal were considered, taken at a frequency of about 2 frames per second. This number of frames was selected on the basis of the optimisation process. Minimisation of the number of frames and the increase in frame rate had potential to minimise the effect of cow movements in the reconstruction process. Also, to further reduce the influence of animal movements, the frame collection process was divided into two groups: including images from the side in one case and from the top of each animal in the other case, as shown in Fig. 3 and 4.

Photos were taken in a dairy barn with no artificial light: diffused daylight was estimated to have 380 lux illuminance in the proximity of the animals.

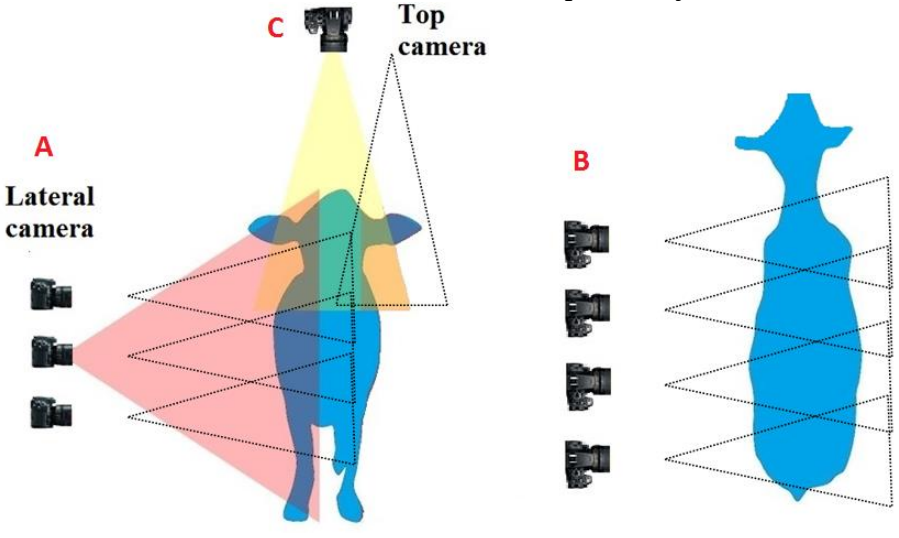


Fig. 3 Visual indication of camera positions for analyses of sides (A and B) and backs (C) of real animals

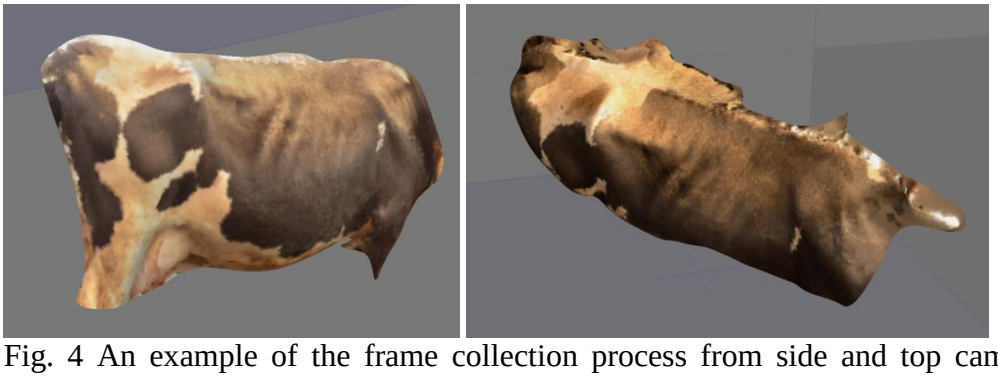


Fig. 4 An example of the frame collection process from side and top camera positions.

In 3D models of live animals, the heights at the withers were set as a scale bar, as in the preliminary test with the fibreglass model.
3D point clouds were processed with a specific filtering tool (Gaussian filter, cut-off 40 mm) which made it possible to remove noise from reconstructed surfaces. From each 3D model, the areas of the reconstructed parts of the animal were determined using a specific tool in the software based on local projection and closure of reconstructed points. Areas of reconstructed parts of the animal were compared to the total body surface estimated on the basis of the weight: values are reported as percentages in Tab. 2.
The RMS of relative noise was determined by comparing the raw and filtered data from the processed models in order to obtain indications of the accuracy of the analyses: the data are reported in Tab. 2 together with valid points which are useful for the calculation.
Results show how the total body area was reconstructed only in the case of the fibreglass model, while for real animals a total body reconstruction was not possible. In fact, for the three live animals, the reconstruction percentage ranged between 14.1% and 43% of the total body area.

Table 2. Comparison of data for reconstructed areas of fibreglass model and real cow

Cow	Body part	Valid points	Reconstructed area [m²]	Reconstructed area [%]	Relative noise RMS [mm]
Fibreglass reference	total	35680	6,43	100%	2,2
1	side	40200	1,35	19,1%	7,1
1	back	n.a.	n.a.	n.a.	n.a.
1	total	40200	1,35	19,1%	7,1
2	side	60450	2,06	27,4%	7,0
2	back	84540	1,09	14,5%	7,2
2	total	144990	3,15	41,9%	7,1
3	side	51870	2,38	32,4%	8,1
3	back	8060	0,80	11,0%	7,6
3	total	59930	3,18	43,3%	8,0

The impossibility of achieving total body reconstruction for a real animal is due to movement of the animal itself during the data collection phase. A better approach which would reduce this problem is to isolate limited groups of images in order to build only specific parts of the animal body. This is the reason why, in the table, the results for each animal are divided by parts of the body: side, back (the upper part of the animal) and side + back (total).

Analyses of the RMS of relative noise show a difference between the ideal situation of the test on a fibreglass model and the situation with real animals. The RMS of relative noise for reconstructions of real animals is in fact about 3-4 times larger than the RMS of relative noise in the case of the fibreglass model. This discrepancy between the ideal and real situations is due to movements of real animals and surfaces of animal bodies.
In any event, the RMS of relative noise ranges between 2 and 8 mm, showing a high accuracy of reconstruction even for real animals. However, animal movement has a dual effect: on the one hand, movements increment the perceived noise of the reconstructed surface and, on the other hand, movements reduce the reconstructed surfaces of bodies of real animals.

Conclusions

In the present work, Structure-from-Motion was studied and proposed as a low-cost and non-invasive technique for three-dimensional reconstruction of the cow body.
Analyses carried out on a fibreglass model clearly show how SfM has the potential to provide a three-dimensional reconstruction with a resolution as high as 3 points/cm^2, which can be used for quantitative extraction of body parameters.
Application of the SfM technique to live animals poses limitations, mainly ascribable to the movements of the animals themselves during image acquisition. As a consequence, specific strategies must be adopted in order to minimise the effect of such movements on 3D reconstruction. In the present paper an approach was implemented to eliminate cow movements, based on a segmented approach, where different portions of the body were imaged during different frame acquisition tasks, focused firstly on the top and secondly on the sides.
Experimental tests demonstrated that body portions ranging between 20 and 40% of the whole cow area could be properly reconstructed, thus providing an adequate data set for extraction of body indices.

References

Dubbini, M., Pezzuolo, A., De Giglio, M., Gattelli, M., Curzio, L., Covi, D., Yezekyan, T., Marinello, F. 2017 Last generation instrument for agriculture multispectral data collection. *CIGR Journal* **19**, 87-93.

Fournel, S., Rousseau, A.N. 2017. Rethinking environment control strategy of confined animal housing systems through precision livestock farming. *Biosystems Engineering*, **155**, 96-123.

Grandin, T. 1997. Assessment of Stress During Handling and Transport. *Journal of Animal Science*, **75**, 249-257.

Halachmi, I., Klopcic, M., Polak, P., Roberts, D.J. and Bewley, J.M. 2013. Automatic assessment of dairy cattle body condition score using thermal imaging. *Computers and Electronics in Agriculture* **99**, 35-40.

Jay, S., Rabatel, G., Hadoux, X., Moura, D., Gorretta, N., 2015. In-field crop row phenotyping from 3d modeling performed using structure from motion. *Comput. Electron. Agric*. **110**, 70-77.

Javernick, L., Brasington, J., Caruso, B., 2014. Modelling the topography of shallow braided rivers using Structure-from-Motion photogrammetry. *Geomorphology*, **213**, 166–182.

Konsgro, J. 2014. Estimation of pig weight using a Microsoft Kinect prototype imaging system. *Computers and Electronics in Agriculture* **109**, 32-35.

Marinello, F., Pezzuolo, A., Cillis, D., Gasparini, F., Sartori, L. 2015. Application of Kinect-Sensor for three-dimensional body measurements of cows. In: 7th European Conference on Precision Livestock Farming, ECPLF 2015, 661-669.

Nilsson, M., Herlin, A., Ardö, H., Guzhva, O., Åström, K., and Bergsten, C. 2015. Development of automatic surveillance of animal behaviour and welfare using image analysis and machine learned segmentation technique. *Animal* **9**, 1859-1865.

Rorie, R.W., Bilby, T.R., Lester, T.D. 2002. Application of electronic estrus detection technologies to reproductive management of cattle. *Theriogenology*, **57**, 137-148.

Savio, E., De Chiffre, L., Schmitt, R., 2007. Metrology of freeform shaped parts. *CIRP Annals - Manufacturing Technology* **56**, 810-835.

Salau, J., Haas, J.H., Thaller, G., Leisen, M. and Junge, W. 2016. Developing a multi Kinect-system for monitoring in dairy cows: object recognition and surface analysis using wavelets. *Animal* **10**, 1513-1524.

Van Hertem, T., Viazzi, S., Steensels, M., Maltz, E., Antler, A., Alchanatis, V., Schlageter-Tello, A., Lokhorst, C., Romanini, C.E.B., Bahr, C., Berckmans, D. and Halachmi, I. 2014. Automatic lameness detection based on consecutive 3D-video recordings. *Biosystems Engineering* **119**, 108-116.

Vázquez-Arellano, M., Griepentrog, H.W., Reiser, D., Paraforos, D.S., 2016. 3-D imaging systems for agricultural applications - a review. *Sensors*, **16**, 618-626

Viazzi, S., Van Hertem, T., Romanini, C.E.B., Bahr, C., Halachmi, I., Tello, A.S., Lokhorst, C., Rozen, D., and Berckmans, D. 2013. Automatic back posture evaluation in dairy cows using a 3D camera. In: *Proc. ECPLF: 6th European Conference on Precision Livestock Farming* Leuven, Belgium, 83-91.

Viazzi, S., Bahr, C., Van Hertem, T., Schlageter-Tello, A., Romanini, C.E.B., Halachmi, I., Lokhorst, C., Berckmans, D., 2014. Comparison of a three-dimensional and two dimensional camera system for automated measurement of back posture in dairy cows. *Comput. Electron. Agric*. **100**, 139-147.

Session 14

Pigs and health/production

Evaluation of using a depth sensor to estimate the weight of finishing pigs

I.C.F.S. Condotta[1], T.M. Brown-Brandl[2], and K.O. Silva-Miranda[1]
[1]*São Paulo University, "Luiz de Queiroz" College of Agriculture (ESALQ), Av. Pádua Dias, 11- Piracicaba/SP – Brazil CEP 13418-900*
[2]*USDA, ARS, U.S. Meat Animal Research Center, P.O. 166 Clay Center, Nebraska, USA 68933*
Tami.BrownBrandl@ars.usda.gov

Abstract
A method of continuously monitoring weight would aid producers by ensuring that all pigs are healthy (gaining weight) and increasing precision at marketing. Therefore, the objective was to develop an electronic method of obtaining pig weights through depth images. Seven hundred and seventy-two images and weights were acquired from four different ages (8, 12, 16, and 21 weeks) of finishing pigs (a mix of gilts and barrows) of three sire-lines (Landrace, Duroc and Yorkshire). Weights ranged from 10.8 – 125.7 kg. The images were analysed using the MATLAB image processing toolbox and summing the columns to calculate the volume. Sixty percent of the data was used for equation development, and 40% was used for testing. Individual equations for weight predictions by volume were developed for gilts and barrows and for the three sire-lines. A global equation using the combined data was developed and then compared with individual equations using the Efroymson's algorithm. The results showed that there was no significant difference between the global equation and the individual equations for barrows and gilts ($p<0.05$), and the global equation was also not different from individual equations for each of the sire lines ($p<0.05$). In addition, the results from the global equation indicate that volume accounted for 99.05% of the variation in weight. Using the test data set, the global equation predicted weights using volume calculated with an average error of 4.6% or 2.2 kg. Therefore, the results of this study show that the depth sensor would be a reasonable approach to continuously monitor weights.

Keywords: real-time recognition, cough analysis, spectral analysis, signal processing

Introduction

Knowledge of the daily variation in the animals' weight in real time would allow producers to improve animal well-being and production. It would be possible to use this information to optimise the space provided per animal, improve nutritional management practices, predict and control weights for the slaughter

and, potentially, serve as a disease outbreak monitor (Brandl & Jørgensen, 1996; Kashiha et al, 2014). Usually, weighing is carried out manually, a process that often requires two workers and can take three to five minutes per animal. This practice can be stressful for both animals and workers, time consuming, and represents an ergonomic risk (Brandl & Jørgensen, 1996).
Therefore, an automated system to determine the animals' weight has potential to assist producers in classifying animals for market and minimise the number of pigs marketed outside of specification, improving the yield from production. Many attempts have been made to find an alternative to the manual weighing process.

Two different approaches to automating animal weighing have been evaluated: automated weighing systems combined with individual animal identification equipment and indirect determination of weight through the animal's dimensions. In general, the automatic weighing systems involve direct contact with the animal. They can be used in the form of semi-automatic scales (Smith & Turner, 1974), significantly reducing the weighing time, and in the form of automatic feeders with automatic scales (Slader & Gregory, 1988; Ramaekers et al, 1995; Schofield et al, 2002). Problems with these direct contact approaches include the presence of more than one animal or other material on the scale during weighing which could generate inaccurate measurements.

The significant correlation between weight and pig dimensions has led many authors to study the possibility of estimating body weight using this relationship (Brandl & Jorgensen, 1996). Alternatively, several authors (Schofield, 1990; Frost et al, 1997; Schofield, 1999; Whittemore & Schofield, 2000; Wang et al. 2008; Kashiha et al, 2014) developed techniques for obtaining animal dimensions through digital images which have been shown to be a non-invasive, efficient method. In general, the difficulty with determining weight through images is that, in order to extract the dimensions of the pig, its colour must be different from the colour of the environment.

A new approach was proposed by Kongsro (2014): the use of a Microsoft® Kinect® sensor to obtain depth images. The volume of the animal obtained through these images was correlated with the weight of Landrace and Duroc boars. The system could acquire the weight of the pigs with an error of 4 to 5%. These images require less attention to calibration and lighting, and also provide a specified time. This paper only used boars, leaving questions remaining as to whether this approach will work for different sexes of pigs (barrows for the US, and gilts) and whether different equations will be required for different genetic lines or sexes.

The objective of this study was to extract pigs' weight data from depth images, using a low-cost depth sensor, for three commercial sire lines (Duroc, Landrace and Yorkshire) and two sexes (gilts and barrows).

Materials and methods

The experiment was conducted in a growing-finishing building at the Meat Animal Research Center, part of the Agriculture Research Service-ARS of the United States Department of Agriculture –USDA (-98.13° W, 42.52° N). Animal weights and digital and depth images were collected in a population of grow-finish pigs during 4 distinct time points through the grow-finish period. All animal procedures were performed in compliance with federal and institutional regulations regarding proper animal care practices (FASS, 2010).

Animal specifics

Seven hundred and seventy-two depth and digital images and weights were collected in a population of grow-finish pigs (equally divided between barrows and gilts). The pigs represented three commercial sire lines (Landrace, Duroc and Yorkshire). Approximately 190 images and weights were collected at each of four approximate ages (8, 12, 16 and 21 weeks old). The pigs weighed 7.6 ± 2.87, 44.66 ± 4.84, 72.04 ± 7.48 and 100.57 ± 9.75 kg at each of the four time periods, respectively.

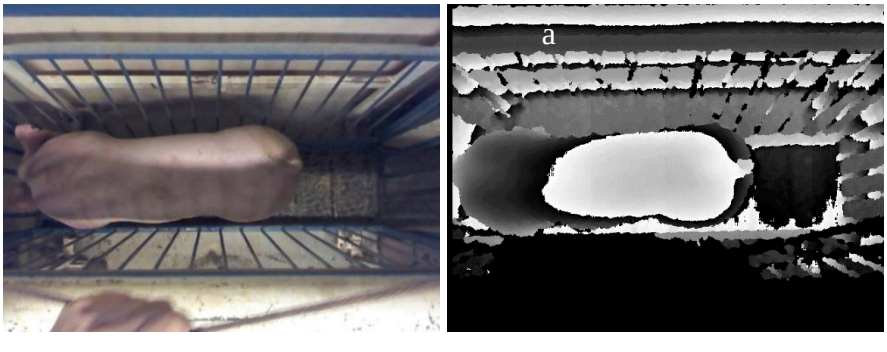
Image acquisition

An image acquisition program was developed in MATLAB software to acquire data from a Kinect® sensor (Version 1) and deployed on a laptop for data collection. The Kinect® sensor was mounted on the wall above the animal scales (Figure 1). Both digital colour images and depth images (Figure 2) were acquired from the Kinect® sensor. The digital RGB colour image was saved in a png (portable network graphics) format; the values from the depth image were saved in a space-delimited text file (txt). Digital colour RGB images were used for animal identification. The depth image was used for animal volume acquisition.

Figure 1. Weights and images were captured on individual pigs using a standard swine scale and Kinect® sensor, version 1. The Kinect® sensor was mounted on the wall directly above the centre of the scale.

Image processing

Pig volumes were obtained by processing the depth images using a program developed in MATLAB. The distance from sensor to animal was converted to the animal's height by subtracting the distance between sensor and floor from the distance between sensor and animal. Then, the values were selected within a limit, covering 250 mm +/- the approximate height of the animal. Other possible noises (e. g. parts of the scale) were eliminated by making the values of rows and columns around the animal equal to zero. The head and tail regions were then eliminated, making their values equal to zero to facilitate location of the animal's shoulders. All remaining values were summed to give the volume of the pig.



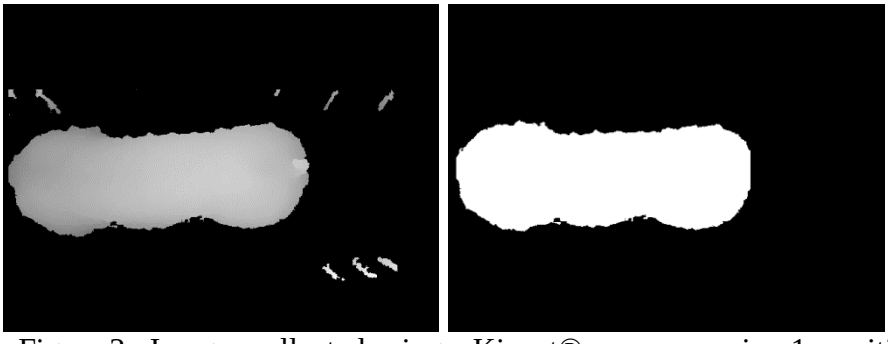


Figure 2. Images collected using a Kinect® sensor, version 1, positioned directing above the scale as the animals were being weighed (a) RGB image, (b) depth image and processed using Matlab (c) shows the elimination of areas in the depth image that were out of a pre-established value, and (d) indicates the selected pig after eliminating the head and tail.

Statistics

A multiple linear regression equation was developed to describe the effects of volume (cm^3) on the weight of the pigs (kg), considering the impacts of sex (barrows and gilts) and sire line (Duroc, Landrace, and Yorkshire). Efroymson's algorithm (stepwise regression) (Efroymson, 1960) was used to test the level of significance of sex and sire line in the multiple linear regression equation.

Results and discussion

Seven hundred and seventy-two images were used in the evaluation. Four hundred and twenty-three images were from barrows, while 349 images were taken from gilts. Approximately equal numbers of images were taken from each sire line: 121 − Landrace, 129 − Yorkshire, 99 − Duroc. The pig weights ranged weight from 10.8 to 125.7 kg.

It was found that the weight of growing-finishing pigs varied with the volume obtained through depth image analysis (Figure 3). Visually, the animals' weight varies linearly with the volume obtained by image analysis, which is proved by Pearson's correlation coefficient (0.9952), shown in Table 1. The result of Efroymson's algorithm (p=0.8237) showed that the effects of sex and commercial line do not need to be considered in the model, indicating that a reduced model is sufficient for weight prediction in the three sire lines used for both gilts and barrows.

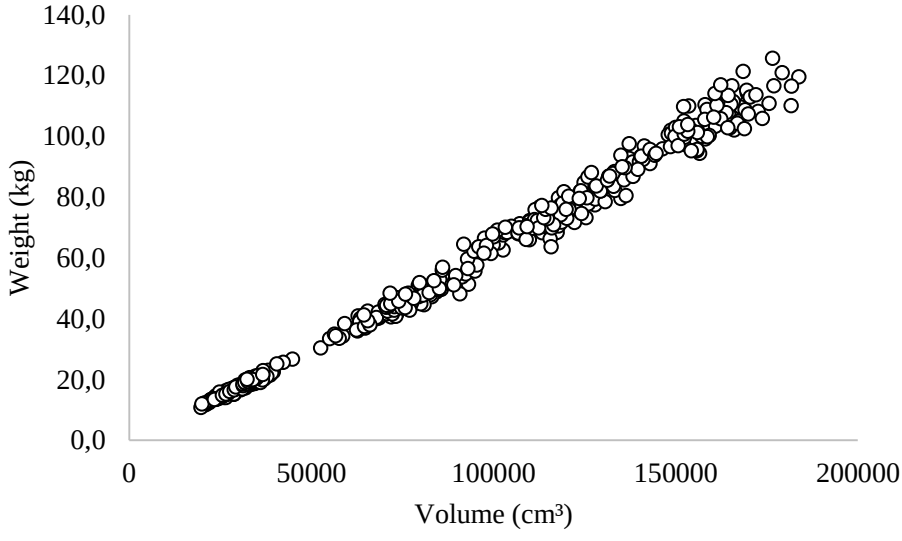


Figure 3 – The relationship of grow-finish pig volume as obtained through in-depth analysis provided by a Kinect® sensor, and the weight of the pigs obtained with a conventional scale.

The equation coefficients obtained are shown in Table 1, as well as the values of the Pearson's correlation coefficient (r), the determination coefficient (R^2) and the Willmott's indexes (d and dr) (Willmott, 1981; Willmott et al, 2012).

The global equation presents an R^2 of 0.9905; indicating that 99.05% of the variability of the weight of the animals can be explained by volume obtained through the data provided by the Kinect® sensor. This value is greater than that obtained (R^2 of 0.92) by Kashiha et al. (2014) using digital images. In addition, it is also equal to the value obtained (R^2 = 0.99) by Kongsro (2014) for boars, also using Kinect® depth images.

Table 1 - Linear regression model coefficients (W = a + bV), where: W = estimated weight (kg) V = volume of the animal obtained through image analysis (cm^3), b and a = estimated coefficients; N: number of data pairs used to fit the model; r: Pearson's correlation coefficient; R^2: coefficient of determination; d: Willmott's concordance index; dr = refined Willmott's index

Intercept	Coefficient	N	r	R^2	d	dr
b	a					
-3.7488 ±0.3160	0.0007 ±3.1 x 10^{-6}	463	0.9952	0.9905	0.9991	0.9731

The Pearson's correlation coefficient obtained (0.9952) indicates that there is a strong positive linear correlation between the volume and the weight of the animal. This value is greater than that obtained by Schofield (1990) (r = 0.97) for correlation between a pig's weight and area on a digital colour image.

Using the test data set (40% of the data), the global equation predicted weights using calculated volumes with an average error of 4.6% or 2.2 kg. Overall, the proposed method showed satisfactory performance in the estimation of the weight of growing-finishing pigs. The responses obtained are as good as or better than those obtained by other authors who correlated the mass of animals with dimensions obtained by images. The method proved to be fast and efficient. The biggest problem with this approach is the difficulty in obtaining reliable depth data in excessively lit environments.

Conclusions

A Kinect® sensor was used to obtain depth images from grow-finish barrows and gilts from 3 different sire-lines. The volume of the pigs was determined through image processing. It was found that the volume obtained with depth images was highly correlated with the weights of grow-finish pigs regardless of sex or sire line. The error in weight was estimated at 4.6%. The method developed and used to obtain volumes of pigs through depth images on this study has the potential to be automated, using the program and equation developed.

Acknowledgements

This project was funded in part by FAPESP, Fundação de Amparo à Pesquisa do Estado de São Paulo. The authors would like to thank John Holman, Dale Janssen and Hannah Speer for their help in collecting the data, and Donna Griess for her help in preparing this manuscript.

References

Brandl, N., Jørgensen, E. 1996. Determination of live weight of pigs from dimensions measured using image analysis. *Computers and Electronics in Agriculture* **15**(1) 57-72.

Draper, N.R., and Smith, H. 1998. *Applied regression analysis*. 3rd ed. New York: John Willey & Sons, pg. 706.

Efroymson, M.A. 1960. Multiple regression analysis. *Mathematical Methods for Digital Computers* **1** 191-203.

Federation of Animal Science Societies. 2010. *Guide for the care and use of agricultural animals in research and teaching*. 3rd edition. FASS, Champaign, IL, USA.

Frost, A. R., Schofield, C. P., Beaulah, S. A., Mottram, T. T., Lines, J. A., & Wathes, C. M. 1997. A review of livestock monitoring and the need for integrated systems. *Computers and Electronics in Agriculture*, **17**(2), 139-159. Kashiha, M.,

Bahr, C., Ott, S., Moons, C.P.H., Niewold, T.A., Ödberg, F.O., and Berckmans, D. 2014. Automatic weight estimation of individual pigs using image analysis. *Computers and Electronics in Agriculture* **107** 38-44.

Kongsro, J. 2014. Estimation of pig weight using a Microsoft Kinect prototype imaging system. *Computers and Electronics in Agriculture* **109** 32-35.

Ramaekers, P.J.L., Huiskes, J.H., Verstegen, M.W.A., den Hartog, L.A., Vesseur, P.C., Swinklels, J.W.G.M. 1995. Estimating individual body weights of group-housed growing-finishing pigs using a forelegs weighing system. *Computers and Electronics in Agriculture* **13**(1) 1-12.

Schofield, C. P. Marchant, J.A., White, R.P., Brand, N., and Wilson, M. 1999. Monitoring pig growth using a prototype imaging system. *Journal of Agricultural Engineering Research* **72**(3) 205-210.

Schofield, C.P., Whittemore, C.T., Green, D.M., and Pascual, M.D. 2002. The determination of beginning-and end-of-period live weights of growing pigs. *Journal of the Science of Food and Agriculture* **82**(14) 1672-1675.

Schofield, C. P. 1990. Evaluation of image analysis as a means of estimating the weight of pigs. *Journal of Agricultural Engineering Research* **47** 287-296.

Slader, R.W., and Gregory, A.M.S., 1998. An automatic feeding and weighing system for ad libitum fed pigs. *Computers and Electronics in Agriculture* **3**(2) 157-170.

Smith, R.A., and Turner, M.J.B. 1974. Electronic aids for use in Fastock weighing. *Journal of Agricultural Engineering Research* **19**(3) 299-311.

Wang, Y., Yang, W., Winter, P., and Walker, L. 2008. Walk-through weighing of pigs using machine vision and an artificial neural network. *Biosystems Engineering* **100** 117-125.

Whittemore, C. T.,and Schofield, C. P. 2000. A case for size and shape scaling for understanding nutrient use in breeding sows and growing pigs. *Livestock Production Scienc***e 65**(3) 203-208.

Willmott, Cort J. 1981. On the validation of models. *Physical Geography* **2**(2) 184-194.

Willmott, C.J., Robesonb, S.M., and Matsuuraa, K. 2012. Short Communication: A Refined Index of Model Performance. Intl. *Journal of Climate*. 32(13):2088-2094.

First results of a warning system for individual fattening pigs based on their feeding pattern

J. Maselyne[1], A. Van Nuffel[1], P. Briene[1,2], J. Vangeyte[1], B. De Ketelaere[2], S. Millet[1], J.Van den Hof[3], D. Maes[3], W. Saeys[2]
[1]*ILVO (Flanders research institute for agriculture, fisheries and food), Technology and food Science Unit and Animal Sciences Unit, Burgemeester Van Gansberghelaan 92 bus 1, 9820 Merelbeke Belgium*
[2]*KU Leuven, Department of Biosystems, MeBioS, Kasteelpark Arenberg 30, 3001 Leuven, Belgium*
[3]*Ghent University, Department of Obstetrics, Reproduction and Herd Health, Porcine Health Management, Salisburylaan 133, 9820 Merelbeke, Belgium*
jarissa.maselyne@ilvo.vlaanderen.be

Abstract

For sustainable pork production and maximum pig welfare, all health, welfare and productivity problems in the barn should be detected as early as possible. In this paper, the first results are presented of an automated warning system that is based on measurements of the feeding pattern. The system is able to give real-time alarms for individual fattening pigs. A validated High Frequency Radio Frequency Identification (HF RFID) system was used to measure the feeding pattern of each pig. Using this data, a warning system was developed with time-varying individual control limits using the concept of Synergistic Control. Synergistic Control is the synergy between the models used in Engineering Process Control (EPC) and the control charts used in Statistical Process Control (SPC). During a validation round, 140 pigs were observed closely and individually by observers to identify true alarms, false alarms and problems missed by the warning system. Using this system, 58.3% of the days where a problem was present in individual pigs were detected and 71.0% of the alarms were correct. Severe problems were detected within 1.4 days on average. The SGC approach gave better results than a fixed group limit. Further improvements in sensitivity and precision are still needed, as well as tests to compare the performance to the farmers' observation. But overall, the system allows better detection and follow-up of individual pigs' problems, which would in turn increase the pigs' health, welfare and productivity, improve labour efficiency and help with decision making.

Keywords: monitoring, pigs, feeding pattern, warning system, RFID, synergistic control

Introduction

The pig farming sector is economically very important, both world-wide as in Belgium (Eurostat, 2014). It is important that the productivity, welfare and health of growing-finishing pigs is kept at an optimal level (Gentry et al., 2008). Better productivity leads to better financial results and more output with less (natural) resources. Good welfare benefits the pigs and the image of the sector. Improving health of the pigs can reduce (veterinary) costs, improve productivity and increase welfare. Healthy pigs produce more and higher quality meat than their unhealthy congeners and require less labour. Most often, the focus is on the group-level when it concerns growing-finishing pigs. The individual pig is the real production unit of growing-finishing farms though and large inter-individual differences exist. Real-time continuous monitoring of each pig is not feasible for a pig farmer, but the combination of sensor technology and automated data-analysis has huge potential here.

Changes in the feeding behaviour of pigs could indicate health, welfare and productivity problems, so in recent years Radio Frequency Identification (RFID) systems have been developed to measure the individual feeding behaviour under normal farm circumstances, using standard commercial feeders. Two other research groups focus on Low frequency (LF) (Brown-Brandl and Eigenberg, 2011; Brown-Brandl et al., 2013) or Ultra-High Frequency (UHF) (Adrion, 2015; Kapun et al., 2016) RFID, but the present paper will show the development and application of a High Frequency (HF) RFID system to measure individual pig feeding behaviour. Also, the development of an automated warning system for health, welfare and productivity problems of individual pigs is discussed and the first results are shown.

Materials and methods

RFID system

The RFID system was installed in a fattening pig barn at ILVO's experimental farm (Melle, Belgium), that was divided into four large pens that could house between 35 and 59 pigs per pen. The pens were with a partially slatted floor, an automatic ventilation and feeding system and sufficient natural and artificial lighting. Each pen was equipped with Swing MIDI feeders (Big Dutchman Pig Equipment GmbH, Vechta, Germany) and nipple drinkers and *ad libitum* feed and water was available. The system was installed in 2012 and in total five full measurement periods were done over the next three years.

The HF RFID system consisted of tags (placed on the pigs' ears – in this case one tag per ear was used), antennas (placed on the feeders), multiplexers and readers connected to a computer (Fig. 1). In previous studies, the HF RFID

system has been validated using video observations of feeding pigs (Maselyne et al., 2014a) and extensive range measurements have been performed (Maselyne et al., 2014b). The results and data presented here are for two tags per pig (one in each ear).

Figure 1: Pig feeding at a feeder equipped with the HF RFID system. The RFID antenna is above the pig's head, the yellow ear tag in its ear contains an RFID tag.

Extraction of pig behaviour information

With the installed HF RFID system, attendance at the feeder was registered for individual pigs. These registrations are not continuous during feeding, which was inherent to the system (Maselyne et al., 2014b). Further data processing is thus needed to construct feeding visits. Several methods were examined and compared in Maselyne et al. (2016), and when two tags per pig are used, a bout criterion of 10 s was found to be best for the reconstruction of the real feeding pattern in this barn. A bout criterion is defined as the maximum time gap between registrations of a pig at a feeder to consider these registrations as part of one feeding visit.

Many possible variables can then be extracted from the feeding visits, the current paper will focus on RFID based feeding duration and the raw RFID registrations. Video observations were recorded during two different fattening rounds, one on 20 pigs aged 16 weeks at one feeder, during 11.5 hours in one day; another on 6 pigs during 14 hours at two feeders on three separate days (aged 13, 19 and 25 weeks) to allow a comparison between observed feeding duration and the RFID measurements. The data of these two observations were combined in the results. In these experiments, 59 pigs were present in the pens (mixed groups of around 50% gilts and 50% barrows). The focal animals were randomly chosen (50%

gilts and 50% barrows), but in different weight categories, and were marked with a specific sign (using coloured spray) before the day of the observations.

Warning systems

Warning systems were developed based on the data of one fattening round, and then validated during the other fattening round. During the latter, the 140 pigs in the barn were followed-up very closely: daily check of the animal caretakers, several hours per day of checking the individual pigs by observers during week-days and weighing, scoring and taking temperature of each pig every two weeks, as well as by a visit by the veterinarian every two weeks. Pigs that gave an alert according to the warning system were also checked individually after the other observations and a checklist was used for this purpose including, amongst others, activity, body shape and checks of various parts of the body, lameness, rectal temperature, skin, ear and tail lesions. Post-mortem the animals were either sent to a lab for autopsy (if this occurred before slaughter), or several internal lesions (long, liver, abscesses) were scored during slaughter.

Based on these observations, every pig was given a daily status: red (severe problem, should be detected), orange (mild problem, nice to detect) and green (no problem, should not get an alert). The status was determined based on a list of criteria established at the beginning of the fattening round (not shown here). Sensitivity, specificity, accuracy and precision of the warning systems were calculated based on this status per pig, per day.

Two types of warning systems were compared: 1) fixed limits, with one control limit for all pigs and all days; 2) Synergistic Control (SGC) limits, a method that allows to determine control limits based on the pig itself and taking into account the normal variation that occurs during a fattening round. SGC can be described as a two-step procedure where first a series of models is used to pre-treat the data before applying a control chart on the residuals that meet the assumptions of stationary, independence and normal distribution (De Ketelaere et al., 2011; Mertens et al., 2011). A pig that crosses the control limit of a certain system, gives an alert for that day.

Results and discussion

RFID registrations and feeding visits

When comparing number of RFID registrations per pig (Fig. 2) and duration of RFID feeding visits (Fig. 3) versus observed feeding duration, one can see that the latter has a better correlation with the true feeding behaviour ($R^2 = 0.86$ versus $R^2 = 0.73$) (see also Maselyne et al., 2016). However, the data post-processing when creating visits always has the risk of creating artefacts in the data (Maselyne et al., 2016). No experiments in other barns have been performed

up till now, so there is no information available to know whether this bout criterion works also for other farms. For these first results, the warning systems were thus developed based on the raw number of RFID registrations as monitoring variable.

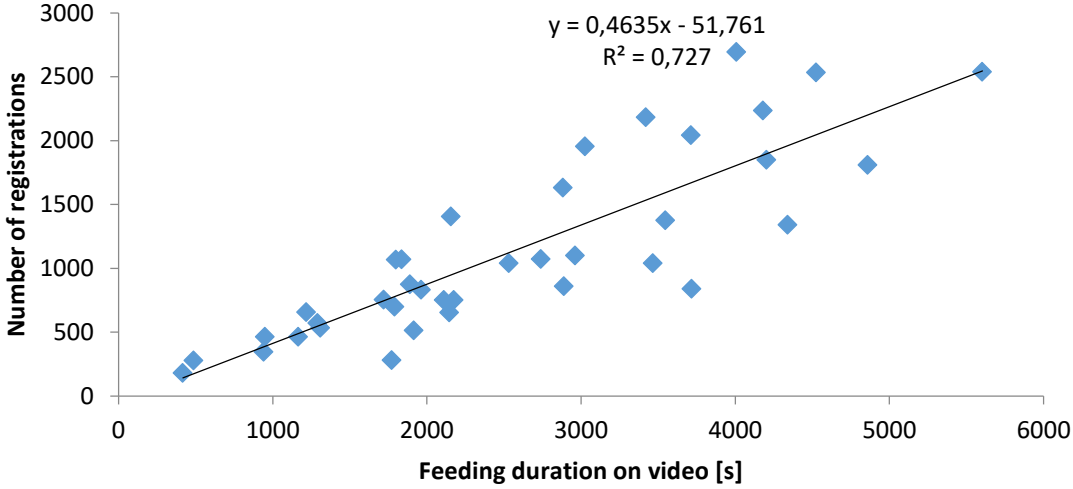


Figure 2: Linear regression of the observed feeding duration per pig versus the number of RFID registrations (two experiments).

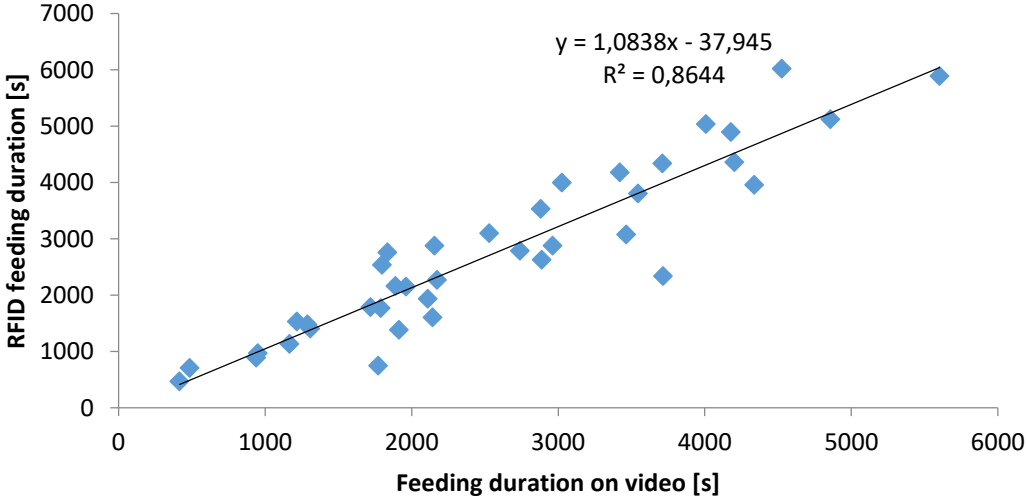


Figure 3: Linear regression of the observed feeding duration per pig versus the RFID based feeding duration (using bout criterion 10 s) (two experiments).

Warning systems

Based on the number of registrations, two warning systems were developed: one with fixed limits and one with individual, time-varying limits using the Synergistic Control procedure. Historical data was used to set the specific limits. The fixed limit was set at 350 registrations per day. The SGC limits were based on a Shewhart control chart (Montgomery, 2009) with a lower control limit based on four times the moving range, after applying a linear regression model that constantly updates with each new day of data (up to 30 days back). To initialise the model and control limits, a five-day reference period is used. Additionally, no alert was given for the SGC procedure when the number of registrations was above 2000, but below 350 registrations an alert was always given.

A comparison between both systems can be found in Table 1. The largest difference can be seen for the sensitivity, where the SGC procedure is more than 10% more sensitive than the fixed limit. An example of this can be seen in Figure 4, where pig 43 does not drop below the fixed limit but clearly has a reduced feeding pattern around day 50. This is correctly detected by the SGC warning system and indeed the pig was severely lame and had fever due to a claw infection.

With this system almost 2/3rd of the problem-days with individual pigs were detected and more than 2/3rd of the alarms were correct. Severe problems were detected within 1.4 days on average. Further improvements are needed to increase sensitivity and precision. During the online validation, some drawbacks of the system were identified such as a lack of sensitivity for slow process shifts or shifts early in the fattening round. Work is going on to further improve the system, several options are possible: looking at other variables, other types of warning systems, using historical data to initialize the system, etc. Also the use of only one tag per pig still needs to be investigated for the warning systems.

As a note to the calculation of the performance, even with extensive daily observations it was very difficult to determine the daily status of a pig. Visual observations only give a snapshot of the outside of a pig and part of its behaviour, but do not give a complete view at all. Problems were something seen one day and not the next, leading to the system being punished for an alert on that second day, although it could be present part of the day or without the observers noticing. Also recovery appeared to sometimes be faster visible in the feeding pattern than in the physical appearance or observations of the pigs.

Table 1: Performance of the warning systems on the number of registrations

	Fixed limit	**SGC limits**
Sensitivity [%]	48.5	58.3
Specificity [%]	99.0	98.7
Accuracy [%]	96.6	96.6
Precision [%]	71.2	71.0

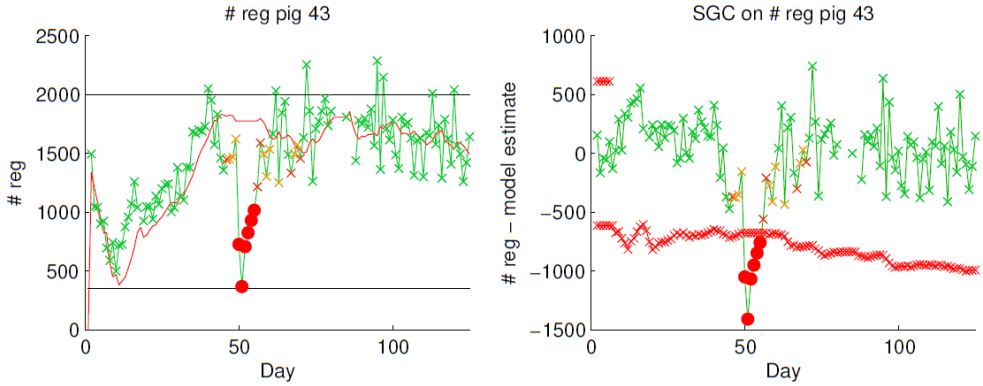


Figure 4: Number of registrations of pig 43, with on the left side the raw data, and the fixed limit (350 reg.), the model of the SGC procedure and on the right side the residuals after model subtraction and the lower control limit of the SGC procedure. Colour of the raw data = status of that day. Dots = alerts of the SGC warning system.

Conclusions

The presented HF RFID system has shown to be a valuable tool in research and possibly also for on-farm management. The data that are generated provide additional information that was previously not available. A substantial amount of problems in the individual pigs indeed give rise to a change in feeding behaviour, and this can be detected by the system. There is still work to do to achieve a system that can work on practical farms, but automated follow-up of individual pigs' feeding patterns has the potential to increase the pigs' health, welfare and productivity, improve labour efficiency and help with decision making.

Acknowledgements

Jarissa Maselyne has been funded by a PhD grant from the Agency for Innovation by Science of Technology (IWT Flanders – project SB 111447). We thank all the colleagues that contributed to this study, such as the people that provided technical support, animal care and support during measurements.

References

Adrion, F., Hammer, N., Eckert, F., Goetz, S., and Gallmann, E. 2015. Adjustment of a UHF-RFID system for hotspot monitoring of fattening pigs. In: *7th European Conference on Precision Livestock Farming* (M. Guarino, Berckmans, D., ed.), pp. 573-582, Milan, Italy.

Brown-Brandl, T. M., and Eigenberg, R. A. 2011. Development of A Livestock Feeding Behavior Monitoring System. *Transactions of the Asabe* **54**, 1913-1920.

Brown-Brandl, T. M., Rohrer, G. A., and Eigenberg, R. A. 2013. Analysis of feeding behavior of group housed growing-finishing pigs. *Computers and Electronics in Agriculture* **96**, 246-252.

De Ketelaere, B., Mertens, K., Mathijs, F., Diaz, D. S., and De Baerdemaeker, J. 2011. Nonstationarity in statistical process control - issues, cases, ideas. *Applied Stochastic Models in Business and Industry* **27**, 367-376.

Eurostat 2014. *Agriculture statistics at regional level.* Vol. 2015.

Gentry, J. G., Johnson, A. K., and McGlone, J. J. (2008). The welfare of growing-finishing pigs. In: *Welfare of pigs from birth to slaughter* (L. Faucitano and A. L. Schaefer, eds.). Wageningen Academic Publishers & Éditions Quae, Wageningen, the Netherlands & Versailles, France.

Kapun, A., Adrion, F., Schmid, L. A., Staiger, M., Holland, E. M., Gallmann, E., and Jungbluth, T. 2016. Test of a UHF-RFID system for health monitoring of finishing pigs. In: *International Conference on Agricultural Engineering - AgEng 2016*.

Maselyne, J., Saeys, W., Briene, P., Mertens, K. C., Vangeyte, J., De Ketelaere, B., Hessel, E. F., Sonck, B., and Van Nuffel, A. 2016. Methods to construct feeding visits from RFID registrations of growing-finishing pigs at the feed trough. *Computers and Electronics in Agriculture* **128**, 9-19.

Maselyne, J., Saeys, W., De Ketelaere, B., Mertens, K., Vangeyte, J., Hessel, E. F., Millet, S., and Van Nuffel, A. 2014a. Validation of a High Frequency Radio Frequency Identification (HF RFID) system for registering feeding patterns of growing-finishing pigs. *Computers and Electronics in Agriculture* **102**, 10-18.

Maselyne, J., Van Nuffel, A., De Ketelaere, B., Vangeyte, J., Hessel, E. F., Sonck, B., and Saeys, W. 2014b. Range measurements of a High Frequency Radio Frequency Identification (HF RFID) system for registering feeding patterns of growing-finishing pigs. *Computers and Electronics in Agriculture* **108**, 209-220.

Mertens, K., Decuypere, E., De Baerdemaeker, J., and De Ketelaere, B. 2011. Statistical control charts as a support tool for the management of livestock production. *Journal of Agricultural Science* **149**, 369-384.

Montgomery, D. C. 2009. *Introduction to Statistical Quality Control.* John Wiley & Sons, Inc., Hoboken, USA.

Reducing alarms and prioritising interventions in pig production by simultaneous monitoring of water consumption in multiple pens

K.N. Dominiak[1,2], J. Hindsborg[1], L.J. Pedersen[2] and A.R. Kristensen[1]
[1]*Department of Veterinary and Animal Sciences, University of Copenhagen, Groennegaardsvej 2, DK-1870 Frederiksberg C*
[2]*Department of Animal Science, Aarhus University, Blichers Allé 20, DK-8830 Tjele*
knd@sund.ku.dk

Abstract

Spatial modelling of water consumption in growing pigs can be a useful tool for identifying high risk pens or sections in early detection of diseases and various behavioural problems.
In this study a multivariate dynamic linear model (DLM) is developed based on data from simultaneous monitoring of water consumption across multiple pens in two separate herds. The two herds consist of a commercial finisher herd (Herd A) and a research farm with weaners (Herd B).
Parameters in the model can be defined individually at herd, section or pen level. This spatial distinction allows early warnings to be generated at pen level or merged at section or herd level to reduce the number of alarms. Information on which specific pens or sections are of higher risk of stress or diseases is communicated to the farmer and target work effort to pens at risk.
For Herd A, all model parameters defined at section level resulted in the best fit (MSE = 13.85 litres^2/hour). For Herd B, parameters defined at both pen and section level resulted in the best fit (MSE = 1.47 litres^2/hour).
For both Herd A and Herd B, preliminary results support the spatial approach by generating a reduced number of alarms when comparing section levels to pen levels.
This study is a part of an on-going project aiming to improve welfare and productivity in growing pigs using advanced ICT methods.

Keywords: dynamic linear model, multivariate, spatial, alarm-reducing, drinking pattern, monitoring

Introduction

A variety of sensor based detection models have been designed to monitor production animals and detect specific diseases or conditions (Kamphuis *et al.*, 2010; Garcia *et al.*, 2014; Ostersen *et al.*, 2010). Often the amount of false

alarms is too high for the model to be implemented (Hogeveen *et al.*, 2010; Dominiak & Kristensen, 2017), and it has proven to be a difficult yet very important task to reduce the number of alarms communicated to the farmer.

Previous research shows that water withholds important information in prediction of diseases in finisher pigs (Jensen *et al.*, 2017). However, changes in pigs' drinking pattern can also indicate general stress and information on the pigs' wellbeing (Madsen, *et al.*, 2005; Andersen *et al.*, 2016).

For bio-security reasons, Danish pig production units for growing pigs are run with a clear spatial separation between pigs of different age groups. Such a construction of the production site enables a spatial approach where the site is modelled as one production unit (the whole herd) consisting of a number of identical subunits (sections) and each subunit consisting of a number of identical sub-subunits (pens).

The objective of this paper is to present a model which detects unexpected changes in the water consumption of growing pigs across a whole production unit, and produces pen, section- or herd- specific alarms. Simultaneous alarms from pens in the same section, or sections in the herd, are merged which reduces the number of alarms communicated to the farmer.

Material and methods

Data

Data of water consumption (litres/hour) were collected from two herds. Herd A is a Danish commercial finisher herd, and water data from seven batches of pigs were obtained in the period from May 2014 to March 2016 (16309 hours). Herd B consist of the weaner sections of a Danish research facility herd, and water data from 13 batches of pigs were obtained in the period from October 2014 to December 2016 (18755 hours). The sensors were photo-electric flow sensors (RS V8189 15mm Dia. Pipe), and they were placed on the water pipe supplying two neighbouring pens (36 pigs, Herd A) or a single pen (15 pigs, Herd B). In Herd A, eight sensors were placed in two identical pens in each of four identical sections. In Herd B, sixteen sensors were placed in four identical pens in each of four identical sections. In total, eight double-pens from Herd A and 16 single pens from Herd B were monitored during the experimental period.

Every morning, the caretakers at each farm registered events of diarrhoea and fouling, which is a behavioural change where the pigs start to lie on the slatted area of the pen and excrete in the lying area (Aarnink *et al.*, 2006). These event registrations constitute the golden standard together with logbook registrations of unexpected managerial situations affecting the pigs.

General model

The water consumption over time is modelled simultaneously for all sensors in the herd using a multivariate dynamic linear model (DLM) as described by West & Harrison (1999). The observation vector, $Y_t = (Y_{1t}, \dots, Y_{nt})'$, is the amount of water consumed per hour at time *t* for each of the *n* sensors. The relation between Y_t and the underlying parameter vector θ_t at time *t*, as well as the evolution of the system over time, is described through an observation equation and a system equation (Equations (1) and (2), respectively):

$$Y_t = \boldsymbol{F}'_t \theta_t + \nu_t, \quad \nu_t \sim N(\mathbf{0}, \mathbf{V}_t), \tag{1}$$
$$\theta_t = \boldsymbol{G}'_t \theta_{t-1} + \omega_t, \quad \omega_t \sim N(\mathbf{0}, \mathbf{W}_t), \tag{2}$$

The aim of the DLM is to predict the next observation. That is to estimate the parameter vectors, θ_1, …, θ_t, from the observations, $Y_1, \dots, Y_t$. Through every hourly observation of water consumed, the model learns more of the general drinking pattern, and it is constantly updating the amount of information adding the newest observation. Any difference between the predicted observation and the actual observation is withheld in the two error terms, $\mathbf{V}_t$ and $\mathbf{W}_t$. If the pigs follow their normal drinking pattern and drink as much water as expected, the prediction of the next observation is close to perfect, and any prediction error will be small. If, on the other hand, something is causing the pigs to drink more or less than expected, the prediction error will be larger. A systematic change in the normal drinking pattern will generate a sequence of larger prediction errors, and this will lead to an alarm, which will be described later.

Modelling diurnal patterns

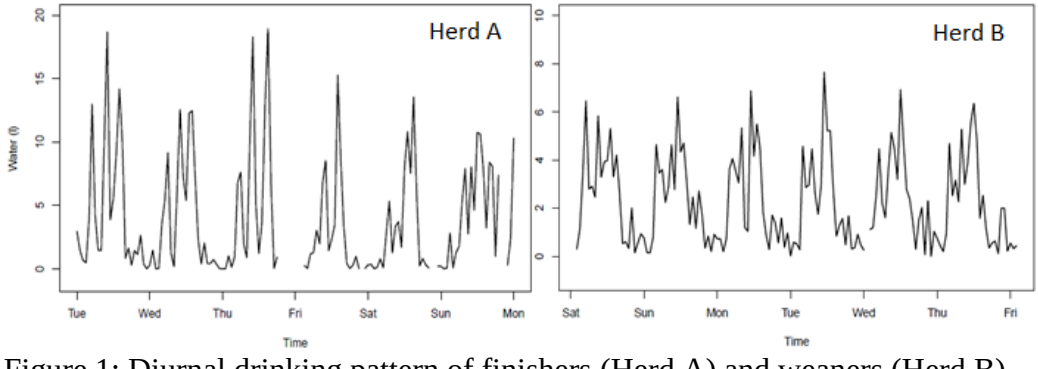


Figure 1: Diurnal drinking pattern of finishers (Herd A) and weaners (Herd B)

The drinking patterns of both finishers and weaners have clear diurnal characteristics (see Figure 1). Furthermore the underlying level of water consumed increases over time indicating that pigs drink more as they grow. A diurnal drinking pattern can be described by the sum of three harmonic waves and an underlying level and trend (Madsen *et al.*, 2005), and the DLM presented here, therefore, consists of four sub-models. The first sub-model, a *linear growth model* (Equation (3)), describes the underlying level and trend,

$$\mathbf{F}_t^l = \begin{pmatrix} 1 \\ 0 \end{pmatrix} \quad \text{and} \quad \mathbf{G}_t^l = \begin{pmatrix} 1 & 1 \\ 0 & 1 \end{pmatrix} \tag{3}$$

whereas the following three sub-models each describes a harmonic wave using the *Fourier form representation of seasonality* (West and Harrison, 1999; Madsen *et al.*, 2005). The Fourier form, as seen in Equation (4), describes a harmonic wave for any frequency, $\omega \in (0, \pi)$, with $\omega = \pi/24$ yielding a wave with a period of 24, $\omega = 2\pi/24$ yielding a wave with a period of 12, and $\omega = 3\pi/24$ yielding a wave with a period of 8.

$$\mathbf{F}_t^h = \begin{pmatrix} 1 \\ 0 \end{pmatrix} \quad \text{and} \quad \mathbf{G}_t^h = \begin{pmatrix} \cos(\omega) & \sin(\omega) \\ -\sin(\omega) & \cos(\omega) \end{pmatrix} \tag{4}$$

Modelling spatial structure

Each of the four sub-models can be defined at herd, section or pen level. A sub-model defined at pen level can evolve differently in each pen over time with no interaction between pens. Defined at section level, a sub-model evolves identically in all pens within the same section but differently between sections. Finally, a sub-model defined at herd level evolves identically in all pens in the herd.

The variances components are estimated by the *Nelder-Mead* algorithm in the statistical software R (R Core Team, 2017). The observation variances, $\mathbf{V}_t$, at herd, section and pen level are estimated directly, whereas a system variances, $\mathbf{W}_t$, for each of the four sub-models are estimated through discount factors as described by Madsen *et al.* (2005).

Evaluation

The models are trained on learning data (Herd A: 68 %, Herd B: 83 %) and tested on test data (Herd A: 32 %, Herd B: 17 %) with no pigs delivering data to both data subsets within the herds. Detection of alarms and irregular drinking patterns is done using Tabular CUSUM as described by Montgomery (2013). The standardised cumulated sum (CUSUM) of the positive prediction errors and the negative prediction errors is plotted over time, and if the sum exceeds a defined threshold, an alarm is generated. An event is registered once per 24 hours, but the alarms can be generated at an hourly basis. A

‘-3/+1’ prediction window is defined according to Jensen *et al.* (2017). Hereby all alarms from three days before an event observation to one day after an event observation are merged and considered true positive (TP). If no alarms are generated within the time window, it is considered false negative (FN), whereas single days with alarms but no events are false positive (FP) and single days without alarms but with events are false negative (FN) (see Figure 2).

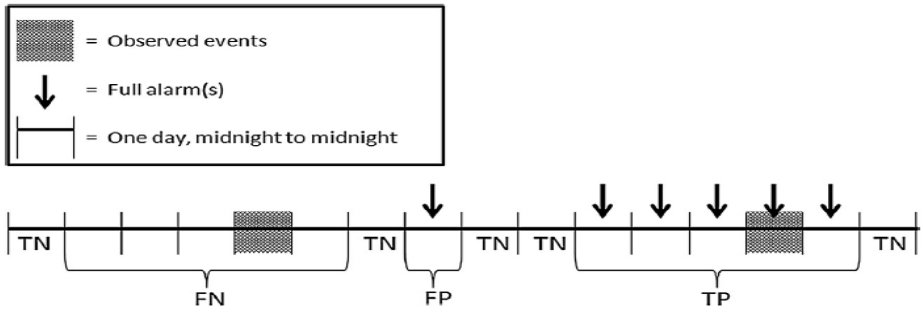


Figure 2: Illustration of the -3/+1 window as described by Jensen *et al.* (2017) with TP,TN, FP and FN alarms defined as described in the text.

Results and Discussion

Model fit

A model with all four sub-models defined at section level, fitted the drinking patterns of pigs in Herd A with MSE = 13.85 litres^2/hour. For Herd B it was a model with the linear growth sub-model defined at section level, and all three cyclic waves defined at pen level, which yielded the lowest MSE (1.47 litres^2/hour). A total of seven models with different level combinations were tested for each herd. In Herd A, each sensor supplies 36 finisher pigs (30-110 kg) which leads to a large variance and hereby a larger MSE. In Herd B, each sensor supplies 15 weaners (7-30 kg), leading to a smaller variance and a smaller numerical MSE.

Detecting events

Based on preliminary results, the spatial DLM is able to detect registered events of either diarrhoea or fouling in both herds. Figure 3 shows how four events were registered in one week in Herd A, and eight in Herd B. Three of the events in Herd A are associated with TP alarms, and all of those would be placed within the same time window, had it been shown. Of the eight events in Herd B, all are associated with TP alarms. No false positive alarms were raised during the week in either herd. The CUSUMS based on prediction errors for a section as compared to prediction errors from individual pens; result in a reduced number

of alarms (Table 1). Although the figures presented in this paper are preliminary, there is reason to expect the alarm reducing feature to show in the finished version as well, given the section based production strategy of Danish herds with growing pigs,. Because alarms can be generated for the whole herd, a section or a pen, the farmer will be informed of which areas of pigs need extra focus. This can be combined with managerial knowledge on age and health status of pigs in the high risk area. Hereby the right intervention for the given age group of pigs can be chosen.

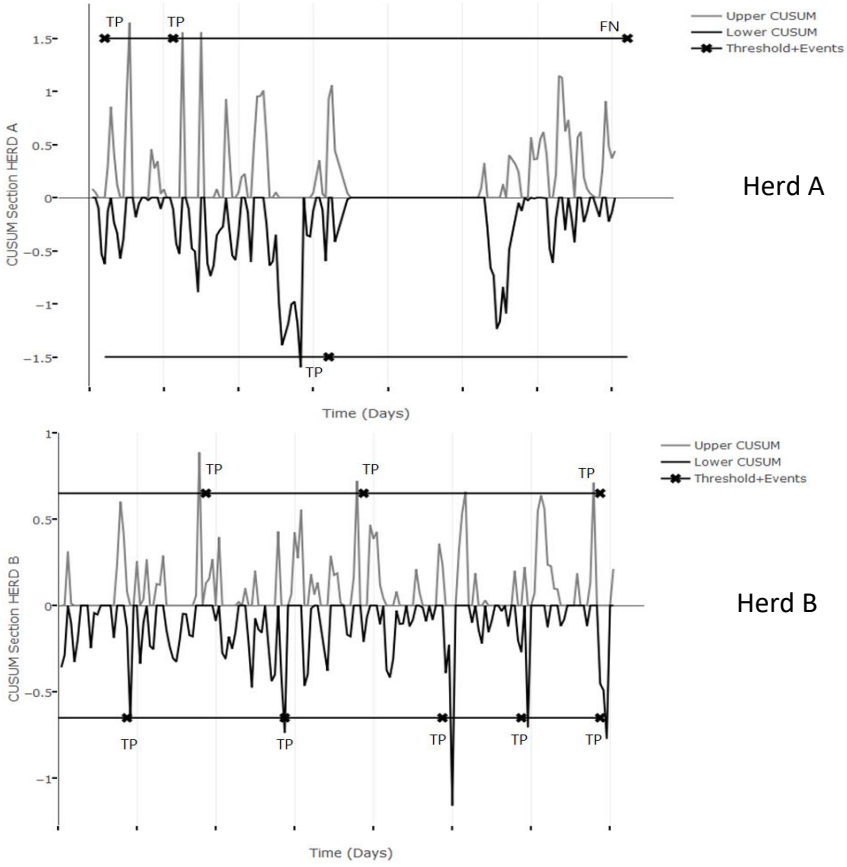


Figure 3: Tabular CUSUM for one week in one section of Herd A and one of Herd B. The two horizontal lines mark the thresholds for the upper CUSUM (grey line) or the lower CUSUM (black line). Four events (marked by **x** on the threshold lines) are registered in Herd A and eight in Herd B. The tabular CUSUM detects three events in Herd A, and eight in Herd B. TP = True Positive, FN = False Negative. The gap around day 5 in the plot is caused by sensor outage.

Table 1: Amount of registered events and CUSUM alarms for one week in pens and the corresponding sections in Herd A and Herd B. With pen level CUSUMS the sum of generated alarms from pens in a section were higher (6 Herd A, 50 Herd B) than with CUSUM at section level (4 Herd A, 8 Herd B). No alarms were merged in time windows; therefore more alarms could be associated to the same event. One section in Herd B was empty.

Herd	CUSUM level	Events	Alarms	Alarm reduction
A	Pen	3	3	From 6 to 4
A	Pen	3	3	
A	**Section**	**4**	**4**	
B	Pen	7	7	From 42 to 8
B	Pen	7	14	
B	Pen	7	21	
B	**Section**	**7**	**8**	

Conclusion

The preliminary results indicate that a spatial modelling of a pig production herd can reduce the number of alarms communicated to the farmer. Changes in water consumption can be used to identify high risk areas so the farmer can choose the optimal intervention for the pigs in the area triggering the alarm.

Acknowledgements

This research was funded by the Danish Council for Strategic Research (The PigIT project, Grant number 11-116191). We further wish to thank the anonymous farmer, the Danish Pig Research Centre and the technical staff at Aarhus University for installing and supervising the sensors and for taking care of the daily observations in the herd.

References

Aarnink, A.J.A., Schrama, J.W., Heetkamp, M.J.W., Stefanowska, J., and Huynh, T.T.T. 2006. Temperature and body weight affect fouling of pig pens. *Journal of Animal Science*, 84:2224-2231

Andersen, H.M.L., Jørgensen, E., and Pedersen, L.J. 2016. Using Evolutionary Operation technique to evaluate different management initiatives at herd level. *Livestock Science*, 187:109-113

Dominiak, K.N. and Kristensen, A.R. 2017. Prioritizing alarms from sensor-based detection models in livestock production – a review on model performance and alarm reducing methods. *Computers and Electronics in Agriculture*, 133:46–67

Garcia, E., Klaas, I., Amigo, J.M., Bro, R., and Enevoldsen, C. 2014. Lameness detection challenges in automated milking systems addressed with partial least squares discriminant analysis. *Journal of dairy science*, 97(12):7476-7486

Hogeveen, H., Kamphuis, C., Steeneveld, W., and Mollenhorst, H. 2010. Sensors and clinical mastitis – the quest for the perfect alert. *Sensors*, 10(9):7991-8009

Jensen, D.B., Toft, N., and Kristensen, A.R. 2017. A multivariate dynamic linear model for early warnings of diarrhea and pen fouling in slaughter pigs. *Computers and Electronics in Agriculture*, 135:51-62

Kamphuis, C., Mollenhorst, A., Feelders, A., Pietersma, D., and Hogeveen, H. 2010. Decision-tree induction to detect clinical mastitis with automatic milking. *Computers and Electronics in Agriculture*, 70(1):60-68

Madsen, T.N., Andersen, S., and Kristensen, A.R. 2005. Modeling the drinking patterns of young pigs using a state space model. *Computers and Electronics in Agriculture*, 48(1):39-62

Montgomery, D. 2013. Statistical Quality Control 7th edition, Hoboken, NJ, USA: *Wiley*

Ostersen, T., Cornou, C., Kristensen, A.R., 2010. Detecting oestrus by monitoring sows' visits to a boar. *Computers and Electronics in Agriculture*, 74(1):54-58

R Core Team (2017). R: A language and environment for statistical computing. *R Foundation for Statistical Computing*, Vienna, Austria.

Sorensen, C.G., Fountas, S., Nash, E., Pesonen, L., Bochtis, D., Pedersen, S.M., Basso, B, and Blackmore, S.B. 2010. Conceptual model of a future farm management information system. *Computers and Electronics in Agriculture*, 72(1):37-47

West, M., and Harrison, J., 1999. Bayesian Forecasting and Dynamic Models 2nd edition, New York, USA: *Springer*.

Session 15

Health, welfare and productivity

Validation of an early warning system for enteric disorders in broiler farming

E. Tullo[1], F. Borgonovo[2*], I. Fontana[1], G. Grilli[3], M. Guarino[1], V. Ferrante[1]
[1]*Department of Environmental Science and Policy, Università degli Studi di Milano, Via Celoria, 10, 20133 Milan, Italy*
[2]*Department of Health, Animal Science and Food Safety, Università degli Studi di Milano, Via Celoria 10, 20133, Milan, Italy*
[3]*Department of Veterinary Medicine, Università degli Studi di Milano, Via Celoria, 10, 20133 Milan, Italy*
federica.borgonovo@unimi.it

Abstract

Enteric disorders represent a major health issue in intensive farming; these pathologies could be caused by bacteria, viruses and parasites and are a major cause of performance reduction. Monitoring of poultry health status plays a key role in farm management by reducing use of chemicals/drugs and their costs.
Nowadays, antibiotics are commonly used preventively in intensive farming systems, a practice which could result in antibiotic resistance. For this reason, there is global interest in reducing the use of antimicrobials (AM). This could be achieved through Precision Livestock Farming (PLF), which can provide valuable information for the early detection of health problems in intensive farming by combining cheap technologies and specific algorithms.
The experimental trial was carried out in the facilities of the Università degli Studi di Milano located in Lodi.
One hundred and twenty Ross 308 one-day-old chicks were divided into two separate boxes (A and B) with standardised management conditions. Air samples from both groups were analysed with a chemical sensor array and processed with multivariate statistical software.
This study aims to develop a PLF diagnostic tool which is sensitive to variations in volatile organic compounds for prompt recognition of enteric problems in intensive farming, providing support for veterinarians and enabling specific treatments to be applied in the event of disease. The innovative approach of this methodology is the capability to provide reliable real-time information and repeatable responses. The advantage of early warning is that it offers potential for using non-conventional therapies instead of AM to treat animals.

Keywords: early warning system; poultry farming; health problem; intensive farming; PLF; volatile organic compounds

Introduction

Enteric disorders represent a major health issue in intensive farming; bacteria, viruses and parasites could cause these pathologies.
One of the most common enteric disorders in poultry farming is Coccidiosis, which is caused by protozoa of the family Eimeriidae or Coccidia. These parasites are present on almost every poultry farm. Most species belong to the genus Eimeria and infect various poultry intestinal tracts.
Clinical disease occurs after ingestion of sporulated oocysts by susceptible birds.
Infections may last up to 4-7 days with parasite replication in host cells causing extensive damage to the intestinal mucosa (Chapman, 2014). The infestation particularly affects the digestive tract of young animals; symptoms include lack of appetite and diarrhoea with a consequent drop in productive performances.
Poor environmental conditions and high animal density, which are features of intensive poultry farming, might promote coccidiosis development (McDougald & Fitz-Coy, 2013).
Subclinical infestations also have consequences for poultry performance, with serious economic losses, poor product quality and increased carcass condemnation at slaughter (Williams, 1999). Nowadays, the available diagnostic techniques use oocyst counts in the faeces or evaluation of lesions caused by coccidia in the intestinal tract of dead/culled animals (Johnson & Reid, 1970). However, these methods are time-consuming, not ethical and very few laboratories perform these analyses.
Due to the ease with which pathologies are transmitted in the high-density, confined environment of intensive farming, diagnostic techniques must be rapid and sufficiently low-cost to avoid improper use of medication (McDougald & Fitz-Coy, 2013). Nowadays, antibiotics are commonly used preventively in intensive farming systems, a practice which could result in antibiotic resistance. For this reasons, there is global interest in reducing the use of antimicrobials (AM). Indeed, reducing the use of medication might help to reduce antimicrobial resistance, which is considered a serious threat to public health (Alali *et al.*, 2009; Berge *et al.*, 2005).
This could be achieved through precision livestock farming (PLF), which can provide valuable information for early detection of health problem in intensive farming by combining cheap technologies and specific algorithms (Tullo *et al.*, 2013).
The PLF approach can easily be applied at farm level (Wathes, 2010), providing farmers with early warning systems for the management of complex biological production processes. For instance, PLF tools based on the collection of sounds (Fontana *et al.*, 2015; Fontana *et al.*, 2016; Guarino *et al.*, 2008; Hemeryck *et al.*, 2015; Meen *et al.*, 2015; Moura *et al.*, 2008; Silva *et al.*, 2009; Vandermeulen *et*

al., 2016; Vandermeulen *et al.*, 2015), images (Aydin *et al.*, 2010; Berckmans *et al.*, 2008; Dawkins *et al.*, 2012; Demmers *et al.*, 2012; Guzhva *et al.*, 2016; Ismayilova *et al.*, 2013; Matthews *et al.*, 2016; Porto *et al.*, 2015; Romanini *et al.*, 2012; Shao & Xin, 2008; Tullo *et al.*, 2016) and data from sensors (Caja *et al.*, 2016; Neethirajan, 2017) have been widely used to monitor animal health, welfare and production performance.

Image analysis has been widely used in many species to investigate thermal comfort.

A prompt response to any change in health, welfare and productive status is the key to reducing drug usage and improving animal wellbeing.

For these reasons, it is necessary to develop an alternative monitoring system which will promptly detect the onset of an infestation. Odour and air quality from livestock can be an indicator of animal health, since the odours from the litter are strongly related to the features of the animal faeces. Therefore, enteric problems are characterised by different chemical odour properties (Sohn *et al.*, 2008).

In this scenario, a sensor-based system was used for early and non-invasive detection of any health problem in intensive farming. This system uses non-specific gas sensors which are sensitive to a wide range of volatile compounds (organic and inorganic) and are able to classify and identify the odours analysed using a pattern recognition system.

The pattern recognition procedure consists of comparative and qualitative analysis of different odour samples and is responsible for discrimination and classification of sensor data into different clusters. Thus, any new odour sample is assigned to a specific class, based on the sensor output, thereby identifying the presence of a particular chemical pattern (identification process) (Green *et al.*, 2006).

This study aims to develop a PLF diagnostic tool which is sensitive to variations in volatile organic compounds (VOCs) for prompt recognition of enteric problems in intensive farming, providing support for veterinarians and enabling specific treatments to be applied in the event of disease.

Materials and methods

The experimental trial was conducted in the facilities of the Università degli Studi di Milano located in Lodi and lasted for 45 days.

One hundred and twenty Ross 308 one-day-old chicks were placed at day 0 and divided into two separate boxes (A and B) with standardised ventilation, rearing conditions and diet. A coccidiostat was added to the feed in group A.

Both boxes measured 2 x 3 m, the floor was covered with wood shavings and the stocking density was 30 kg/m^2.

Litter sampling was performed at six different locations within the box and the level of infestation was evaluated weekly according to the McMaster method (Conway & McKenzie, 2007). The gold standard for coccidiosis is the oocyst count per gram (opg).
Meanwhile, air sampling was carried out following recommendations described in the European Standard EN 13725 (CEN, 2003). Air samples were drawn into Nalophan® bags using a special sampler operating with the lung principle. The sampler draws the air directly into the bag by evacuating the tightly closed atmospheric pressure vessel in which it was placed (Dincer *et al.*, 2006).
Air samples were analysed with a chemical sensor array and processed with multivariate statistical software.
In order to discriminate between air samples collected in the two groups, data were first analysed using principal component analysis (PCA), then processed using discriminant analysis (LDA) and 'Odour-prints' were subsequently compared.
PCA is a statistical procedure which is useful for data analysis and classification and is the most widely used pattern recognition method for evaluation of the sensor responses.
LDA is a classification procedure which maximises the variance between categories (defined by PCA) and minimises the variance between categories, taking into account the distance between and within different classes.

Results and discussion

During the production cycle, group B developed a coccidiosis infection. At day 21 the oocyst count was 250 opg, with the infection reaching the highest value of 37.000 opg at day 35.
The score plot in Figure 1 reports the results of PCA performed on samples collected at day 21 and 35 in both groups (group A – no coccidiosis, group B – coccidiosis).
The analysis showed that the system was able to find differences between air samples collected in group A and group B, even when the oocysts in group B were in the order of 250 opg.

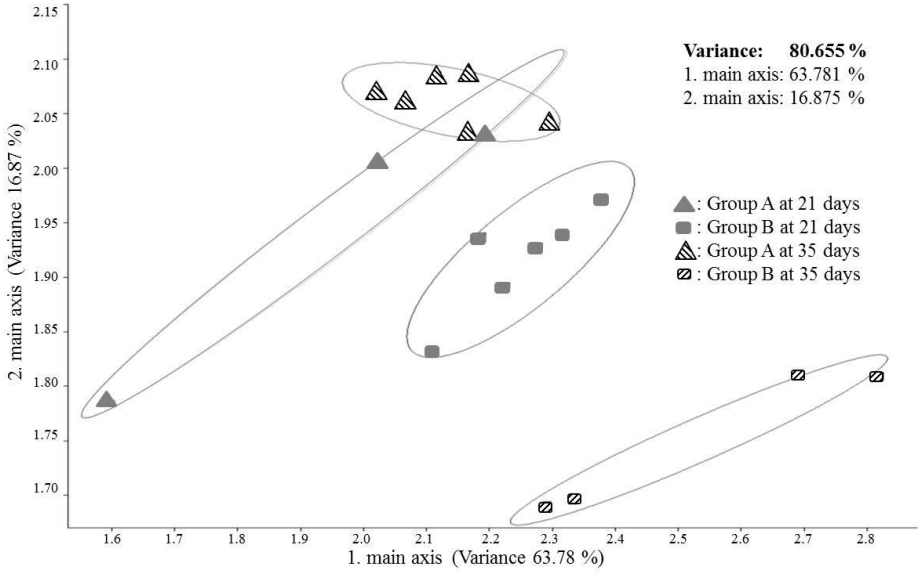


Figure 1. Score plot performed for group A and group B at day 21 and 35 of the production cycle.

The score plot reported in Figure 1 shows that the sum of variances is higher than 80% and the majority of the data was explained by the first axis (63.7% of the total variance).

This score plot also shows that samples can be clustered into two groups; the first (group A at day 21 and 35) represents the broilers that did not develop coccidiosis while the other (group B at day 21 and 35) identifies those animals that developed the pathology. Figure 1 clearly shows how samples collected from group B at day 35 are highly separated from samples collected from both group A (at day 21 and 35) and from group B (at day 21). This separation of samples might be related to the high number of oocysts found in the litter of group B at day 35 (37,000 opg); indeed, at that moment, the broilers were severely infested with coccidia. Furthermore, as shown in Table 1, the discrimination performance was high (0.70 – 0.80), indicating the good separability of the classes (group A and B).

Table 1. Discrimination performance for group A and B at day 21 and 35

	Group A day 21 (0 opg)	Group B day 21 (250 opg)	Group A day 35 (0 opg)	Group B day 35 (37k opg)
Group A day 21 (0 opg)		0.76	0.69	0.65

Group B day 21 (250 opg)	0.76		0.83	0.76
Group A day 35 (0 opg)	0.69	0.83		0.71
Group B day 35 (37k opg)	0.65	0.76	0.71	

The system based on chemical sensors is able to recognise the difference between the characteristics of air sampled in the two groups at an early stage. This ability in relation to litter sampling may represent a diagnostic tool for early detection of health problems due to enteric disorders.

Conclusions

The results of this preliminary study might be useful for development of an alternative diagnostic tool for prompt detection of the onset of infestations by monitoring air quality in poultry houses.
Further samples should be collected at farm level in order to build up a sufficiently large database so that 'odour-prints' of litter samples collected in broiler houses can be defined with greater reliability.
Moreover, this system might be a very useful tool for detecting enteropathy in farmed animals housed under controlled environmental conditions. Further studies will be necessary to develop and implement an automated tool which is able to recognise enteric disorders in intensive farming promptly and automatically.
The innovative approach of this methodology is the capability to provide reliable real-time information and repeatable responses. The advantage of early warning is that it offers potential for using non-conventional therapies instead of AM to treat animals.

The results presented in this study were patented under Italian patent application number 102016000059153 on 9th June 2016.

References

Alali, W., Scott, H., Christian, K., Fajt, V., Harvey, R., Lawhorn, D. 2009. Relationship between level of antibiotic use and resistance among Escherichia coli isolates from integrated multi-site cohorts of humans and swine. *Preventive Veterinary Medicine* **90**, 160-167.

Aydin, A., Cangar, O., Ozcan, S.E., Bahr, C., Berckmans, D. 2010. Application of a fully automatic analysis tool to assess the activity of broiler chickens with different gait scores. *Computers and Electronics in Agriculture* **73**, 194-199.

Berckmans, D., Leroy, T., Borgonovo, F., Costa, A., Aerts, J.M., Guarino, M. 2008. Real-time measurement of pig activity in practical conditions. In: *Proc. 8th International Livestock Environment Symposium, ILES 2008* Iguassu Falls, Brazil, 957-962.

Berge, A., Atwill, E.R., Sischo, W. 2005. Animal and farm influences on the dynamics of antibiotic resistance in faecal Escherichia coli in young dairy calves. *Preventive Veterinary Medicine* **69**, 25-38.

Caja, G., Castro-Costa, A., Knight, C.H. 2016. Engineering to support wellbeing of dairy animals. *Journal of Dairy Research* **83**, 136-147.

Chapman, H. 2014. Milestones in avian coccidiosis research: a review. *Poultry Science* **93**, 501-511.

Conway, D., McKenzie, M. 2007. Poultry Coccidiosis. Diagnostic and Testing Procedures. 168. Wiley-Blackwell, Iowa, USA.

Dawkins, M.S., Cain, R., Roberts, S.J. 2012. Optical flow, flock behaviour and chicken welfare. *Animal Behaviour* **84**, 219-223.

Demmers, T., Cao, Y., Parsons, D.J., Gauss, S., Wathes, C.M. 2012. Simultaneous Monitoring and Control of Pig Growth and Ammonia Emissions. In: *Proc. 9th International Livestock Environment Symposium 2012, ILES 2012* Valencia, Spain, 452-458.

Dincer, F., Odabasi, M., Muezzinoglu, A. 2006. Chemical characterization of odorous gases at a landfill site by gas chromatography–mass spectrometry. *Journal of chromatography A* **1122**, 222-229.

Fontana, I., Tullo, E., Butterworth, A., Guarino, M. 2015. An innovative approach to predict the growth in intensive poultry farming. *Computers and Electronics in Agriculture* **119**, 178-183.

Fontana, I., Tullo, E., Scrase, A., Butterworth, A. 2016. Vocalisation sound pattern identification in young broiler chickens. *Animal* **10**, 1567-1574.

Green, G.C., Chan, A.D., Goubran, R.A. 2006. An investigation into the suitability of using three electronic nose instruments for the detection and discrimination of bacteria types. In: *Proc. Engineering in Medicine and Biology Society, 2006. EMBS'06. 28th Annual International Conference of the IEEE* 1850-1853.

Guarino, M., Jans, P., Costa, A., Aerts, J.-M., Berckmans, D. 2008. Field test of algorithm for automatic cough detection in pig houses. *Computers and Electronics in Agriculture* **62**, 22-28.

Guzhva, O., Ardö, H., Herlin, A., Nilsson, M., Åström, K., Bergsten, C. 2016. Feasibility study for the implementation of an automatic system for the

detection of social interactions in the waiting area of automatic milking stations by using a video surveillance system. *Computers and Electronics in Agriculture* **127**, 506-509.

Hemeryck, M., Berckmans, D., Vranken, E., Tullo, E., Fontana, I., Guarino, M., Van Waterschoot, T. 2015. The Pig Cough Monitor in the EU-PLF project: Results and multimodal data analysis in two case studies. In: *Proc. 7th European Conference on Precision Livestock Farming, ECPLF 2015* 147-155.

Ismayilova, G., Costa, A., Fontana, I., Berckmans, D., Guarino, M. 2013. Labelling the Behaviour of Piglets and Activity Monitoring from Video as a Tool of Assessing Interest in Different Environmental Enrichments. *Annals of Animal Science* **13**, 611-621.

Johnson, J., Reid, W.M. 1970. Anticoccidial drugs: lesion scoring techniques in battery and floor-pen experiments with chickens. *Experimental parasitology* **28**, 30-36.

Matthews, S.G., Miller, A.L., Clapp, J., Plötz, T., Kyriazakis, I. 2016. Early detection of health and welfare compromises through automated detection of behavioural changes in pigs. *The Veterinary Journal* **217**, 43-51.

McDougald, L., Fitz-Coy, S. 2013. Coccidiosis, Disease of Poultry, 13th ed. Iowa State Press Ames, 1148-1163.

Meen, G.H., Schellekens, M.A., Slegers, M.H.M., Leenders, N.L.G., van Erp-van der Kooij, E., Noldus, L.P.J.J. 2015. Sound analysis in dairy cattle vocalisation as a potential welfare monitor. *Computers and Electronics in Agriculture* **118**, 111-115.

Moura, D.J., Silva, W.T., Naas, I.A., Tolón, Y.A., Lima, K.A.O., Vale, M.M. 2008. Real time computer stress monitoring of piglets using vocalization analysis. *Computers and Electronics in Agriculture* **64**, 11-18.

Neethirajan, S. 2017. Recent advances in wearable sensors for animal health management. *Sensing and Bio-Sensing Research* **12**, 15-29.

Porto, S.M., Arcidiacono, C., Anguzza, U., Cascone, G. 2015. The automatic detection of dairy cow feeding and standing behaviours in free-stall barns by a computer vision-based system. *Biosystems Engineering* **133**, 46-55.

Romanini, C.E.B., Viazzi, S., Borgonovo, F., Costa, A., Guarino, M., Leroy, T., Berckmans, D. 2012. Farm animals monitoring tool based on image processing technique. In: *Proc. 1st International Workshop on Veterinary Biosignals and Biodevices, VBB 2012, in Conjunction with BIOSTEC 2012* Vilamoura, Algarve, Portugal, 60-68.

Shao, B., Xin, H. 2008. A real-time computer vision assessment and control of thermal comfort for group-housed pigs. *Computers and Electronics in Agriculture* **62**, 15-21.

Silva, M., Exadaktylos, V., Ferrari, S., Guarino, M., Aerts, J.M., Berckmans, D. 2009. The influence of respiratory disease on the energy envelope dynamics of pig cough sounds. *Computers and Electronics in Agriculture* **69**, 80-85.

Sohn, J.H., Hudson, N., Gallagher, E., Dunlop, M., Zeller, L., Atzeni, M. 2008. Implementation of an electronic nose for continuous odour monitoring in a poultry shed. *Sensors and Actuators B: Chemical* **133**, 60-69.

Tullo, E., Fontana, I., Gottardo, D., Sloth, K., Guarino, M. 2016. Technical note: Validation of a commercial system for the continuous and automated monitoring of dairy cow activity. *Journal of Dairy Science* **99**, 7489-7494.

Tullo, E., Fontana, I., Guarino, M. 2013. Precision livestock farming: An overview of image and sound labelling. In: *Proc. 6th European Conference on Precision Livestock Farming, ECPLF 2013* Leuven, Belgium, 30-38.

Vandermeulen, J., Bahr, C., Johnston, D., Earley, B., Tullo, E., Fontana, I., Guarino, M., Exadaktylos, V., Berckmans, D. 2016. Early recognition of bovine respiratory disease in calves using automated continuous monitoring of cough sounds. *Computers and Electronics in Agriculture* **129**, 15-26.

Vandermeulen, J., Bahr, C., Tullo, E., Fontana, I., Ott, S., Kashiha, M., Guarino, M., Moons, C.P.H., Tuyttens, F.A.M., Niewold, T.A., Berckmans, D. 2015. Discerning pig screams in production environments. *PloS one* **10**.

Wathes, C.M. 2010. The prospects for precision livestock farming. *Journal of the Royal Agricultural Society of England* **171**, 26-32.

Williams, R. 1999. A compartmentalised model for the estimation of the cost of coccidiosis to the world's chicken production industry. *International journal for parasitology* **29**, 1209-1229.

The use of sensor technology and genomics to breed for laying hens that show less damaging behaviour

T.B. Rodenburg[1,2], J. Bennewitz[3], E.N. de Haas[1,2], L. Košťál[4], K. Pichová[1,4], D. Piette[5], J. Tetens[6], J. van der Eijk[1,2], B. Visser[7], E.D. Ellen[8]
[1]*Behavioural Ecology Group,* [2]*Adaptation Physiology Group, Wageningen University & Research, P.O. Box 338, 6700 AH Wageningen, The Netherlands*
[3]*Institute of Animal Science, University of Hohenheim, Garbenstraße 17, 70599 Stuttgart, Germany*
[4]*Slovak Academy of Sciences, Institute of Animal Biochemistry and Genetics, Moyzesova 61900 28 Ivanka pri Dunaji, Slovak Republic*
[5]*M3-BIORES, KU Leuven, Kasteelpark Arenberg 30, B-3001 Heverlee, Belgium*
[6]*Functional Breeding Group, Department of Animal Sciences, Georg-August University, Burckhardtweg 2, 37077 Göttingen, Germany*
[7]*Hendrix Genetics, P.O. Box 114, 5830 AC Boxmeer, The Netherlands*
[8]*Animal Breeding and Genomics Centre, Wageningen University & Research, P.O. Box 338, 6700 AH Wageningen, The Netherlands*
bas.rodenburg@wur.nl

Abstract

The European COST Action GroupHouseNet aims to provide synergy for preventing damaging behaviour in group-housed pigs and laying hens. One area of focus of this network is how genetic and genomic tools can be used to breed animals that are less likely to develop damaging behaviour to their pen-mates. When focussing on laying hens, one of the main problems is that feather pecking (FP) occurs in large groups, making it difficult to identify birds performing damaging behaviour. We propose a combination of sensor technology and genomic methods to solve this issue. Research on genetic lines selected divergently on high and low FP as well as on a F2 cross established from these lines has pointed to mechanisms that may underlie this behaviour, revealing relationships between FP, fearfulness and activity levels and locating genomic markers related with FP. Birds selected for high FP were found to be less fearful and highly active in a range of tests and home pen situations. This knowledge may be used to automatically detect high feather-pecking individuals in a group setting. Research on using novel methods such as ultra-wideband tracking to detect phenotypic differences between individuals in a group is ongoing. First results confirm previously found line differences in fearfulness and activity. Future work will focus on exploring potential of other sensor-based methods to accurately measure individual phenotypes, and linking this information to

genomic markers. This should lead to the development of novel breeding methods to select against damaging behaviour in laying hens.

Keywords: laying hens, damaging behaviour, sensor technology, genomics, transcriptomics

Introduction

Damaging behaviour, like feather pecking (FP) in laying hens, is a welfare and economic problem in commercial livestock production. There is an urgent need to reduce FP, especially due to the ban on conventional cages in the European Union and the expected future ban on beak trimming in many European countries. Several studies showed that FP can be reduced using genetic selection (Muir, 1996; Kjaer et al., 2001). FP depends on the behaviour of the individual itself and the behaviour of its group members. Associations between fearfulness and FP or feather damage have been found (Hughes and Duncan, 1972; Rodenburg et al., 2004). Several studies found that fearful chicks in an open field test showed more FP behaviour as adults (Jones et al., 1995; Rodenburg et al., 2004). Furthermore, it was found that activity of birds was related to FP behaviour (Kjaer, 2009). To select against FP, it is important to take both the genotype of the individual itself (direct genetic effect or victim effect; DGE) and the genotype of the group members into account (indirect genetic effect or pecker effect; IGE) (Bijma et al., 2007; Ellen et al., 2007). For plumage condition, it was found that DGE contribute 6-31% of the total heritable variation, while IGE contribute 70-94% of total heritable variation (Brinker et al., 2014). Together they explain 10-54% of total phenotypic variation in plumage condition. Therefore, it is important to use a selection method that takes both DGE and IGE into account (Ellen et al., 2014). Nowadays, there is a tendency to keep commercial laying hens in large groups. To identify peckers and victims in these large groups is a challenge. With the use of sensor technology, like ultra-wideband tracking, video tracking, or radio frequency identification (RFID), there is a possibility to track and trace individuals in large groups. Sensors can be used to track individual interactions in large groups, and to identify peckers and victims. Using genomic approaches, we can link the information from sensor technologies to the individual's genotype. This could also help us to identify regions or gene expression patterns and to further understand FP behaviour. Here, we propose a combination of sensor technology and genomic methods to select against FP in large groups of laying hens. In this review, we will give an overview of sensor technologies that can be used for breeding, present the first results of experiments performed in PhenoLab, describe the use of omics approaches to understand FP, and discuss the

identification of indicator traits from both technologies. In this review the focus is on FP behaviour in laying hens.

Use of sensor technology to inform breeding

Researchers have developed a variety of technologies to monitor the activity and behavioural patterns of laying hens in an automated way. For instance sound analysis, image analysis and IR thermography are used to continuously monitor the activity and presence of laying hens (Lee et al., 2010; Quwaider et al., 2010; Mench and Blatchford, 2014). The major advantage of these technologies is that they are cheap (one sensor for the entire house) and non-invasive. However, they do not allow us to monitor the activity of individual birds unless individual markings are applied on the birds, which is a time consuming process that must be repeated regularly since the markings fade away after some time. In recent years, researchers have also started using accelerometers as well as RFID, ultra-wideband and geographic information system (GIS) technology where birds are equipped with a body worn sensor to monitor their individual behaviour patterns. Although these systems make it possible to monitor individual birds, they are difficult and expensive to upscale to farm size (one sensor per bird + transmitters) and often require a lot of battery power for the transmission of data (Banerjee et al., 2014; Nakarmi et al., 2014; Rodenburg and Naguib, 2014; Zaninelli et al., 2016). Furthermore, it is not certain that these body worn sensors can survive the harsh environment of the bird house during the entire life span of the laying hens.

In all this, it is important to take into account that when birds receive markings or are equipped with a sensor, which is often placed on their back, their physical appearance is changed which could make them more susceptible to receive pecking by other birds, enhancing the problem rather than solving it (Daigle et al., 2012). To date, there is no system available that can accurately monitor individual behaviour of laying hens in a real farm setting. Nevertheless, the currently existing technology can be used in research settings where the number of laying hens is small and where time efficiency is less important than in commercial conditions. According to literature, body worn sensors can reach an agreement of up to 95% between automated measurement and labelling by human observers to monitor the behaviour of individual laying hens (Nakarmi et al., 2014). This makes that this technology has potential to automatically phenotype FP behaviour in laying hens, either by recording the behaviour itself or by recording related traits. Such technology could potentially also be used by breeding companies to phenotype their selection candidates, as this is a much smaller number of birds then their crossbred offspring and generally the selection candidates are housed in smaller groups than birds in commercial flocks.

PhenoLab: automatic tracking of laying hens

One possibility for automatic tracking of laying hens is by using ultra-wideband tracking. Here, hens are outfitted with an active tag in a small backpack and the location of each bird is detected by sensing beacons based on time and angle of arrival of the signal. In the PhenoLab project, we compared ultra-wideband tracking using TrackLab (Noldus Information Technology, Wageningen, The Netherlands) with video tracking of individual hens using Ethovision from the same company. As can be seen from Figure 1, both systems yielded very similar data and the ultra-wideband system was able to detect the location of the bird with an 85% accuracy.

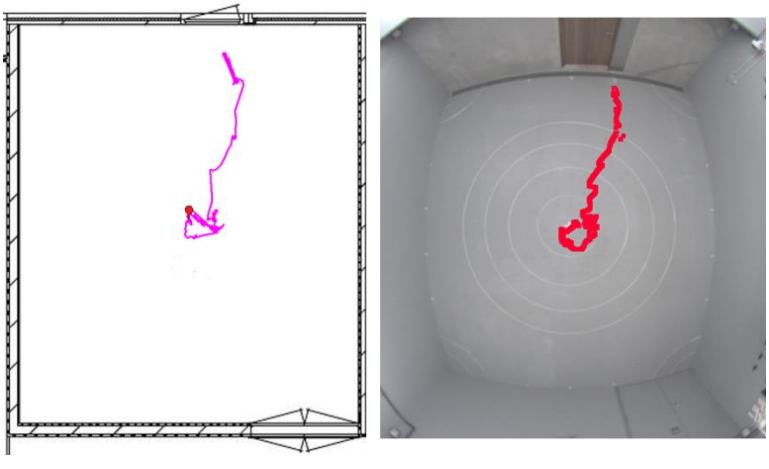


Figure 1. Tracking an individual laying hen in the PhenoLab using ultra-wideband tracking (left panel) and video tracking (right panel).

One of the major benefits of ultra-wideband tracking over video tracking is that tracking is based on a unique tag that is fixed to the individual animal. With current video tracking technology, tracking individuals in groups still seems challenging. However, recent developments in the field of video tracking seem promising (Perez-Escudero et al., 2014). We used PhenoLab to explore behavioural differences between lines selected for high and low FP. We were interested to see if we could record previously found differences in activity between the lines automatically, with the high FP line being hyperactive. This was indeed the case, with the High FP line moving almost twice the distance as the Low FP and unselected control line. Furthermore, based on the tracking data also individual differences within lines could be investigated. This showed by birds characterised as feather peckers (based on video observations) were much more active than birds characterised as victims, an observation that was very much in agreement with the line differences found. Next steps in the PhenoLab

project include measuring distances between individual animals and linking this information to relevant phenotypes (sociality, damaging behaviour). Furthermore, we would like to compare the ultra-wideband tracking method with RFID tracking, as RFID tracking might have potential as a cheaper and more robust technology that could be applied on commercial farms (Richards et al., 2011; Gebhardt-Henrich et al., 2014; Rodenburg et al., 2015).

Understanding feather pecking through 'omics' approaches

As compared to other traits, the number of available genome-wide mapping studies for FP is sparse. Buitenhuis et al. (2003) conducted a microsatellite-based study in an F2 population established from the cross of commercial lines differing in their propensity for FP. They reported three suggestive QTL for gentle and one significant QTL for severe FP. Another group only identified a single QTL in an F2 cross of Red Jungle Fowl and White Leghorn (Jensen et al., 2005). Later, studies were conducted based on SNP genotypes. In an across-line association study using a low-density panel of approximately 1000 SNPs, Biscarini et al. (2010) analysed a direct as well as an associative effect of cage mates on feather damage, where the latter can be interpreted as the propensity to perform FP. A major finding was the implication of a serotonin receptor in FP supporting earlier evidence for a prominent role of monoamine signaling. The total number of QTL identified in this study, however, was very large. The most recent mapping studies applied the Illumina 60k SNP chip in lines divergently selected for FP (the same lines as used in the PhenoLab project) and an F2 cross of these lines. Mapping results based on selection signatures between the lines (Grams et al., 2015b) and association results from the F2 cross were jointly analyzed in a meta-study (Lutz et al., 2017) revealing 13 clusters of significantly associated markers and pointing to a candidate gene that might also be related to monoamine signaling. Available large-scale transcriptomic studies have so far been performed in chicken lines divergently selected for FP propensity applying microarray technology. In the high FP selection line, Labouriau et al. (2009) found significant gene expression differences between extreme feather peckers and other birds performing FP at a lower level. These authors proposed the presence of a single allele affecting severe pecking behaviour. Later, Hughes and Buitenhuis (2010) reported a globally reduced variance of gene expression in high FP animals and found distinct expression patterns associated with gentle and severe FP, which supports the hypothesis mentioned above. Brunberg et al. (2011) studied differential hypothalamic gene expression in FP hens, victims and controls. Their findings fitted with the hypothesis that FP is redirected foraging behavior. Wysocki et al. (2013) identified a number of candidate genes related to neurotransmission and psychopathological disorders including monoamine signaling. The available genomic and transcriptomic studies so far point to a

major role of monoamine signaling in FP, which fits well with other available data (Kops et al., 2013a; Kops et al., 2013b; Kops et al., 2014; Kops et al., 2017). Otherwise, however, little congruence is found between studies. This can be expected given the fact that FP is a complex trait. It has a heritability ranging from 0.1 to 0.4 (Kjaer et al., 2001; Rodenburg et al., 2003; Bennewitz et al., 2014; Grams et al., 2015a) and a large number of genes can be supposed to contribute to this phenotype. With respect to breeding for low FP propensity, however, a major outcome of '-*omics'* studies would be biomarkers and indicator traits that can be applied in selection. Future research in this area will likely also focus on the metabolome and microbiome.

Conclusions

We are now at a point where both sensor technology and omics approaches have the potential to provide a large amount of data at the level of the individual. If we take the example of the selection lines, selected on high and low FP: these lines have now been characterised in genomic and transcriptomic studies. These studies have added to our knowledge of the mechanism underlying FP behaviour, but can also be used to record genomic profiles of individual birds. Similarly, using sensor technology we can record an individual behavioural profile, describing activity, location and distance to other individuals. If we can combine both approaches in a breeding population, we can link the genomic data to the sensor data, and define the genomic profile of individuals that show the desired behaviour (e.g. low of no FP). This approach may be feasible, because breeding companies have begun to genotype their breeding stock routinely. Once the desired genomic profile has been defined, the method should be put to the test by breeding a next generation based on genomic selection and then phenotype this generation with the same tools that were used to phenotype the parent stock. We feel this approach has great promise to select against complex behavioural traits that involve multiple individual animals in a group, such as FP in laying hens.

Acknowledgements

This article is based upon work from COST Action CA 15134 GroupHouseNet, supported by COST (European Cooperation in Science and Technology). The PhenoLab project was financially supported by the Dutch Ministry of Economic Affairs (project TKI-AF12018) and the Breed4Food partners Cobb-Europe, CRV, Hendrix Genetics and Topigs Norsvin.

References

Banerjee, D., Daigle, C.L., Dong, B., Wurtz, K., Newberry, R.C., Siegford, J.M., Biswas, S., 2014. Detection of jumping and landing force in laying hens using wireless wearable sensors. *Poultry Science* **93**, 2724-2733.

Bennewitz, J., Bogelein, S., Stratz, P., Rodehutscord, M., Piepho, H.P., Kjaer, J.B., Bessei, W., 2014. Genetic parameters for feather pecking and aggressive behavior in a large F2-cross of laying hens using generalized linear mixed models. *Poultry Science* **93**, 810-817.

Bijma, P., Muir, W.M., Ellen, E.D., Wolf, J.B., Arendonk, J.A.M., 2007. Multilevel selection2: estimating the genetic parameters determining inheritance and response to selection. *Genetics* **175**.

Biscarini, F., Bovenhuis, H., Van der Poel, J.J., Rodenburg, T.B., Jungerius, A.P., VanArendonk, J.A.M., 2010. Across-line SNP association study for direct and associative effects on feather damage in laying hens. *Behavior Genetics* **40**, 715-727.

Brinker, T., Bijma, P., Visscher, J., Rodenburg, T.B., Ellen, E.D., 2014. Plumage condition in laying hens: Genetic parameters for direct and indirect effects in two purebred layer lines. *Genetics Selection Evolution* **46**, 33.

Brunberg, E., Jensen, P., Isaksson, A., Keeling, L., 2011. Feather pecking behavior in laying hens: hypothalamic gene expression in birds performing and receiving pecks. *Poultry Science* **90**, 1145-1152.

Buitenhuis, A.J., Rodenburg, T.B., Siwek, M., Cornelissen, S.J., Nieuwland, M.G., Crooijmans, R.P., Groenen, M.A., Koene, P., Bovenhuis, H., Poel, J.J.v.d., 2003. Identification of quantitative trait loci for receiving pecks in young and adult laying hens. *Poultry Science* **82**, 1661-1667.

Daigle, C.L., Banerjee, D., Biswas, S., Siegford, J.M., 2012. Noncaged laying hens remain unflappable while wearing body-mounted sensors: Levels of agonistic behaviors remain unchanged and resource use is not reduced after habituation. *Poultry Science* **91**, 2415-2423.

Ellen, E.D., Muir, W.M., Teuscher, F., Bijma, P., 2007. Genetic improvement of traits affected by interactions among individuals: Sib selection schemes. *Genetics* **176**, 489-499.

Ellen, E.D., Rodenburg, T.B., Albers, G.A.A., Bolhuis, J.E., Camerlink, I., Duijvesteijn, N., Knol, E.F., Muir, W.M., Peeters, K., Reimert, I., Sell-Kubiak, E., Van Arendonk, J.A.M., Visscher, J., Bijma, P., 2014. The prospects of selection for social genetic effects to improve welfare and productivity in livestock. *Frontiers in Genetics* **5**.

Gebhardt-Henrich, S.G., Toscano, M.J., Fröhlich, E.K.F., 2014. Use of outdoor ranges by laying hens in different sized flocks. *Applied Animal Behaviour Science* **155**, 74-81.

Grams, V., Bogelein, S., Grashorn, M.A., Bessei, W., Bennewitz, J., 2015a. Quantitative genetic analysis of traits related to fear and feather pecking in laying hens. *Behavior Genetics* **45**, 228-235.

Grams, V., Wellmann, R., Preuss, S., Grashorn, M.A., Kjaer, J.B., Bessei, W., Bennewitz, J., 2015b. Genetic parameters and signatures of selection in two divergent laying hen lines selected for feather pecking behaviour. *Genetics Selection Evolution* **47**, 77.

Hughes, A.L., Buitenhuis, A.J., 2010. Reduced variance of gene expression at numerous loci in a population of chickens selected for high feather pecking. *Poultry Science* **89**, 1858-1869.

Hughes, B.O., Duncan, I.J.H., 1972. The influence of strain and environmental factors upon feather pecking and cannibalism in fowls. *British Poultry Science* **13**, 525-547.

Jensen, P., Keeling, L., Schütz, K., Andersson, L., Morméde, P., Brändström, H., Forkman, B., Kerje, S., Fredriksson, R., Ohlsson, C., Larsson, S., Mallmin, H., Kindmark, A., 2005. Feather pecking in chickens is genetically related to behavioural and developmental traits. *Physiology & Behavior* **86**, 52-60.

Jones, R.B., Blokhuis, H.J., Beuving, G., 1995. Open-field and tonic immobility responses in domestic chicks of two genetic lines differing in their propensity to feather peck. *British Poultry Science* **36**, 525-530.

Kjaer, J.B., 2009. Feather pecking in domestic fowl is genetically related to locomotor activity levels: implications for a hyperactivity model of feather pecking. *Behavior Genetics* **39**, 564-570.

Kjaer, J.B., Sorensen, P., Su, G., 2001. Divergent selection on feather pecking behaviour in laying hens (*Gallus gallus domesticus*). *Applied Animal Behaviour Science* **71**, 229-239.

Kops, M.S., de Haas, E.N., Rodenburg, T.B., Ellen, E.D., Korte-Bouws, G.A., Olivier, B., Güntürkün, O., Bolhuis, J.E., Korte, S.M., 2013a. Effects of feather pecking phenotype (severe feather peckers, victims and non-peckers) on serotonergic and dopaminergic activity in four brain areas of laying hens (Gallus gallus domesticus). *Physiology & Behavior* **120**, 77-82.

Kops, M.S., de Haas, E.N., Rodenburg, T.B., Ellen, E.D., Korte-Bouws, G.A.H., Olivier, B., Güntürkün, O., Korte, S.M., Bolhuis, J.E., 2013b. Selection for low mortality in laying hens affects catecholamine levels in the arcopallium, a brain area involved in fear and motor regulation. *Behavioural Brain Research* **257**, 54-61.

Kops, M.S., Kjaer, J.B., Gunturkun, O., Westphal, K.G.C., Korte-Bouws, G.A.H., Olivier, B., Bolhuis, J.E., Korte, S.M., 2014. Serotonin release in the caudal nidopallium of adult laying hens genetically selected for high and low feather pecking behavior: an in vivo microdialysis study. *Behavioural Brain Research* **268**, 81-87.

Kops, M.S., Kjaer, J.B., Gunturkun, O., Westphal, K.G.C., Korte-Bouws, G.A.H., Olivier, B., Korte, S.M., Bolhuis, J.E., 2017. Brain monoamine levels and behaviour of young and adult chickens genetically selected on feather pecking. *Behavioural Brain Research.*

Labouriau, R., Kjaer, J.B., Abreu, G.C.G., Hedegaard, J., Buitenhuis, A.J., 2009. Analysis of severe feather pecking behavior in a high feather pecking selection line. *Poultry Science* **88**, 2052-2062.

Lee, H.-j., Roberts, S.J., Drake, K.A., Dawkins, M.S., 2010. Prediction of feather damage in laying hens using optical flows and Markov models. *Journal of The Royal Society Interface*, doi 10.1098/rsif.2010.0268.

Lutz, V., Stratz, P., Preuss, S., Tetens, J., Grashorn, M.A., Bessei, W., Bennewitz, J., 2017. A genome-wide association study in a large F2-cross of laying hens reveals novel genomic regions associated with feather pecking and aggressive pecking behavior. *Genetics Selection Evolution* **49**, 18.

Mench, J.A., Blatchford, R.A., 2014. Determination of space use by laying hens using kinematic analysis. *Poultry Science* **93**, 794-798.

Muir, W.M., 1996. Group selection for adaptation to multiple-hen cages: Selection program and direct responses. *Poultry Science* **75**, 447-458.

Nakarmi, A.D., Tang, L., Xin, H., 2014. Automated tracking and behavior quantification of laying hens using 3D computer vision and radio frequency identification technologies. *Transactions of the ASABE* **57**, 1455-1472.

Perez-Escudero, A., Vicente-Page, J., Hinz, R.C., Arganda, S., de Polavieja, G.G., 2014. idTracker: tracking individuals in a group by automatic identification of unmarked animals. *Nature Methods* **11**, 743-748.

Quwaider, M.Q., Daigle, C.L., Biswas, S.K., Siegford, J.M., Swanson, J.C., 2010. Development of a wireless body-mounted sensor to monitor location and activity of laying hens in a non-cage housing system. *Transactions of the ASABE* **53**, 1705-1713.

Richards, G.J., Wilkins, L.J., Knowles, T.G., Booth, F., Toscano, M.J., Nicol, C.J., Brown, S.N., 2011. Continuous monitoring of pop hole usage by commercially housed free-range hens throughout the production cycle. *Veterinary Record* **169**, 338-U358.

Rodenburg, T.B., Buitenhuis, A.J., Ask, B., Uitdehaag, K.A., Koene, P., van der Poel, J.J., Bovenhuis, H., 2003. Heritability of feather pecking and open-field response of laying hens at two different ages. *Poultry Science* **82**, 861-867.

Rodenburg, T.B., Buitenhuis, A.J., Ask, B., Uitdehaag, K.A., Koene, P., van der Poel, J.J., van Arendonk, J.A.M., Bovenhuis, H., 2004. Genetic and phenotypic correlations between feather pecking and open-field response in laying hens at two different ages. *Behavior Genetics* **34**, 407-415.

Rodenburg, T.B., Gerritsen, M.A., Topelberg, E., Stump, R., Naguib, M., 2015. Distance to the popholes does not influence use of the winter garden in laying hens, In: Guarino, M., Berckmans, D. (Eds.), *Precision Livestock Farming '15 Milan, Italy*, pp. 547-551.

Rodenburg, T.B., Naguib, M., 2014. Tracking individual laying hens in group housing, In: Spink, A.J., Loijens, L.W.S., Woloszynowska-Fraser, M., Noldus, L.P.J.J. (Eds.), *Measuring Behavior*, Wageningen, The Netherlands.

Wysocki, M., Preuss, S., Stratz, P., Bennewitz, J., 2013. Investigating gene expression differences in two chicken groups with variable propensity to feather pecking. *Animal Genetics* **44**, 773-777.

Zaninelli, M., Redaelli, V., Tirloni, E., Bernardi, C., Dell'Orto, V., Savoini, G., 2016. First Results of a Detection Sensor for the Monitoring of Laying Hens Reared in a Commercial Organic Egg Production Farm Based on the Use of Infrared Technology. *Sensors* **16**, 13.

Market consultation for a multi-level monitoring system with robots to support poultry farmers

M. Timmerman[1], R. A. van Emous[1], J. W. van Riel[1], B. A. Vroegindeweij[2] and C. Lokhorst[1]
[1]*Livestock Research, Wageningen University & Research, PO Box 338 6700 AH Wageningen, The Netherlands*
[2]*Livestock Robotics, Middelveld 50, 4051 DB Ochten, The Netherlands*
Maikel.Timmerman@wur.nl

Abstract

Monitoring health and welfare of poultry is a highly demanding task for a farmer in time, health and complexity, and it is usually combined with routine actions such as collecting floor eggs, removing dead animals and checking feeding and drinking lines. The expectation is that a robot also can execute such tasks and could do it 24 hours 7 days a week if needed. A concept of a multi-layer monitoring support system has been designed to assist the poultry farmer. The multi-layer support system consists of a static system for flock observation (existing PLF technology), and robot(s) for in-between bird observation of health and behaviour and for performing routine daily tasks. Poultry farmers, researchers and companies have been consulted in two workshops to identify the needs and wishes for such a system. The results of the consultations could be grouped into the following six main categories: 1) bird monitoring (e.g. behaviour, health); 2) data sharing (e.g. production, health); 3) eggs (e.g. selection, collection of floor eggs); 4) vaccination (e.g. treatment, evaluation); 5) quality control (e.g. manure consistency, litter); and 6) selection of birds (e.g. collecting dead birds, identifying non-productive birds). The overall results showed that there is a market demand of poultry farmers for such a multi-level monitoring system. A first economic survey showed that broiler farmers were willing to invest €0.58 per bird place with an desired payback time of 2 years and other poultry farmers were willing to invest €1.04 per bird place with a desired payback time of 4 years.

Keywords: poultry, robotics, support system, monitoring, market research, farm automation

Introduction

Due to pressure from and developments in market and environmental legislation the number of animals on poultry farms has increased fourfold since the 80's.

Due to the increase in scale it has become more difficult to notice disturbances in the animals in early stage, because the available time per bird has decreased. In short, the poultry farmer is lacking the time to use his senses (eyes, ears and nose) in a sufficient manner to get a good sensitivity of arising problems with his chickens. Besides the increase in work load, in animal-friendly housing systems, monitoring health and welfare status of animals are highly demanding tasks for the farmer in both complexity and time (Van Emous and Van Fiks - van Niekerk, 2003; Niebuhr *et al.*, 2006). Usually, these tasks are also combined with routine actions such as collecting floor eggs and removing dead animals.

Automatic monitoring of bird behaviour seems to offer an important addition in the toolbox of a poultry farmer, allowing for faster identification of disturbances. Next to the automatic monitoring of disturbances there is a need for an extra hand to take care of simple actions such as collecting floor eggs, removal of dead animals and cultivate wet spots in the litter. Considering the current developments in robotics and increasing cost of labour, a robotic device seems to hold prospects of executing such tasks for the poultry farmer (e.g. Vroegindeweij *et al.*, 2014; Vroegindeweij *et al.*, 2016). A robot can work 24 hours 7 days a week and gives the poultry farmer more time to concentrate on important (management) tasks. Therefore, poultry farmers will benefit from automated extra sensing to gather information about bird behaviour and health, while also robots are desired for simple and heavy tasks, in order to relieve the farmer.

A concept of a multi-layer support system has been designed for commercial poultry houses to assist the poultry farmer in his daily tasks by developing and integrating systems for flock observation and robots for observation of health and behaviour and for performing daily tasks. Part of the design of the concept was to gather information on requirements and expectations of the concept in the market. Therefore the objective of this market study was to gather information from poultry farmers and poultry supply industry to identify functional needs and wishes for such a high-tech multi-layer support system and were in the poultry husbandry most benefits can be expected, how much money a poultry farmer would be willing to pay for such a system and a first estimation of the financial feasibility of using a robot.

Material and methods

Concept of the high-tech multi-layer support system

The multi-layer support system that has been designed for commercial poultry houses to assist the poultry farmer in his daily tasks consists of the following three main support levels:

1. FLOS (Flock Observation System): A fixed installation, that uses computer vision and sound analysis to observe flock behaviour and status. The farmer can use this (continuously available) information to improve the conditions of his animals as well as his management. The Eyenamic™ system from Fancom can be seen as an existing FLOS that is already sold in the market.
2. BIRD (Behaviorial Identifying Robotic Device): A mobile platform that operates in-between the birds, to observe bird and group behaviour on and in-between bird level. Beside birds also the litter, micro climate on bird level and the feeding and drinking lines can be monitored.
3. OPA (Operational Poultryfarmer Assistant): An autonomous mobile robot or a group of connected robots (robot swarm) performing actions in the poultry house, to take over heavy or undesired tasks from the farmer, to solve actual problems or to create new control and interaction possibilities.

This system will provide the farmer with additional information on flock health, welfare and housing conditions in his daily observations. Also, it will guide him to take preventive or corrective actions. If possible, autonomous vehicles will be used to perform such actions as well, based on acquired information. Also, they can function as assistant to the farmer, by taking over undesired or heavy tasks such as floor egg collection (Vroegindeweij *et al.*, 2014) and offering new possibilities for interaction with the animals. This multi-layer support system is sketched in figure 1.

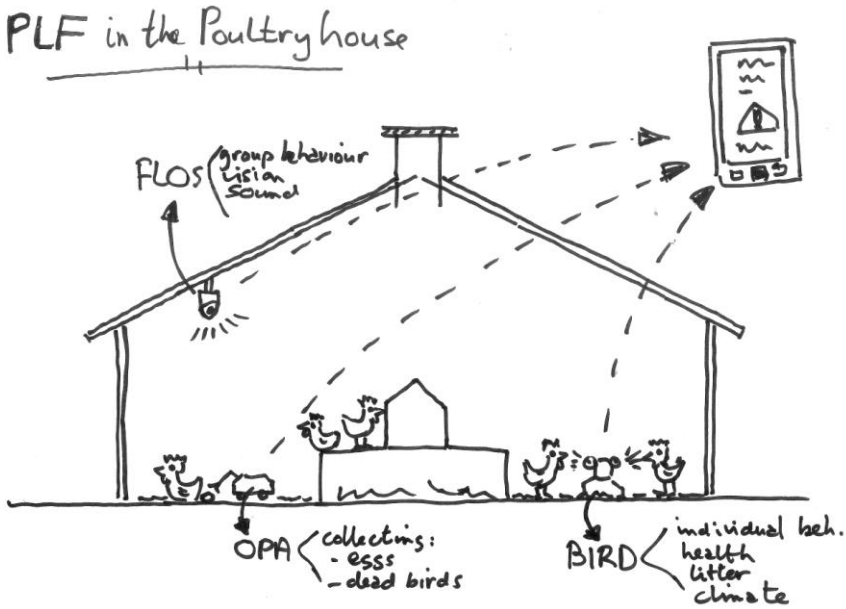


Figure 1: A sketch of the three levels of the high-tech multi-layer support system

Consultation of poultry farmers and equipment

A group of poultry farmers was invited for a workshop to gather information, ideas and wishes for a high-tech support system. In total 11 poultry farmers (4 broiler, 4 laying hen, and 3 broiler-breeder farmers) joined the workshop. In a separate workshop poultry supply industry were consulted to gather ideas and information about desired features of the high-tech support system. In total 18 persons with varying background (feed supplier, pharmacy, veterinarian, hatchery, and equipment supplier) joined the workshop. In this workshop, the focus group method as described in Krueger and Casey (2001) was used to ask participants on their ideas regarding undesired work and new features. Next, the participants ranked these ideas on perceived importance, and the outcome and implications of this were discussed.

Willingness to invest in a high-tech support system

An online survey was designed to ask poultry farmers on their willingness to invest in a high-tech support system and on the payback time they would accept for such a system. The survey consisted of 11 questions. The online survey was submitted by a professional poultry journal in the Netherlands to their subscribers of their newsletter. In total 18 poultry farmers responded, but one response was removed from the results due to odd answers. Of the 17 usable responses seven were from laying hen, three from broiler and seven from other poultry farmers or farmers with several bird species.

Estimation of the financial feasibility of a robot

A first estimation of the financial feasibility of using a robot was made completely separate from the workshops and online survey of poultry farmers. The results of this calculation were not available during the workshops and also not shared in the online survey. The following assumptions were made in case a robot was used for collecting floor eggs and dead birds on a farm with 40000 laying hens: one hour labour savings per day in collecting floor eggs, 50% labour savings in collecting dead birds, a decrease in floor eggs of 1.5% and a savings in labour for routine control of 0.5 hours per day. The labour was valued at a price of €24 per hour and the discount for second quality eggs was valued at €0.015 per egg. Collecting 30 dead birds per hour. The yearly depreciation cost was assumed to be 10%, maintenance costs of 2% and an interest rate of 3.5% over the average invested money.

Results and Discussion

The outcomes of the workshops with the poultry farmers and supply business about a high-tech support system were quite similar and could be grouped into the following six main categories:

1. Bird monitoring
   - Observation of animal behaviour with regard to distribution of the animals, interaction between animals, movement of the animals, deviations in behaviour and assessment of the animals.
   - Observation of animal health with regard to occurrence of pathogens in the poultry house, disease syndromes, gut health and blood sugar.
   - Observation and performance of individual animals with regard to appearance (e.g. colour, feathers, temperature), weight, food and water consumption.
   - Observation of living environment with regard to climate (e.g. temperature, air speed, relative humidity and air quality) and adjustments according to animal behaviour.
   - Processing of data with regard to interpretation, predictions, attention list and daily data.
2. Data sharing
   - Sharing of data in the supply chain with regard to egg quality, climate, health and production.
   - Processing of data with regard to collecting, analysing, actions and sharing.
3. Eggs
   - Feedback of information about eggs.
   - Selection of eggs (e.g. dirty, abnormal shell, broken eggs).
   - Quality of eggs with regard to weight, colour and shell quality.
   - Floor eggs: location and collection.
4. Vaccination
   - Vaccinate animals and evaluation of the vaccination and treatments
   - Treatment of animals with sprays and injections.
5. Quality control
   - Manure: digestion of feed, consistency of the manure, composition and quality of the manure.
   - Litter: optimization of the thickness and the quality.
   - Hygiene: input of materials into poultry house.
6. Selection of birds
   - Selection and sorting of live animals: weight, non-laying hens, selection of breeding animals, feed regime.

– Collection of dead animals: recognizing, location, cause of death, weight and time.

Monitoring of the birds got by far the highest ranking. Second and third were data sharing and eggs, but their score was very close together. The remaining categories were at a similar level of ranking.

The results of the short market survey showed that 15 of the 17 respondents expected that a robot could add value to their farm. The main reason was labour savings followed by relieve of labour, and an increase of reliability and speed of information access. Table 1 shows the willingness of poultry farmers to invest in high-tech support systems or robots.

Table 1: Willingness to invest in and payback time of high-tech support systems or robots

Farm type	Responses	Acceptable investment amount (€ per animal place) (minimum and maximum)	Desired payback-time (minimum and maximum)
Laying hens	7	€ 1.04 (0.25 – 2.25)	4.2[a] (2.5 – 5.0)
Broilers	3	€ 0.58 (0.25 – 1.25)	2.3[b] (2.0 - 2.5)
Other or combination	7	€ 1.04 (0.25 – 2.25)	3.7[ab] (2.0 – 4.5)

The acceptable investment sum for broilers farmers is €0.58 per bird place with a payback-time of two years and for other poultry farmers €1.04 per bird place with a payback-time of four years. Broiler farmers named also less advantages and applications than other poultry farmers. Furthermore, there is a remarkable large variation in the investment preparedness between farms of the same type. There seems to be no relation with age, farm scale, location and other business activities.

Table 2 shows the outcome of the first estimation of the financial feasibility of using a robot on a farm with laying hens.

Table 2: First estimation of the financial feasibility of a robot on a farm with laying hens

	Situation with robot	Current situation
# laying hens	40000	40000
Laying percentage	90%	90%
Floor eggs	0.5%	2.0%

Mortality rate	14%	14%
Discount 2nd quality eggs	€ 0.015 per egg	€ 0.015 per egg
Labour price	€ 24 per hour	€ 24 per hour
Labour collecting floor eggs	1 hour/day	2 hours/day
Routine control	0.5 hour/day	1.0 hour/day
Duration laying period	365 days	365 days
Dead animals to collect by farmer	7.7 per day	15.3 per day
Costs		
Labour collecting floor eggs	€ 8760	€ 17520
Discount 2nd quality eggs	€ 986	€ 3942
Labour routine control	€ 4380	€ 8760
Labour collecting dead animals	€ 2240	€ 4480
Total costs	€ 16366	€ 34702
Yearly savings	€ 18337	

The estimation of the financial feasibility shows a reduction in costs of €18000 per year by using a robot. With a pay-back time of 3 years the maximum investment sum would be €49400 and with a pay-back time of 5 years the maximum investment sum would be €77100. For a farm with 40000 laying hens this would mean an investment of €1.24 per bird place for a 3 year pay-back time. This value compares quite well with the outcome of the online survey which showed that laying hen farmers would on average accept an investment of €1.04 per bird place. It seems that a robot should roughly meet an investment of €1.00 per bird place with a pay-back time of 4 years or less to be financial feasible for laying hens farmers.

Conclusions

The results of the study showed that the desired capabilities of a multi-level support system with robots could be grouped into six main categories: bird monitoring, data sharing, eggs (selection and collecting floor eggs), vaccination, quality control of manure and litter, and selection of birds (collecting dead birds and selection of birds). The overall results showed that there is a market demand of poultry farmers for such a multi-level monitoring system. A first economic survey showed that broiler farmers were willing to invest €0.58 per bird place with a desired payback time of 2 years and other poultry farmers €1.04 per bird

place with a desired payback time of 4 years. A first estimation of the financial feasibility showed a reduction in costs of €18000 per year by using a robot for collecting floor eggs and dead birds on 40000 laying hen farm. With a pay-back time of the 3 years the maximum investment would be €1.24 per bird place.

Acknowledgements

This project was funded by the High Tech to Feed the World cross-over program of the Dutch ministry of Economic Affairs.

References

Krueger, R.A. and Casey, M.A. 2001. Designing and conducting focus group inter-views. In: *Social Analysis: Selected tools and Techniques.* The world Bank; Social De-velopment Paper Number 36 (4-23)

Niebuhr, K., Zaludik, K., Gruber, B., Thenmaier, I., Lugmaier, A., Baumung, R. and Troxler, J. 2006. *Survey on the epidemiology of cannibalism and feather pecking in alternative laying hen husbandry in Austria.* Endbericht Forschungsprojekt 1313, BMFLUW, Wien, Österreich.

Van Emous, R.A. and van Fiks - van Niekerk, T.G.C.M. 2003. Praktijkinventarisatie volièrebedrijven met uitloop = *Inventory on commercial layer farms with aviaries and free range*. PraktijkRapport Pluimvee 7, Praktijkonderzoek Veehouderij, Lelystad, The Netherlands.

Vroegindeweij, B.A., van Willigenburg, L.G., Groot Koerkamp, P.W.G., van Henten, E.J. 2014. Path planning for autonomous collection of eggs on floors. *Biosystems Engineering* **121** 186-199.

Vroegindeweij, B.A., IJsselmuiden, J., van Henten, E.J. 2016. Probabilistic localisation in repetitive environments: Estimating a robot's position in an aviary poultry house. *Computers and Electronics in Agriculture* **124** 303-317.

Precision slaughter – improving welfare at slaughter and killing through technological innovation

R. García Pinillos[1]
[1]*Animal and Plant Health Agency / Department for Environment, Food and Rural Affairs, Animal Welfare Team, Nobel House, 17 Smith Square, London, SW1P 3JR, United Kingdom.*
rebeca.garcia@apha.gsi.gov.uk

Abstract
Over time, with the increased global consumption of meat, demand has forced slaughterhouses to become highly specialised establishments where animals are slaughtered for the production of meat in the most cost-effective way. Equally, increasing concerns about animal welfare in society have sustained a parallel stream where technological advances have been made to support both productivity and animal welfare.
Precision farming has made great progress in recent years. Considering how successful innovations might be applied to animal and food production related areas outside the farm will help accelerate improvement and build upon ongoing work in more efficient and effective ways.
This paper highlights key technological developments in the following areas of slaughterhouse operation: unloading, lairaging, restraining, stunning, post-mortem, surveillance/data analysis and education. All of them play a unique role, providing significant benefits to animal welfare.
The paper studies this topic from two angles:

1. Technological developments that are already fully operational at, mainly, high throughput slaughterhouses, such as the use of infrared technology;
2. Innovative developments that are already in use in other animal related areas, such as farms, but have not yet been transferred to the slaughterhouse environment.

Keywords: Killing, technology, innovation, slaughterhouse, animal welfare, precision slaughter

Introduction

With the development of precision farming, aiming to make farming processes more accurate, efficient, and sustainable through the use of technologies such as advanced satellite navigation systems (like GPS) and Information Technology (IT) parallels can be explored and developed with animal welfare at slaughter in mind too.

Precision Farming or smart farming is about taking the 4 Rs in agriculture to a new level: doing the right thing, in the right place, the right way, at the right time in the field (CEMA, 2016). In the context of animal welfare at slaughter we could also maximise the use of technology for slaughtering animals by using the right equipment, in the right place, in the right way and at the right time, without causing unnecessary pain, suffering or distress. [insert Figure 1]

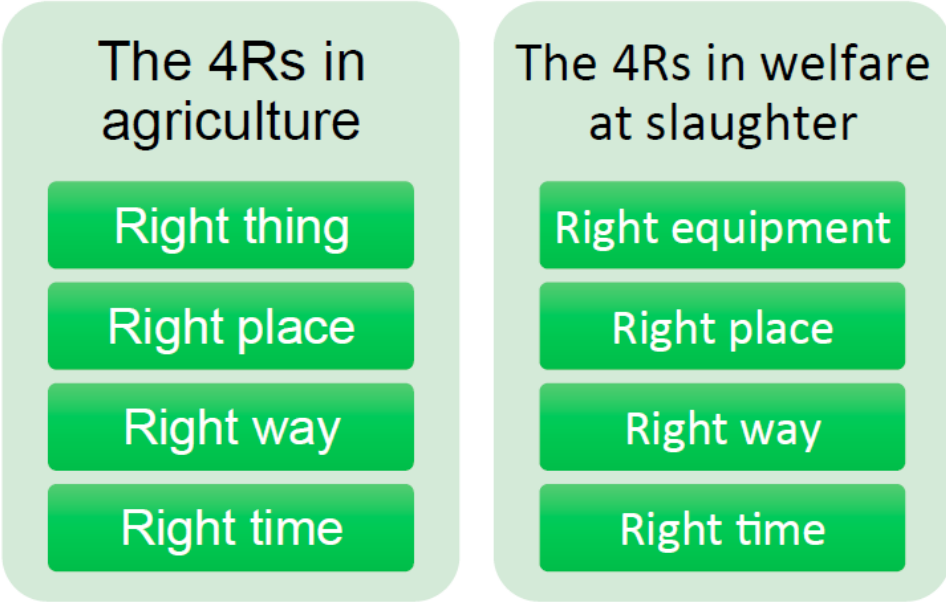


Figure 1 – The 4 Rs in welfare at slaughter

In a world with increasing pressure for food and decreasing natural resources, available technology becomes a key tool on the way to **'precision slaughtering' or 'smart slaughtering'** (i.e: *making the slaughter process more productive and effective whilst enhancing animal welfare, productivity and staff wellbeing*). Technological advances supplement and enhance progress in good slaughterhouse management together with the use of appropriately trained, proficient and diligent workers. Although this paper focuses mainly on animal welfare advances, in an ideal world technological innovation in this area would aim to target not just animal welfare but also animal and public health as well as the environmental impact of different slaughter systems.

Improvements in animal welfare at the time of slaughter can have a direct impact on meat quality and productivity. By enhancing animal welfare precision slaughtering can help improve economic returns within the industry. There are

many literature studies reporting, for example, direct links between improved pre-slaughter handling and higher meat quality, helping reduce the prevalence of dark, firm and dry (DFD), pale exudative soft (PSE) meat and/or bruising which will lead to trimming and total profit loss (Frimpong et al, 2014; Immonen et al, 2000).

To highlight the potential economic savings of welfare improvements, indicative figures of total losses to the EU meat industry due to PSE reported back in 2005 ranged from 60.5 million EUR to 140.5 million EUR (and an additional 14.2 million EUR for bruises. Implementing a precision slaughter approach that leads to, for example, reduced pre-slaughter stress, could enhance reductions in the incidence of carcasses with PSE muscle by over the estimated 10% to 12% that just handling improvements would achieve . This would imply EU-wide economic loss reduction greater than 6.05 million EUR to 16.86 million EUR (EU, 2007). A separate paper reported that the mean weight and standard error of condemned trimmed meat due to bruising in Uruguay was 1602 ± 212 g., which amounted to a loss of 899 g. per bovine animal slaughtered in Uruguay (Huertas et al. 2015)

Whilst technology may appear very costly to some, in terms of investment and/or operational costs, most times, the overall benefits of yield higher meat quality, access to new markets, and/or operational improvements help off-set the higher costs of the initial investment on the overall slaughterhouse economic situation (EU, 2007).

It is also important to consider welfare at slaughter an intrinsic part of the process rather than something isolated which delivers no benefits within the production chain. For this we can apply the concept of ‘one welfare’ to different aspects of welfare at slaughter; for example:

- Improved animal handling systems will help staff moving animals, result in a better working environment and overall improve the operation and staff wellbeing (i.e. unloading of a lorry full of pigs by skilled handlers would generally take a shorter time than the same operation undertaken by unskilled workers).
- Improved stunning equipment and facilities make the slaughterman’s work easier as well as supporting better animal welfare.

Material and methods

The content of this paper has been gathered through online searches and email exchanges with key stakeholders and officials within the slaughter industry across a number of countries.

Results and discussion

The slaughter industry has undergone major improvements and, in a world with increasing demand for meat, is constantly on the lookout for new tools to increase efficiency within the slaughter operation.
Tools already used in the farming industry based on camera observations, such as the eYenamic system, have the capacity to deliver early warnings to farmers in case of unexpected changes in the livestock house. These technologies have the potential to automate elements of welfare monitoring in real-time (EU-PLF, 2016) at a number of slaughterhouse areas and could alert personnel to specific issues by sending an SMS. Moreover, automated solutions operate without the limitations and constraints of human labour and thus provide more freedom for animals for self-determined, species-appropriate behaviour (EU-PLF, 2016).
Camera-based tools have the capacity to monitor the weight of pigs, their drinking behaviour and their activity. Sound monitoring is very effective in detecting incoming respiratory problems 2 to 12 days before the farmer notices the problem in pigs and calves. This is very valuable to avoid full development of disease on farm (EU-PLF, 2016) but could also be explored as a tool to monitor welfare in the slaughterhouse lairage.

During **unloading, handling or lairaging operations**, further work could be done, for example, to consider and refine the use of movement detection equipment used for locomotion scoring. Sound based tools could equally support monitoring and verification of animal welfare. Research still needs to develop in this area but some studies have already shown that, for example, pig vocalisation is directly related to pain and classification of these sounds has been attempted (Berkcman, 2014, Marx et al, 2003).

Lairaging of animals requires environmental monitoring and control; in this area technology systems such as ‘envirodetect’, created for commercial livestock farms, can help monitor ammonia, dust; CO_2, temperature, humidity, ventilation rate and improve environmental conditions of stock (PLF Agritech, 2016), abattoir workers and reduce pollutant and GHG emissions.
The latest technology working on audio-visual sensors to detect stress (i.e. fights) of pigs in farm-stalls could eventually also be used in lairages

(Vandermeulen et al., 2013). Research to explore visual technology used in other areas, such as drones or advanced CCTV cameras, could help address remote monitoring of blind spots or provide wider vision and advanced features to cameras commonly used nowadays.

Considering how genotype/phenotype and different breeds/conformation relate to animal handling and management systems, genetics technology could play a key role with the underpinning research in improving animal welfare through the production chain.

High precision positioning systems are used in farming via satellite technology – at slaughterhouses positioning of the animal / equipment at different stages of the process is key; for example, to ensure **restraint** is as comfortable and efficient as possible – are there lessons learned from sensor technology that could be applied to improve animal welfare at the time of restraint? Equally these technologies could be explored further in relation to stunning equipment position or adjustment. For example captive bolt shot position or adjustment of stunning electrodes in automated systems.

Variable rate technology also applies within welfare at slaughter. For improvement of **stunning** we already have technology that enables the operator to vary the rate of parameters input to deliver constant current, reducing the chances of animals receiving a sub-optimal stun. Tools that provide real time electrical parameters measurements, such as the stun assurance monitor for head only electrical stunning or the poultry stunning water bath current calibration monitor (PSM), are already a reality.

The University of Bristol has suggested that the next generation of captive-bolt technology could include a sensing mechanism to measure and record bolt speed. This could help troubleshooting stunning problems related to equipment.

In the same way that some speak already about iFarming we could also speak about **iSlaughter monitoring** which would capture automated procedures such as:

- post-mortem inspection of broilers with computerised calculation of foot-pad dermatitis using visual-capture(broiler welfare indicators on farm) – these are already in use and some countries, such as the Netherlands, have set up systems to collate farm results and evaluate yearly performance and links to stocking densities
- smartphones to send lesion photographs from the field or augmented reality technology for remote post-mortem inspection could enable additional welfare monitoring checks, Sweden is currently considering a study looking at augmented reality support for inspections

The use of integrated electronic communications for **smart veterinary surveillance** and data analysis can be applied to the field of welfare at slaughter,

and there are already some working examples, such as that of the 'Semaga' system used in Galicia, a Spanish Autonomous Community, which already has functional systems where data collated is pooled centrally and integrated with on farm data by Government departments. This can be a great tool to not only improve welfare at slaughter but also to support reductions of endemic disease and improve welfare and productivity.

Training and education are also important elements that underpin welfare at slaughter. New technologies now enable remote education via online training, webinars or augmented reality (3D goggles).

Conclusions

In summary, there are many examples of technological innovations that have a positive impact on animal welfare at slaughter. It is however important to remember that training of personnel, maintenance and the way technology is used in practice are key requirements to underpin novel technologies benefits.
As technological innovation advances the future of ‘precision slaughter’ in improving animal welfare is becoming a reality and more efforts should be made to adopt such innovations in this field to underpin the implementation of welfare legislation and global animal welfare standards as well as to foster continuous improvement within the industry.

Acknowledgements

Patrick Caruana (FVO); Steve Wotton (University of Bristol), Lotta Berg (SLU, Sweden), Michael Seals (AHAWB, UK), Marien Gerritzen (Lelystad University, NL); Jose Angel Vinuelas Rodriguez (Sergas, SP), Karen Von Holleben (BSI, Germany), Sophie Vickery (APHA, UK), Neil Sampson (APHA,UK)

References:

Berckman, 2014 - Precision livestock farming technologies for welfare management in intensive livestock systems. Rev. sci. tech. Off. int. Epiz., 2014, 33 (1), 189-196

CEMA, 2016 – Smart equipment for sustainable agriculture – precision farming: producing more with less – frequently asked questions. www.cema-agri-org (Accessed on 01/11/2016)

EU - Study on stunning/killing practices in slaughterhouses: Final Report

- Part I: Red meat http://www.civic-consulting.de/reports/slaughter_study_part1.pdf (Accessed on 20/06/2017)
EU-PLF, 2016 – Smart farming for Europe – Value Creation Through Precision Livestock Farming http://www.eu-plf.eu/ (Accessed on 01/11/2016)

Frimpong et al, 2014 - Samuel Frimpong, Girma Gebresenbet, Emmanuel Bobobee, Elias D. Aklaku and Ibrahim Hamdu. Effect of Transportation and Pre-Slaughter Handling on Welfare and Meat Quality of Cattle: Case Study of Kumasi Abattoir, Ghana. Vet. Sci. 2014, 1, 174-191; doi:10.3390/vetsci1030174

Huertas et al, 2015 - Huertas, S. M., van Eerdenburg, F., Gil, A. and Piaggio, J. (2015), Prevalence of carcass bruises as an indicator of welfare in beef cattle and the relation to the economic impact. Vet Med Sci, 1: 9–15. doi:10.1002/vms3.2

Immonen et al, 2000 - Immonen, K.; Ruusunen, M.; Puolanne, E. Some effects of residual glycogen concentration on the physical sensory quality of normal pH beef. Meat Sci. 2000, 55, 33–38.

Marx et al, 2003 - Marx G., Horn T., Thielebein J., Knubel B. & von Borell E. (2003). – Analysis of pain-related vocalisation in young pigs. *J. Sound Vib*., **266**, 687–698. 10. Moreaux B., Beerens D. & Gustin
PLF Agritech, 2016 - PLF Agritech – Enviro-detect http://www.plfag.com/enviro-detect (Accessed on 01/11/2016)

Vandermeulen et al., 2013 - Combination of image and sound analysis for behaviour monitoring in pigs Precision Livestock Farming 13 pages:262-268Joint European conference on Precision Livestock Farming location:Leuven date:10-12 September 2013

Using models for optimum growing cattle harvest endpoint

J. W. Oltjen
Department of Animal Science, University of California, Davis, California 95616, USA
jwoltjen@ucdavis.edu

Abstract

An important question for those feeding growing cattle is "How long to feed a pen to maximize profit?" We developed a precision management tool to answer this question. Generally the strategy is to feed cattle until costs for that day exceed the gain in value, that is, the marginal net revenue becomes negative. If a business owns many pens of cattle, the objective is to maximize profit of all pens over time; the economic principle is to feed each pen until marginal net revenue no longer exceeds the average daily net revenue for the replacement pen. However, complex interactions between type of cattle, markets, and application of marketing and management tools make profit prediction difficult. To address this, the beef cattle simulation module in UC software TAURUS is employed to dynamically predict animal value. This method integrates the biology of the animal, its management, and market prices to project animal and carcass characteristics through time, and associated costs and potential revenue. Results show an interaction between frame size and optimal feeding period, with larger frame cattle benefiting from earlier age at feedlot entry, or smaller frame cattle benefiting by being grown on forage diets or pastures before feedlot entry. If cattle are bought at low and sold at high prices, then average daily revenue is greater, and cattle are fed shorter times. Also, if average daily net revenue is projected to decrease after a set of cattle may be sold, that set of cattle should be fed longer.

Keywords: beef cattle, feedlot profit, mathematical models

Introduction

One of the basic principles of microeconomics is profit maximization. However, for cattle fed in feedlots, one needs to determine who is trying to maximize profit on a pen of cattle—the owner of the cattle or the feedlot. If the feedlot also owns the cattle, there are different constraints and objectives than if the cattle are owned, or partly owned by another person. Also, whether a pen of cattle can be replaced with another, as opposed to one pen per year or time period, makes a difference. The objective of this paper is to show how to use the Davis Growth

Model in Taurus software (Oltjen and Ahmadi, 2013) which uses incoming data daily to continuously update performance and economic predictions. Most US feedlots have this information daily, but do not use it appropriately--that is, to give the microeconomic application of the results.

Material and Methods

In the case of an owner independent of the feedlot, and assuming this person's capital is not limited by a particular pen of cattle, the profit maximizing strategy is to feed the pen of cattle until the costs for that day exceed the pen's gain in value, that is, the marginal net revenue becomes negative. Hence, the cattle are fed until the feed and other costs for the last day exceed that day's cattle gain multiplied by the cattle's value per unit weight, 182 days for a typical pen under current economic conditions (Figure 1). Special attention is warranted in this scenario with discounts in cattle price for increasing carcass weight or decreasing yields, as this decrease in the pen's value may be sudden. For this reason the more variable the cattle in a particular pen, the shorter is the optimum feeding period for profit maximization (Smith *et al*., 1988).

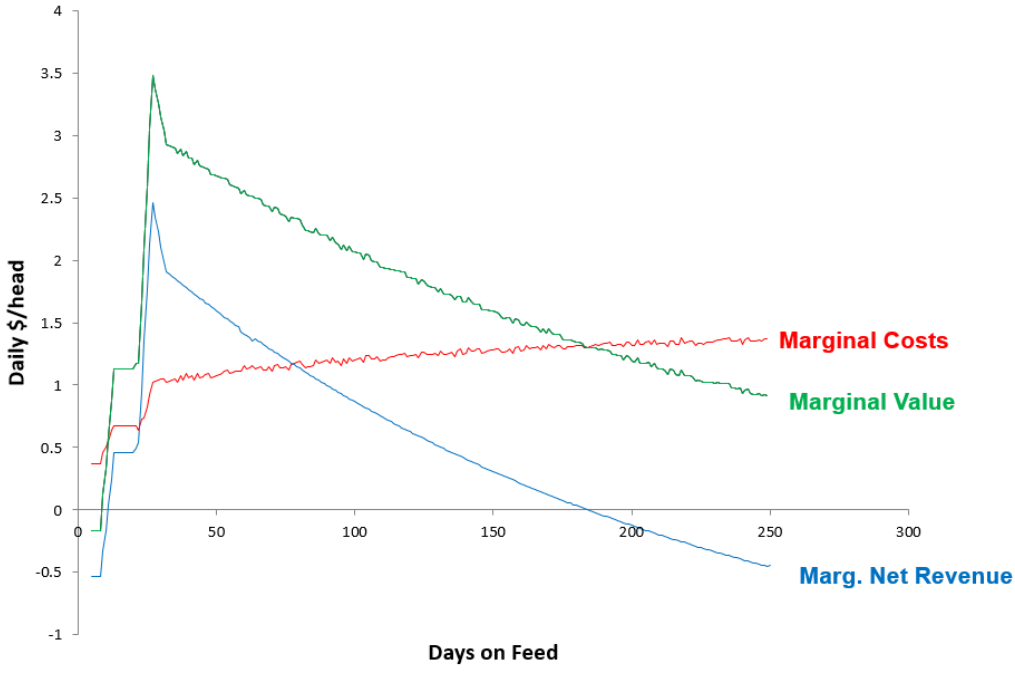


Figure 1. Marginal economic values of a typical pen of feedlot cattle over a feeding period; marginal net revenue is marginal value minus marginal costs

In the case of a feedlot owning the cattle, and recognizing that the feedlot's profit maximizing objective is to make money on the pens over time, not just for any particular pen of cattle, then the economic principle is to feed cattle until their marginal net revenue (daily increase in value minus daily cost) no longer exceeds the average daily net revenue for an average animal in a pen in the feedlot. Average daily net revenue is the profit for an animal divided by the number of days that animal was in the feedlot. As long as the average net revenue is positive (the feedlot is making a profit on the cattle, as well as on the feedlot enterprise), cattle owned by the feedlot will be fed fewer days than those owned by others, 142 days under current conditions and expectations (Figure 2). Note that if profit expectation of an incoming pen is negative, the cattle would be optimally fed more than 182 days. Again, as in the case above, more variable cattle will be fed fewer days than more uniform ones, but this is less important in the feedlot owning the cattle scenario since the shorter days on feed reduce the chance of discounts.

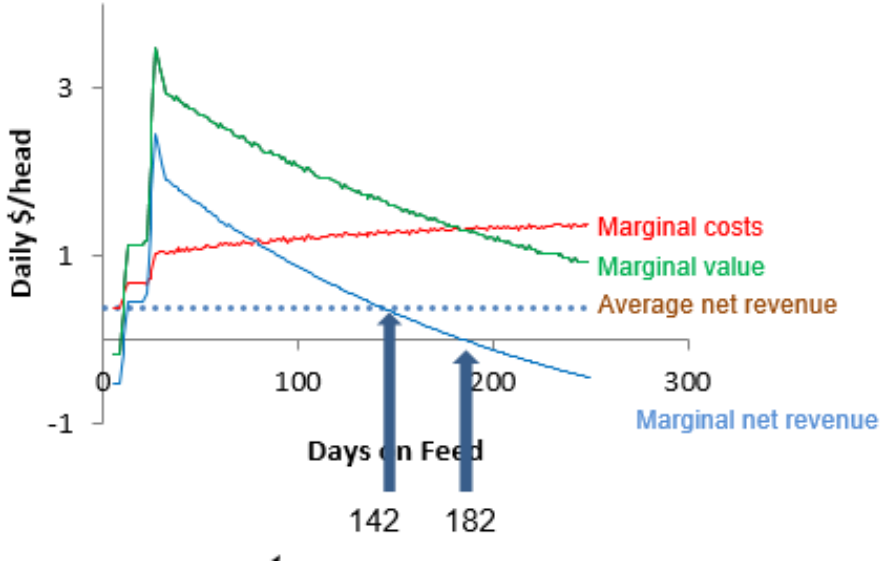


Figure 2. Marginal economic values of a typical pen of feedlot cattle over a feeding period considering the expected profit of a replacement pen; marginal net revenue is marginal value minus marginal costs

There are two exceptions or alternatives in the above scenarios. If the cattle owner cannot feed additional cattle until a pen of cattle is sold, then the objective is profit maximization over time, not for a pen of particular pen of cattle. Therefore, their cattle should be fed as in the case of the feedlot owning the cattle above. If the feedlot owns the cattle, and for some reason cannot use the pen again after the cattle are sold/removed (often in case where only one set of cattle

are fed in each physical pen annually), then their profit maximization objective is as first scenario above where the cattle are owned independently of the feedlot—indeed the cattle profit is then independent of the feedlot profit.

Results and Discussion

Profit depends on the difference between marginal net revenue and costs as cattle progress in a feeding period. Note that in the early days after a pen of cattle is put on feed, their total value is less than the money invested and the early feed and processing costs (which would result in negative returns if sold at that point). However, the marginal net revenue is usually positive—the value of their daily gain exceeds the daily feed cost. Hence profits are increasing, or losses decreasing. If this is not the case, and marginal returns are negative, prolonging the feeding period increases the loss, and the cattle should be sold. This is not unusual for chronically sick individuals. Even for well animals, a pen of cattle can lose money if fed to the proper endpoint—it is just that they will lose less money if fed to that endpoint.

Marketing is a major consideration—that is the relative difference between the price paid for cattle and that for which they are sold. In the case of an independent owner, it is often the difference between profit and loss, independent of the discussion above on proper time of marketing the animals. For the feedlot owning the cattle (or the capital limited outside owner), it is more interesting. Since the optimal feeding strategy is to feed until marginal net revenue decreases to average daily revenue for typical pens in the feedlot, the average daily revenue is important—and depends more on the difference between the prices paid and received for cattle. If the feedlot does an exceptionally good job of buying cattle low and selling them high, then the average daily revenue is high, and cattle are fed shorter times. In fact, if it is quite high days on feed approaches zero, and the feedlot simply becomes a holding pen for cattle being transferred in ownership—a cattle broker's location. Understanding how a feedlot's average daily net revenue may change over time is thus important to optimizing profit for cattle owned by that feedlot. Thus if average daily net revenue is projected to decrease in the coming months after a set of cattle may be sold (incoming cattle prices too high, market cattle prices declining, feed prices increasing), the argument is to feed the cattle longer.

The above economic discussion seems to ignore the resulting animal's product and its growth. However, this is not the case because the animal's value is quite dynamic, depending on carcass weight, quality, possible defects and other market factors; its profit also depends on efficiency of gain. These biological

parameters are complex and have been the focus of much beef cattle research for over fifty years. Rather than summarize all the literature, an overview of the major factors affecting how animal value changes as feedlot animals approach slaughter endpoints follows.

Carcass weight is a major driver of revenue, and animal value increases in direct proportion unless other factors interact to decrease value per unit carcass weight. Thus, in most analysis, feeding animals to heavier weights usually increases profit. Constraints due to excessive carcass size in slaughter plants, or undesirably large muscle cuts limit carcass size by decreasing value of the carcass. Increasing cost of gain as animals age also constrain carcass size, usually as a result of an increasing proportion of the feed being used for animal maintenance (related to body weight) instead of gain. Hyer *et al*. (1986) also showed that as steers reached or exceeded normal market weight, feed intake decreased, further exacerbating the above effect of less feed available for gain.

Carcass weight and the yield of retail cuts in the carcass change with increasing body weight, and result in value differences as well. Pricing cattle on a live weight basis requires consideration of the relative increase in carcass weight as a proportion of live weight. But pricing cattle on either a live weight or carcass weight basis must also consider the decrease in retail cut yield as carcass fatness increases. As animals finish in a feedlot fatness increases, so beef yield as a proportion of carcass decreases, particularly so for genetically fatter animals. In the US this is called Yield Grade, and steep discounts for animal with higher Yield Grades effectively limit time on feed.

Although Yield Grades, or carcass yield, become less desirable with time on feed, carcass quality, Quality Grade in the US, generally improve. Genetics and feeding strategy affect carcass quality with certain breeds (and sires) exhibiting greater marbling and other improved meat qualities. Steroid status of the animal often affects marbling, and interacts with age the animal enters the feedlot. Aggressive anabolic implant use earlier in life seems to decrease marbling; the younger the animal is when entering the feedlot enhances marbling. This probably depends on the endpoint at which marbling is measured—calves are often fed longer before slaughter at a lighter weight than yearling or older cattle. Backfat of calves reaches a given level at a lighter body weight than for older cattle, so they are often slaughtered younger and lighter, to avoid carcass yield discounts and possibly resulting in decreased total value due to lighter carcasses. Yearlings may be more profitable if the cost of gain is high, and the trend to feed these older cattle increases with feed and grain prices.

An interesting interaction between frame size (mature weight of the animal) and optimal feeding period exists, with larger frame cattle benefitting from earlier feedlot entry, or smaller frame cattle benefitting by being grown on forage diets or pastures before feedlot entry. On forage diets, backfat does not increase with body weight as it does on feedlot rations (Sainz *et al*., 1995), thus the smaller frame animal can be fed to larger, more profitable weights after a period of restricted growth on a lower energy diet. The NRC (2000) accounts for this using an equivalent weight concept, the weights at which different animals reaches 28% body fat. Thus, one makes an adjustment on body weight to account for different frame size and management effects.

Conclusions

As feedlots are used to finish more cattle, improved strategies evolve. One of the most important management questions once cattle are in the feedlot is "How long to feed them to maximize profit?" However, complex interaction between type of cattle, market demand and price, ownership of the feedlot and/or the cattle, and application of marketing and management tools make profit prediction difficult. Addressing these interactions requires proper application of economic principles, identifying the relevant biology of the animals being fed, and tools such as bioeconomic models to estimate animal performance. When used properly to answer the appropriate question, these tools provide insight into improved management of feedlot cattle. I have addressed this issue in my extension program; this is an important real-world application of Precision Livestock Farming.

References

Hyer, J. C., Oltjen, J.W., and Owens, F.N. 1986. The relationship of body composition and feed intake of beef steers. *Oklahoma Agricultural Experiment Station* **MP-118** 96.

NRC. 2000. *Nutrient Requirements of Beef Cattle, 7th Rev. Ed*. National Academy Press, Washington, D.C.

Oltjen, J.W. and A. Ahmadi. 2013. Taurus: A ration formulation program for beef cattle. Nat. Sci. Educ. 42:145-159.

Sainz, R.D., De la Torre, F., and Oltjen, J.W. 1995. Compensatory growth and carcass quality in growth-restricted and refed beef steers. *Journal of Animal Science* **73** 2971-2979.

Smith, M. T., Oltjen, J.W., and Gill, D.R. 1988. Simulation of the economic effect of variability within a pen of feedlot steers. *Oklahoma Agricultural Experiment Station* **MP-125** 155.

Session 16

Pigs and feeding

Effect of precision feeding on environmental impact of fattening pig production

A.N.T.R. Monteiro[1,2], F. Garcia-Launay[2], L. Brossard[2], A. Wilfart[3], J.-Y. Dourmad[2]
[1]*Animal Science Department, Maringá State University, 91540-000, Maringá, PR, Brazil.*
[2]*INRA, Agropcampus-Ouest, UMR1348 Pegase, 35590 Saint-Gilles, France.*
[3]*INRA, Agrocampus-Ouest, UMR1069 SAS, 35000 Rennes, France..*
jean-yves.doumad@inra.fr

Abstract

Various studies have shown that improved feed efficiency is an efficient lever to reduce the environmental impact of pig production. The development of feeders which allow the distribution of different diets, together with new low-cost animal identification technologies and sensors for high-throughput collection of information on animals (body weight, feed intake), should allow the development in practice of individual feeding of fattening pigs in the near future. With this in mind, a modelling approach was used to evaluate the potential of this strategy to reduce the environmental impact of pig fattening. Eight populations of 2000 pigs, fed according to either a conventional two-phase (2P) or a precision feeding (PR) strategy, were simulated using the population version of InraPorc. This was performed for two geographical production contexts (Brazil and France) with two soyabean meal origins (Centre West Brazil, a region with deforestation, and South Brazil, without deforestation). Environmental impacts were evaluated using a cradle-to-farm gate life cycle assessment and were expressed per kg of weight gain. Compared to 2P, PR improved average daily gain and feed efficiency by about 4-5% and reduced feed costs by 7-10%. It reduced nitrogen excretion by about 20%. On average, compared to 2P, the PR feeding strategy reduced environmental impacts for climate change, energy use, eutrophication, acidification and land occupation by 6.1%, 6.9%, 10.3%, 12.7% and 3.5%, respectively. It was concluded that PR appears to be a very interesting strategy for improving economic and environmental dimensions of sustainability in pig production.

Keywords: fattening pig, precision feeding, environmental evaluation, life cycle assessment

Introduction

The environmental impacts of pig production have been debated increasingly in recent years, resulting in a greater focus on identifying and mitigating the environmental degradation they may cause. Better adjustment of nutrient supply to animal requirements (Dourmad and Jondreville, 2007) may be a key factor in improving the efficiency of nutrient retention, reducing excretion and consequently increasing the sustainability of pig production. The development of innovative feeders which allow the distribution of different diets, together with new low-cost animal identification technologies and sensors for high-throughput collection of animal information (body weight, feed intake), should allow the development of individual pig feeding in practice in the near future.

Precision feeding appears to be the most promising approach to improving the efficiency of nutrient use. This technique has been successfully tested on growing-finishing pigs (Pomar et al., 2009; Andretta et al., 2014). The strategy is to predict the expected performance of each individual pig according to previous real-time measurements of feed intake and body weight, and to feed it with a ration which provides the amount of nutrient required to achieve the expected performance (Hauschild et al., 2012).

In recent years, life cycle assessment (LCA) has been widely used in agriculture (Guinée et al., 2002) and several studies of swine production chains have been conducted (Nguyen et al., 2010, Garcia-Launay et al., 2014). LCA makes it possible to perform an integrated environmental evaluation of the whole production chain, considering the potential impacts associated with the raising of pigs as well as those related to the production of inputs (e.g. the feed) and the disposal of waste (e.g. the manure produced).

The aim of this study was thus to use a simulation approach to evaluate the potential for precision feeding of fattening pigs, compared to phase feeding, in two different production contexts, in southern Brazil and western France.

Materials and methods

Feeding strategies and feed specifications

The study considered the growing-finishing pig production system, with three different feeding programmes: two phases (2P), four phases (4P) and precision feeding (PR). Two experimental feeds (named A and B) were independently formulated at least cost for each sex (females and castrated males) in each country. Feeds A and B differed in their amino acid and mineral concentrations,

with feed A being formulated with a high nutrient density to meet the estimated nutrient requirements at the beginning of the growing period, and feed B formulated with a low nutrient density to meet the estimated nutrient requirements at the end of the finishing period. Feeds A and B were combined according to the feeding programme. In the 2P feeding programme, feeds A and B were combined in the following proportions: 100% and 0% in phase 1, and 42% and 58% in phase 2 for feeds A and B, respectively. In the 4P feeding programme, feeds A and B were combined in the following proportions: 100% and 0% in phase 1, 65% and 35% in phase 2, 42% and 58% in phase 3 and 15% and 85% in phase 4 for feeds A and B, respectively. In the precision feeding strategy, the proportion of feed A and B was calculated each day for each pig according to its expected amino acid requirement (Hauschild et al., 2012). Feeds contained the usual feed ingredients, including industrial amino acids, used in each country and were formulated at least cost using OpenSolver for Excel®, using the mean prices of feed ingredients in Brazil and France for the year 2014.

Pig production

Performance data from experimental studies in Brazil (Monteiro et al., 2017) and France (Brossard et al., 2014) were used to adjust average animal profile parameters for growth and feed intake using InraPorc® software. These profiles were used to calculate, according to InraPorc®, the average nutritional requirement curves for each sex (females and castrated males), these requirements being used for diet formulation. To take account of the variability, the nutrient requirement of the population was calculated as 110% of the mean requirement as generally recommended (Pomar et al., 2009; Brossard et al., 2009). Parameters for growth and feed intake profiles were thus defined for a population of 1000 castrated males and 1000 females for each country, according to the method described by Brossard et al. (2009) using a variance-covariance matrix. Simulations for 2000 pigs (50% females, 50% castrated males) were performed for each feeding scenario in each country in order to determine animal performance, and nutrient balance and excretion.

Life Cycle Assessment

LCA was performed according to Nguyen et al. (2010) and Garcia-Launay et al. (2014). The LCA considered the entire pig farming activity, including crop production, grain drying and processing, production and transport of feed ingredients, feed production at the feed factory, transport of the feed to the farm, growing to finishing pig production, and manure storage, transport and spreading. The pig production system considered was typical of conventional growing-finishing pig farms located in Brittany and southern Brazil. The environmental consequences of manure utilisation were evaluated using system

expansion as described by Nguyen et al. (2010). It was assumed, for both countries, that soyabean was produced in Brazil either in the Centre West (CW), a region with recent deforestation, or in the South (SO) where there is no deforestation. For Brazilian crops, the life cycle inventory (LCI) came from Prudêncio da Silva et al. (2010), taking into account the effect of land-use change on carbon release due to conversion of Brazilian forest to cropland. For French crops, the LCI came from a national database developed by French research institutes with data for the environmental impacts of all main ingredients used in animal feeds (Wilfart et al., 2015). Emissions to air during swine production and management of manure were estimated according to Rigolot et al. (2010) and IPCC (2006). The following potential impacts of pig production were considered: climate change (CC, kg CO_2-eq.), eutrophication potential (EP, g PO_4-eq.), acidification potential (AP, g SO_2-eq.), terrestrial ecotoxicity (TE, g 1,4-DCB-eq.), cumulative energy demand (CED, MJ), and land occupation (LO, m^2.year). The CC was calculated according to the 100-year global warming potential factors in kg CO_2-eq. Impacts were calculated at the farm gate and the functional unit considered was one kg of body weight gain (BWG) over the fattening period.

Results and discussion

Animal performance

Simulated pig performance and the results for nitrogen excretion are presented in Table 1. Average dietary crude protein (CP) content was significantly affected by country and feeding programme. Compared with 2P, the PR feeding programme reduced dietary CP by 7% and 13% for Brazil and France, respectively. The reduction of CP content was accompanied by a decrease in feeding cost (-7 and -8% between 2P and PR programmes for Brazil and France, respectively). In both countries, ADG was affected by the feeding programme: the highest growth performance was obtained for PR (946 g/d on average) and the lowest (914 g/d on average) for 4P. Similar effects were observed for feed conversion ratio, which was lower for PR than for 4P (2.66 vs. 2.75 kg/kg). Compared with the 2P programme, the PR programme reduced nitrogen excretion by 19 and 21% in Brazil and France, respectively, 4P feeding programmes being intermediate.

Acidification and eutrophication potential

With soyabean from SO, the AP values for the different feeding programmes ranged from 53.9 to 60.2 g SO_2-eq. per kg BWG in Brazil and from 40.8 to 47.1 g SO_2-eq. per kg BWG in France (Table 1). With soyabean from CW the values increased slightly to 54.7 to 61.3 g SO_2-eq. per kg BWG in Brazil and 41.3 to 48.0 g SO_2-eq. per kg BWG in France. The lowest AP impact was obtained for

PR, both for soyabean from SO and CW, with on average about a 12% reduction in AP impact for PR compared to 2P and 4P, which did not differ from each other. The EP values for the feeding programmes ranged from 15.6 to 17.5 g PO_4-eq. per kg BWG, with no difference between countries and with similar results for soyabean from SO and CW (Table 1). The lowest EP impact was obtained for PR in both countries (mean of 15.6 g PO_4-eq. per kg BWG) and the highest for 2P and 4P which did not differ (mean of 17.2 g PO_4-eq. per kg BWG). Since nitrogen contributes to eutrophication and to acidification through ammonia emissions (Guinée et al., 2002), the AP and EP impacts were reduced in both countries by increasing the number of feeding phases and to a higher extent by precision feeding. This was not surprising because these strategies reduce nitrogen excretion and, consequently, also reduce NH_3 emissions from animal housing, manure management and field application.

Table 1. Performance and environmental impacts of growing-finishing pigs fed with different feeding strategies, in 2-phase (2P), 4-phase (4P) or individual precision feeding (PR)

	Brazil[1]			France			Stat Sign.[2]		
	2P	4P	PR	2P	4P	PR	C	S	CxS
CP, g/kg	145^{a}	139^{b}	135^{b}	158^{a}	149^{b}	137^{c}	**	***	***
ADG, g/d	842^{ab}	830^{b}	878^{a}	909^{ab}	899^{b}	915^{a}	***	*	
FCR, kg/kg	2.75^{b}	2.79^{a}	2.64^{c}	2.69^{b}	2.72^{a}	2.69^{b}	**	***	***
Cost, €/kg ADG	0.54^{a}	0.53^{a}	0.50^{b}	0.60	0.58	0.55	***	***	
N exc., kg/pig	3.39^{a}	3.25^{a}	2.75^{b}	3.69^{a}	3.43^{a}	2.91^{b}	***	***	
LCA per kg BWG (SO)[3]									
CC, kg CO_2 eq.	2.40^{a}	2.43^{a}	2.30^{b}	2.33^{ab}	2.35^{c}	2.32	**	***	*
CED, MJ	13.4^{b}	13.5^{a}	12.9^{b}	12.7^{a}	12.6^{a}	12.1^{b}	***	***	
AP, g SO_2 eq.	60.2^{a}	59.6^{a}	53.9^{b}	47.1^{a}	45.3^{a}	40.8^{b}	***	***	
EP g PO_4 eq.	17.5^{a}	17.3^{a}	15.7^{b}	17.2^{a}	16.8^{a}	15.7^{b}		***	
LO, m^2.year	2.39^{a}	2.40^{a}	2.26^{b}	3.78	3.82	3.79	***	**	**
LCA per kg BWG (CW)[3]									
CC, kg CO_2 eq.	2.81^{a}	2.80^{a}	2.61^{b}	2.65^{a}	2.61^{a}	2.48^{b}	***	***	
CED, MJ	15.5^{a}	15.4^{a}	14.5^{b}	13.8^{a}	13.5^{a}	12.7^{b}	***	***	
AP, g SO_2 eq.	61.3^{a}	60.5^{a}	54.7^{b}	48.0^{a}	46.0^{a}	41.3^{b}	***	***	
EP g PO_4 eq.	17.4^{a}	17.2^{a}	15.6^{b}	17.1^{a}	16.8^{a}	15.6^{b}		***	
LO, m^2.year	2.35^{a}	2.36^{a}	2.22^{b}	3.75	3.80	3.77	***	**	**

[1]Within-country means followed by same or no letter do not differ ($P > 0.05$)
[2]Statistical significance of effects of Country (C), Feeding Strategy (S) and their interaction (CxS), * $P<0.05$., ** $P< 0.01$, *** $P<0.001$
[3]Life Cycle Assessment with soyabean from Centre West (CW) or South (S) Brazil

The distribution of EP impact among pigs is presented in Figure 1 which shows a non-normal distribution for phase feeding, indicating that the highest performing pigs (i.e. those with the lowest impact) are not able to achieve their expected performance, probably because of insufficient amino acid supplies during the

transition periods. With the change in diet composition, this explains the lower average EO impact obtained with precision feeding.

Climate change potential

With soyabean from SO, the average CC values for the different feeding programmes ranged from 2.30 to 2.40 kg CO_2-eq. per kg BWG in Brazil and from 2.32 to 2.33 kg CO_2-eq. per kg BWG in France (Table 1). When soyabean meal from CW was used, CC values increased to 2.61 to 2.81 kg CO_2-eq. per kg of BWG in Brazil and to 2.48 to 2.65 kg CO_2-eq. per kg BWG in France. The impact on CC did not differ between the 2P and 4P feeding programmes. Conversely, the PR feeding programme significantly reduced the CC impact, with values on average 3% and 6% lower than for the two other strategies, for soyabean from SO or from CW, respectively. The effect of the PR feeding programme on CC was thus more pronounced with soyabean from CW. This indicated that the effect of phase feeding on CC may depend on the origin and the amount of soyabean, in agreement with the studies of Eriksson et al. (2005) and Garcia-Launay et al. (2014).

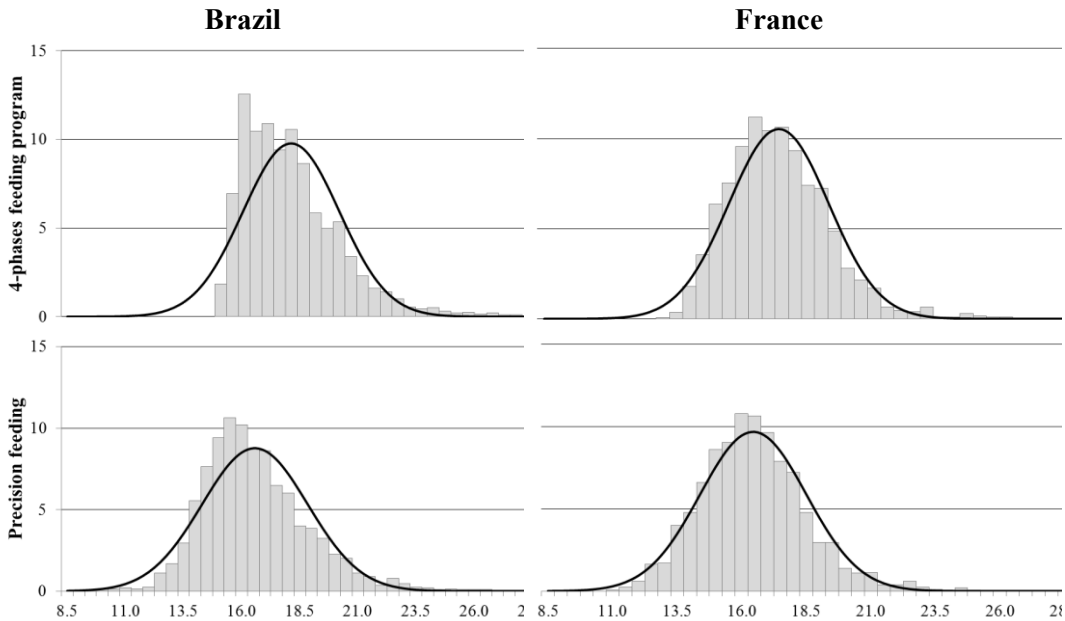


Figure 1. Frequency of distribution of pigs (%) and normal curve for eutrophication potential, according to the feeding programme and country (soyabean from SO).

Cumulative energy demand

With soyabean from SO, the CED values for the different feeding programmes ranged from 12.9 to 13.4 MJ-eq. per kg of BWG in Brazil and from 12.1 to 12.7 MJ-eq. per kg of BWG in France. With soyabean from CW, the values increased to 14.5 to 15.5 MJ-eq. per kg BWG in Brazil and to 12.7 to 13.8 MJ-eq. per kg of BWG in France. The lowest CED impact was calculated for PR, with a 4% and 7% reduction in CED impact compared to 2P and 4P, for soyabean from SO and CW, respectively. The possibility of reducing the CED impact by increasing the number of feeding phases was confirmed for diets based on soyabean meal from CW, but not for soyabean from SO. Precision feeding only resulted in reduced CED impact in that situation.

Land occupation

The LO values for the different feeding programmes ranged from 2.22 to 2.39 m^2.year per kg BWG in Brazil and from 3.77 to 3.82 m^2.year per kg BWG in France, with similar results for soyabean from both origins (Table 1). The feeding programme affects LO in Brazil, with the lowest impact for PR which was 6% lower than 2P and 4P, but not in France.

Conclusions

The results of this study indicate that precision feeding would be the most efficient approach for reducing the life cycle impact of pig fattening, whereas the potential of phase feeding programmes depends on the impact considered, soyabean origin and the geographical context of pig production. The benefit of phase feeding for reducing the climate change impact is limited with soyabean from South Brazil, whereas it appears to be an efficient strategy with soyabean from the Centre West. Conversely, potential eutrophication and acidification impacts are largely reduced by phase feeding in a rather similar way in all situations.

Acknowledgements

This project was conducted within a sandwich PhD thesis programme supported by the CAPES Foundation, Brazil.

References

Andretta, I., Pomar, C., Rivest, J., Pomar, J., Lovatto, P.A., and Neto, J.R. 2014. The impact of feeding growing-finishing pigs with daily tailored diets using precision feeding techniques on animal performance, nutrient utilization, and body and carcass composition. *Journal of Animal Science 92*, 3925-3936.

Brossard L., Vautier B., van Milgen J., Salaun Y., Quiniou N. 2014. Comparison of in vivo and in silico growth performance and variability in pigs when applying a feeding strategy designed by simulation to control the variability of slaughter weight. *Animal Production Science 54*, 1939-1945.

Brossard, L., Dourmad, J.-Y., Rivest, J., van Milgen, J. 2009. Modelling the variation in performance of a population of growing pig as affected by lysine supply and feeding strategy. *Animal 3*, 1114–1123.

Dourmad, J.-Y., Jondreville C. 2007. Impact of nutrition on nitrogen, phosphorus, Cu and Zn in pig manure, and on emissions of ammonia and odours. *Livestock Science 112*, 192-198.

Eriksson, I.S., Elmquist, H., Stern, S., Nybrant, T. 2005. Environmental systems analysis of pig production - the impact of feed choice. *The International Journal of Life Cycle Assessment 10*, 143-154.

Garcia-Launay F., van der Werf H.M.G., Nguyen T.T.H., Le Tutour L., Dourmad J.-Y. 2014. Evaluation of the environmental implications of the incorporation of feed-use amino acids in pig production using Life Cycle Assessment. *Livestock Science 161*, 158-175.

Guinée J. B., Gorrée M., Heijungs R., Huppes G., Kleijn R., de Koning A., Oers L.V., Sleeswijk A.W., Suh S., de Haes H.A.U.. 2002. Handbook on life cycle assessment: Operational guide to the ISO standards. Kluwer Academic Publishers, Leiden, The Netherlands.

Hauschild, L., Lovatto, P.A., Pomar J., and Pomar C. 2012. Development of sustainable precision farming systems for swine: estimating real-time individual amino acid requirements in growing-finishing pigs. *Journal of Animal Science 90*, 2255–2263.

IPCC. 2006. IPCC Guidelines for National Greenhouse Gas Inventories: Emissions from Livestock and Manure Management. http://www.ipcc-nggip.iges.or.jp/public/2006gl

Monteiro, A.N.T.R., Bertol, T.M., de Oliveira, P.A.V., Dourmad, J.-Y., Coldebella, A., Kessler, A.M. 2017. The impact of feeding growing-finishing pigs with reduced dietary protein levels on performance, carcass traits, meat quality and environmental impacts. *Livestock Science 198*, 162-169.

Nguyen,T.L.T., Hermansen J.E., Mogensen L. 2010. Fossil energy and GHG saving potentials of pig farming in the EU. *Energy Policy 38*, 2561-2571.

Pomar, C., Hauschild, L., Zhang, G.H., Pomar, J., and Lovatto, P.A. 2009. Applying precision feeding techniques in growing-finishing pig operations. *Revista Brasileira de Zootechnia 38*, 226-237 (supl. especial).

Prudêncio da Silva V., van der Werf H.M., Soares S.R., Corson M.S. 2014. Environmental impacts of French and Brazilian broiler chicken production scenarios: an LCA approach. *Journal of Environmental Management 133*, 222-231.

Rigolot C., Espagnol S., Robin P., Hassouna M., Beline F., Paillat J.-M., Dourmad J.-Y., 2010. Modelling of manure production by pigs and NH_3, N_2O and CH_4 emissions. Part II: effect of animal housing, manure storage and treatment practices. *Animal 4*, 1413-1424.

Wilfart A., Dauguet S., Tailleur A., Willmann S., Laustriat M., Magnin M., Espagnol S. 2015. LCIA results of feedstuffs for French livestock. *Proc. 66th Ann. Meet. Europ. Fed. Anim. Sci., Warsaw, Poland*, p. 411.

Selection of methods to analyse body weight and feed intake data used as inputs for nutritional models and precision feeding in pigs

L. Brossard[1], I. Taoussi[2], J. van Milgen[1], J.Y. Dourmad[1]
[1]*PEGASE, INRA-Agrocampus Ouest, 35590 Saint-Gilles, France*
[2]*INSA Rennes, 20 Avenue des Buttes de Coesmes, 35708 Rennes, France*
ludovic.brossard@inra.fr

Abstract

The progress of technologies (sensors, automates) in precision livestock farming enables the development of innovative feeding techniques such as precision feeding of individual animals. In addition to the design of adapted feeders, precision feeding requires decision-support tools to manage data and apply nutritional models that calculate the optimal feed composition and allowance. These calculations require to forecast body weight (BW) and feed intake (FI) of individual pigs according to past performance. To select the most accurate forecasting method, three statistical methods were tested on a dataset of measurements of BW and FI for 117 pigs: the double exponential smoothing (DES) method, multivariate adaptive regression splines (MARS), and the k-nearest neighbours (kNN) method. These methods were tested in relation to data sampling frequency (i.e., daily or weekly measurements) and data availability. The capacity to forecast BW or FI was evaluated through the mean error of prediction. The kNN method appeared suitable if few historical data are available as it requires not more than 3 historical data. The MARS method was better than the DES method to forecast daily BW, but the DES method was better in forecasting the daily cumulated FI. The DES method also seemed more appropriate for weekly BW data, requiring only 3 historical data to make a forecasting. These methods can be used for performance forecasting in a decision-support tool for precision feeding. This study was performed in the Feed-a-Gene Project funded by the European Union's H2020 Programme (grant agreement no 633531).

Keywords: pig, precision feeding, body weight, feed intake, real-time analysis

Introduction

As other livestock production systems, pig production is continuously facing the challenge of sustainability. To contribute to the growing demand for animal protein, feed efficiency in pig production has to be optimised. This optimisation will contribute to reduce the environmental impact and to improve

competitiveness of a production system where feed represents a major part of the production costs (typically 60 to 70%). The progress of technologies (sensors, automates) in precision livestock farming enables the development of potentially novel feeding techniques such as precision feeding. Precision feeding is based on the dynamic adjustment (if possible day by day) of the nutrient supply to the requirement, at a group or at an individual level (Pomar *et al.*, 2009). Recent studies have shown that precision feeding is a promising way to improve feed efficiency (e.g., Andretta *et al.*, 2014). Compared to common phase-feeding programs applied to groups of pig, precision feeding allows a better consideration of the change in requirements during growth and of the variability among pigs of the same age, sex, and genotype (Brossard et al., 2009).

In addition to the design of adapted feeders (e.g., Pomar *et al.* (2009) for *ad libitum* feeding, Marcon *et al.* (2015) for restricted feeding), and a precise evaluation of feed ingredients, precision feeding requires decision-support tools to manage data and apply nutritional models that calculate the optimal feed composition and allowance. Current models developed to simulate pig growth and to determine nutrient requirements (e.g. van Milgen *et al.*, 2008) are difficult to be used in real-time decision-support tools as they require historical data on body weight (BW) and daily feed intake (DFI) data to characterize the animal. However, in precision feeding, nutrient requirements for individuals need to be determined in real time on the basis of their own growth and FI patterns. Hauschild *et al.* (2012) proposed a model for pigs fed *ad libitum* with empirical and mechanistic components, where the empirical model allowed the estimation of DFI and BW at time t+i from historical information measured for each individual animal up to time t. Hauschild *et al.* (2012) used the double exponential smoothing (DES) forecasting time series method on DFI and on weekly BW. However, with the technological development of sensors, BW can now also be obtained daily and individually (e.g., Marcon *et al.*, 2015).

The aim of this study was to test the most accurate forecasting method for BW and DFI for *ad libitum* feed allowance among three statistical methods: the DES method, the multivariate adaptive regression splines (MARS) method, and the k-nearest neighbours (kNN) method. These methods were tested in relation to data sampling frequency (i.e., daily or weekly measurements) and data availability.

Material and Methods

Dataset

A dataset on 119 pigs from Topigs was used for the analyses and calculations. During collection of data, animals had *ad libitum* access successively to two diets formulated to meet or exceed nutritional requirements (National Research Council, 1998), with a diet change at 65 kg BW: a growing diet (18.7% crude protein (CP), 10.51 MJ net energy (NE)/kg, 1.06 g standard ileal digestible lysine (SID Lys) / MJ NE on an as-fed basis), and a finishing diet (15.6% CP, 10.24 MJ NE/kg and 0.89 g SID Lys / MJ NE on an as-fed basis). During the test, DFI was recorded for each pig using automatic feeder systems. Animals were weighed daily by automatic weighing devices. Mean BW at the beginning and end of the data collection period were 34.0 ± 4.7 kg (75.9 ± 6.6 d of age) and 139.9 ± 9.8 kg (176.0 ± 9.2 d of age), respectively. Average DFI observed during the data collection was 2.32 ± 0.73 kg/d. On average, 99 and 101 data were available per animal for BW and DFI, respectively.

Calculation methods

To estimate the BW or DFI at a time t+i, using data up to time t, three forecasting methods were tested: the DES method, the MARS method, and the kNN method.

Double exponential smoothing (DES) method

In the panel forecasting time series methods, exponential smooting techniques are appropriate to reduce fluctuations from irregular observations in the studied time series (Claycombe and Sullivan, 1977), with a goal of short-time forecasting. As indicated by Hauschild *et al.* (2012), the DES is well adapted to the study of DFI and BW in pigs as they show long-run trends without seasonal components and because the method works with a limited number of observations (at least 3). At a given time t, the DES forecasting of the series to i days ahead is given by:

$$\hat{X}_t(i) = a_t i + b_t$$

where the coefficients $\mathbf{a_t}$ and $\mathbf{b_t}$ vary with time. In the DES method, the smoothed series $\mathbf{S_1}$ is smoothed a second time to obtain $\mathbf{S_2}$ with

$$S_1(t) = \alpha y_t + (1-\alpha)\, S_1(t-1) \;\; and \;\; S_2(t) = \alpha S_1(t) + (1-\alpha) S_2(t-1)$$

where α is the smoothing constant comprised between 0 and 1 and used to weigh differently past and recent observations. Values of α close to 1 give a greater weight to recent observations, while values of α close to 0 have a greater smoothing effect and are less responsive to recent changes.

Multivariate adaptive regression splines (MARS) method

The MARS method is an adaptation of techniques developed by Friedman (1991) to resolve regression problems, with the aim to predict values of one or several continuous variables using a set of explicative variables. This non-parametric method has been largely used in data mining because it does not require a hypothesis on residues or relationships. The MARS method can be seen as an extension of linear regression to model automatically interactions and non-linearity. The method uses a database to establish functional relationships between explicative and predicted variables, even if the relationship between variables is not continuous and difficult to approximate with parametric models. In the MARS method, these relationships are approximate using linear-based functions such as:

$$B(x) = \begin{cases} (x - t) \;\; if \; x \geq t \\ \quad else \; 0 \end{cases}$$

where t points are nodes connecting two regression segments. The general equation of the model for the variable t depending on the variable x is obtained by combining the linear-based functions estimated through the least squares method:

$$y = f(t) = \beta_0 + \sum_{m=0}^{M} \beta_m B_m(t)$$

where B_m are linear-based functions with associated coefficients β_m.

K-nearest neighbours (kNN) method

The kNN method is an intuitive and non-parametric method used for classification and regression (Altman, 1992). The method is based on the determination of the k-nearest neighbours in a population of training values. In the regression application, the predicted value is the average of the k-nearest neighbours. To forecast a variable value at time t, the kNN method requires the use of historical data from the individual to be forecasted, and a learning database with values for previous days and time t for a population of individuals. Different parameters have to be determined for the calculation: the number k of neighbours, the type of distance to be calculated between individuals, the possible weighing of distance in calculation of the average (to assign weights to the contributions of the neighbours, so that the nearer neighbours contribute more to the average than the more distant ones), the number of previous days to be used to determine the nearest neighbours, and the weight to give to recent observations compared to past observations. For continuous variables such as BW or DFI, the Euclidian distance is commonly

used. Preliminary tests we made showed that a triweight kernel and k = 3 could be considered for calculations on BW and DFI.

Calculations

For daily measurements of FI and BW, the forecasting performance at day+1 of the DES and MARS methods were compared. For the DES method, values for the smoothing constant α ranging from 0.1 to 0.9 by a 0.1 increment were tested. As DFI can vary considerably from one day to another, we considered that the forecasting of DFI may be too sensitive to forecast these variations. Consequently, and similarly to BW, the cumulative FI was forecasted. The DFI can be determined from the cumulative FI.

For weekly available data, we considered that forecasting of DFI is required for the application of precision feeding. Consequently only forecasting of BW at day+7 was tested. The MARS method requires at least 8 historical data to perform forecasting whereas the DES method requires 3 data. Considering that this limits the usefulness of the MARS method, only the DES method was tested on BW for weekly data, with α ranging from 0.1 to 0.9. BW data at 7 day intervals were extracted from the original dataset to perform calculations.

The kNN method was used to illustrate the possibility to forecast BW or DFI at day+1 when only 1 or 2 historical data are available. This occurs for example at the beginning of data collection where the MARS or DES methods cannot be used. In the original dataset, data of 83 animals were used to create a learning database to forecast BW and DFI of the 36 other pigs.

All calculations were performed every day (or week) for each pig using the R software (version 3.3.2). The following functions and R packages were used: the earth function from the earth package (Milborrow, 2011) for the MARS method; the HoltWinters function from the stats package for the DES method; the kkNN function from the FNN (Beygelzimer *et al.*, 2013) and kknn (Schliep and Hechenbichler, 2016) packages.

Number of previous data used in calculation

The DES and MARS methods were tested on daily BW and cumulative DFI data using the 8, 13 or 20 historical (i.e., latest) data (the 8 data corresponds to the minimal number of data for the MARS method). Moreover, the 8 historical data refer approximatively to one week of data recording. The 13 and 20 historical data were chosen as they refer to a BW or DFI forecasting at 14th or 21st days, i.e. at the end of the 2 or 3 last weeks of data collection. Thus, the calculation started at day 9 and was performed on 8 historical data or integrated

progressively up to 13 or 20 historical data depending on the targeted number of historical data. For the weekly BW, the calculation started at day 4 and a maximum of 8 historical data was used.

Missing data

For some pigs, data for BW or DFI were missing in the dataset. As the methods used cannot deal with missing values, missing data were created to obtain a specific completed datasets for each tested method. For data before day 4, BW and DFI were created by adding 0.75 kg and 27 g to previous BW and DFI, respectively. From day 4, data were created using the tested method with corresponding number of historical data.

Statistics

The residual mean square error of prediction (RMSEP) was calculated between forecasted values and measured value for each pig, excluding the first 8 days for tests on DFI and daily BW forecasting, and the first 3 days for weekly BW forescasting. The RMSEP were submitted to an analysis of variance (proc MIXED, SAS v9.4, Inst. Inc. Cary, NC). Least-square means were compared. For the daily BW or cumulative FI, the main effects were the forecasting method (with MARS and DES with α ranging from 0.1 to 0.9), the number of historical data (8, 13 or 20) and their interaction. For the weekly BW, the main effect was the α value (ranging from 0.1 to 0.9).

Results and Discussion

Daily forecasting of BW

The RMSEP of daily BW decreased with increasing number of historical data used (Table 1). However, this decrease was significant only from 8 to 13 data for MARS method and $\alpha = 0.1$ and 0.3 for DES method and from 13 to 20 data for $\alpha = 0.3$ (method x number of historical data interaction, $P < 0.001$). The lowest RMSEP (1.1 kg) were obtained with the MARS method (13 or 20 historical data). This corresponds to 3% and 0.7% of BW at the beginning and the end of test period, respectively. For the DES method, the lowest RMSEP were obtained with $\alpha = 0.3$ to 0.6. These α values give an intermediate weight between recent and less recent data. This means that most recent or oldest historical data should not be given too much weight to forecast BW. The results indicate that the MARS method used with 13 to 20 historical data could be preferred to the DES method for daily forecasting of BW, avoiding the choice of an α value. Quiniou et al. (2017) observed that the DES method with $\alpha = 0.6$ to obtain the best RMSEP for data from pigs restrictively fed. Hauschild et al. (2012) used $\alpha = 0.1$ to forecast BW (BW range = 25 to 105 kg,

without reporting the RMSEP), giving a high weight to less recent data. This indicates that such comparisons could be influenced in part by the BW range or by the feeding level that can affect BW.

Weekly forecasting of BW

The RMSEP of weekly BW were lowest with α = 0.5 to 0.6 (2.14 kg; Table 2) and increased for lower or higher α values. The highest RMSEP were obtained with α = 0.1 and 0.2. As for daily BW forecasting, giving a quite balanced weight to recent and less recent data allowed to better forecast BW, especially compared to privileging oldest data. The RMSEP values observed for weekly BW were 1 to more than 2 kg higher than for daily BW forecasting. The BW varies from day to day because of growth but also due to eating, defecating and urinating patterns. Consequently the precision of forecasting is affected when using weekly data where the difference between two successive points can be sensitive to the conditions of BW measurement.

Table 1: RMSEP (kg) of daily BW forecasting using the double exponential smoothing (α value ranging from 0.1 to 0.9) or MARS methods and 8, 13, or 20 historical data[1].

Nb. of data	Method									
	MARS	Double exponential smoothing (α value)								
		0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
8	1.34^{a}	2.00^{b}	1.23^{c}	1.29^{ac}	1.21^{cd}	1.19^{cd}	1.22^{c}	1.27^{ac}	1.34^{a}	1.46^{e}
13	1.13^{a}	1.79^{b}	1.27^{c}	1.21^{cd}	1.18^{ad}	1.19^{ac}	1.22^{cd}	1.27^{c}	1.34^{c}	1.46^{e}
20	1.11^{a}	1.43^{b}	1.26^{c}	1.19^{cd}	1.18^{ad}	1.19^{cd}	1.22^{cd}	1.27^{ce}	1.34^{e}	1.46^{b}

1. Least-square means. The main effects of method, number of historical data and their interaction were significant at P < 0.001 (residual standard deviation of the model = 0.31 kg). Within a row, values followed by common letters are not significantly different for the method effect (P < 0.05).

Table 2: RMSEP (kg) of weekly BW forecasting using the double exponential smoothing method on 8 historical data with α values ranging from 0.1 to 0.9[1].

	α value								
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
RMSEP (kg)	4.18^{a}	2.79^{b}	2.43^{c}	2.23^{cd}	2.14^{d}	2.14^{d}	2.19^{d}	2.28^{cde}	2.45^{cde}

1. Least-square means. Effect of α value significant at P < 0.001 (residual standard deviation = 0.90 kg). Values followed by common letters are not significantly different (P < 0.05).

Daily forecasting of cumulated FI

With the MARS method, the RMSEP of cumulated FI significantly increased with an increasing number of historical data used (Table 3). With the DES

method, the number of historical data did not influence the RMSEP ($P > 0.05$), except for $\alpha = 0.2$ where the RMSEP was significantly lower for 8 historical data compared to 13 or 20 historical data. The lowest RMSEP values (0.49 kg) were obtained with the DES method and $\alpha = 0.6$ to 0.8, even though the difference between the MARS and DES methods was not significant for 8 historical data. These RMSEP values are lower than those obtained for daily BW, despite the fact that the daily increase in FI is higher than in BW (ADFI = 2.3 kg/d vs average daily gain = 1.06 kg/d) and the variation in DFI can be important from a day to another. This potential less smooth evolution of cumulative FI could also explain the increase in RMSEP with increasing number of historical data observed with the MARS method that uses combination of linear regressions. For the cumulative FI, the best forecasting was obtained by giving a higher weight to more recent data ($\alpha > 0.6$). In contrast, Hauschild et al. (2012) used $\alpha = 0.1$ to forecast DFI (rather than cumulated FI). The present results indicate that the DES method used with 8 to 20 historical data could be preferred to the MARS method for daily forecasting of the cumulative FI, with $\alpha = 0.6$ to 0.8, taking advantage of using a larger number of available historical data (more than 8) with a better RMSEP.

Table 3: RMSEP (kg) of cumulated FI forecasting using the double exponential smoothing (α value ranging from 0.1 to 0.9) or MARS methods and 8, 13, or 20 historical data[1].

Nb. of data	Method									
	MARS	Double exponential smoothing (α value)								
		0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
8	0.52^{a}	1.06^{b}	0.67^{c}	0.60^{d}	0.54^{ae}	0.50^{ae}	0.48^{a}	0.48^{a}	0.49^{a}	0.51^{a}
13	0.60^{a}	1.04^{b}	0.73^{c}	0.61^{a}	0.54^{d}	0.50^{de}	0.49^{e}	0.49^{e}	0.49^{e}	0.52^{de}
20	0.70^{a}	1.02^{b}	0.75^{c}	0.61^{e}	0.54^{f}	0.51^{fg}	0.49^{g}	0.49^{g}	0.50^{fg}	0.52^{fg}

1. Least-square means. The main effects of method, number of historical data and their interaction were significant at $P < 0.001$ (residual standard deviation of the model = 0.17 kg). Within a row, values followed by common letters are not significantly different for the method effect ($P < 0.05$).

<u>The kNN method for obtaining initial data</u>

We forecasted the BW and DFI with the kNN method at day 2 and 3 of data collection, on the basis of the first day or first 2 days of available data. The RMSEP of BW and DFI were 0.86 kg (± 0.73 kg) (n = 35 due to an outlier) and 0.33 kg (± 0.16 kg) (n = 36), respectively. This RMSEP was lower than for the two other methods although obtained with fewer data. The RMSEP of BW was higher and more variable than that for DFI, probably due to differences in the absolute value between BW and DFI at this stage (38 kg vs 1.27 kg/d, respectively). This method can be useful for forecasting when other methods

cannot be used. However it requires a database on BW and DFI obtained in similar pigs reared in similar conditions. It is likely to be more sensitive to day-to-day variation than the DES or MARS methods that can smooth variation by using a larger number of historical data for the same pig.

Conclusions

The results of this study indicated that the MARS method used with 13 to 20 historical data is to be preferred to the DES method for daily forecasting of BW. Conversely the DES method is preferred to the MARS method for daily forecasting of cumulative FI, and can be used to forecast weekly BW. The kNN method can be useful to forecast BW or DFI at the start of data collection, when the two other methods cannot be used. The results about DES and MARS methods have to be confirmed on larger datasets and on different rearing conditions (e.g., with restricted feeding). However, the methods can be integrated for an efficient forecasting of BW and FI in a decision-support tool for precision feeding.

Acknowledgements

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant N° 633531. The authors gratefully acknowledge N. Quiniou and M. Marcon (IFIP) for methodological support.

References

Altman, N. S. 1992. An introduction to kernel and nearest-neighbor nonparametric regression. *The American Statistician* **46** 175–185.

Andretta, I., Pomar, C., Rivest, J., Pomar, J., Lovatto, P.A., and Neto, J.R. 2014. The impact of feeding growing-fisnihing pigs with daily tailored diets using precision feeding techniques on animal performance, nutrient utilization, and body and carcass composition. *Journal of Animal Science* **92** 3925-3936.

Beygelzimer, A., Kakadet, S., Langford, J., Arya, S., Mount, D., and Li, S. 2013. *FNN: Fast Nearest Neighbor Search Algorithms and Applications*. R package version 1.1. https://CRAN.R-project.org/package=FNN

Brossard, L., Dourmad, J.-Y., Rivest, J., and van Milgen, J. 2009. Modelling the variation in performance of a population of growing pig as affected by lysine supply and feeding strategy. *Animal* **3** 1114-–1123.

Claycombe, W., and Sullivan, W. 1977. *Fundamentals of forecasting.* Reston Publishing, Reston, VA.

Friedman, J. H. 1991. Multivariate Adaptive Regression Splines. *Annals of Statistics* **19** 1–67.

Hauschild, L., Lovatto, P. A., Pomar, J., and Pomar, C. 2012, Development of sustainable precision farming systems for swine: Estimating real-time individual amino acid requirements in growing-finishing pigs. *Journal of Animal Science* **90** 2255-–2263.

Marcon, M., Brossard, L., and Quiniou, N. 2015. Precision feeding based on individual daily body weight of pigs with an automatic feeder developed to allow for restricting feed allowance. In: *Proc. of the 7th European conference on Precision Livestock Farming*, Guarine M. and Berckmans D. (Ed), Milan, Italy, 592-602.

Milborrow, S. 2011. *Earth: multivariate adaptive regression spline models.* R package version 4.4.9.1. URL http://CRAN.R-project.org/package=earth

National Research Council (NRC), 1998. *Nutrient requirements of swine, 10th revised edition.* National Academic Press, Washington, DC, USA.

Pomar, C., Hauschildt, L., Zhang, G.H., Pomar, J., and Lovatto, P.A. 2009. Applying precision feeding techniques in growing-finsihing pig operations. *Revista Brasileira de Zootechnia* **38** 226-237 (supl. especial).

Quiniou, N., Brossard, L., and Marcon, M. 2017. Assessment of the dynamic growth of the fattening pigs from body weight measured daily and automatically to elaborate precision feeding strategies In: *Proc. of the 8th European conference on Precision Livestock Farming*, XXXX and XXX (Ed), Nantes, France, XX-XX.

R Core Team (2016). *R: A language and environment for statistical computing.* R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/.

Schliep, S., and Hechenbichler, K. 2016. *kknn: Weighted k-Nearest Neighbors.* R package version 1.3.1. https://CRAN.R-project.org/package=kknn

van Milgen, J., Valancogne, A., Dubois, S., Dourmad, J. Y., Sève, B., and Noblet, J. 2008. InraPorc: A model and decision support tool for the nutrition of growing pigs. *Animal Feed Science and Technology* **143** 387-405.

Development of a decision support tool for precision feeding of pregnant sows

J.Y. Dourmad[1], L. Brossard[1], C. Pomar[2], J. Pomar[3], P. Gagnon[4], L. Cloutier[4]

[1]*INRA, UMR Pegase, 35590 Saint-Gilles, France,*
[2]*Agriculture and Agri-Food Canada, 2000 rue Collège, Sherbrooke J1M 0C8, Canada,* [3]*Universitat de Lleida, Dep. Agricultural Engineering, 25198 Lleida, Spain,*
[4]*Centre de Développement du Porc du Québec inc., 2590 bd Laurier, Québec G1V 4M6, Canada;*
jean-yves.doumad@inra.fr

Abstract

Nutritional studies indicate that nutrient requirements for pregnancy largely differ among sows and according to the stage of pregnancy, whereas in practice the same diet is generally fed to all sows from a given herd. In this context, the availability of new technologies for high throughput phenotyping of sows and their environment, and of innovative feeders that allow the distribution of different diets, offers opportunities for a renewed and practical implementation of prediction models of nutrient requirements, in the perspective of improving feed efficiency and reducing feeding costs and environmental impacts. The objective of this study was thus to design a decision support tool that could be incorporated in automated feeding equipment. The decision support tool was developed on the basis of InraPorc® model. The optimal supply for a given sow is determined each day according to a factorial approach considering all the information available on the sow: genotype, parity, expected prolificacy, gestation stage, body condition (i.e. weight and backfat thickness), activity and housing (i.e. type of floor and ambient temperature). The approach was tested using data from 2500 pregnancies on 540 sows. Energy supply was calculated for each sow to achieve, at farrowing, a target body weight established based on parity, age at mating and backfat thickness (18 mm). Precision feeding (PF) with the mixing of two diets was then simulated in comparison with conventional (CF) feeding with a single diet. Compared to CF, PF reduced protein and amino-acid intake, N excretion and feeding costs. At the same time, with PF, amino acid requirement was met for a higher proportion of sows, especially in younger sows, and a lower proportion of sows, especially older sows, received excessive supplies. This project has received funding from the European Union's Horizon 2020 research and innovation programme, grant agreement No 633531. The data

used for the simulations were issued from a project conducted within the AgriInnovation Program from Agriculture and Agri-food Canada.

Keywords: sow, gestation, precision feeding, decision support tool

Introduction

Nutrient requirements for pregnant sows largely differ among animals according to their body condition at mating, their parity, their expected reproductive performance, their stage of pregnancy, their physical activity and the housing conditions (Dourmad et al., 2008). In practice, the feeding level of pregnant sows is to some extent adapted to take account of these variations, but generally the same diet is fed to all sows from a given herd. Moreover, the group housing of pregnant sows, for welfare issues, makes it sometime difficult to feed each animal individually, especially when sows are raised in small groups with a common feeding trough. Conversely, the group housing of pregnant sows also favoured the development of innovative technologies allowing the distribution of feed individually, for sows raised in large groups, using automated electronic feeders and animal identification.

The objective of this study was thus to design a decision support tool to be incorporated in automated feeding equipment, as already developed for fattening pigs (Cloutier et al., 2015), and to test it using a set of data already available from an experimental farm.

Development of the decision support tool

Description of the general approach

The description of the general approach is illustrated in Figure 1. The final objective is to send a command to the automated feeder to proceed with feed distribution. This command informs the feeder with the amount of each of the different diets, generally two diets differing in their nutrient content, to be fed to a given sow over a given day or period.

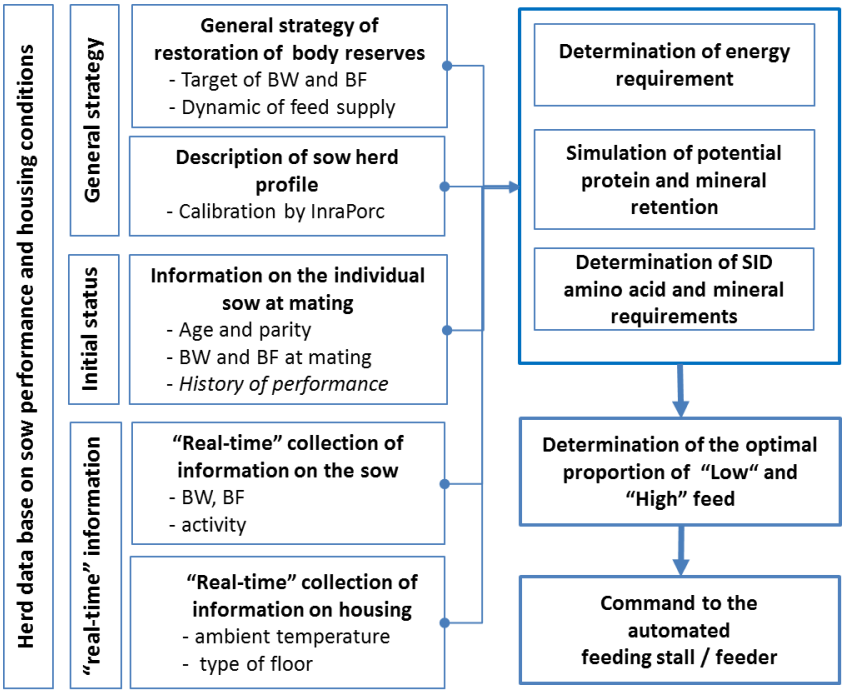


Figure 1. General description of the approach

To take that decision, the decision support system (DSS) uses information relative to the individual sow to be fed, her housing conditions and the general feeding strategy in the farm. This information is stored in a herd database that will not be described in detail in this paper. Different types of information are stored in this database: (i) the description of herd profile and performance, and the general strategy of management of sow body reserves, as described in InraPorc tool (Dourmad et al., 2008), (ii) information about each individual sow at mating, especially their age, parity, body weight (BW) and backfat thickness (BF), and their history of performance, and (iii) real time data collected either automatically by different sensors about the sows (e.g. BW, physical activity, feeding or drinking activity…) or their environment (ambient temperature, humidity…).

From the available information, which may vary according to the equipment available on the farm and the data management system, the DSS build the "best guess" decision to be transmitted to the automated feeder. This involves mainly two steps: (i) the determination of energy, amino acid and mineral requirements and (ii) the determination of the amount and composition of the ration to be fed. This ration is prepared from the mixing of different diets, generally two diets, available in the automated feeder.

Determination of energy and amino acid requirements

Energy and nutrient requirements are determined according to a factorial approach. Metabolizable energy (ME) requirement is calculated as the sum of the requirements for maintenance, physical activity and thermoregulation, growth and constitution of body reserves, and development of foetuses and uterine contents (Table 1, eq. 1).

Table 1. Main equations describing nutrient utilization (from Dourmad et al., 2008)

Energy utilisation	$ME = ME_m + ER_c / k_c + ER_m / k_m$	[1]
	ME_m : ME for maintenance	
	ER_c : energy retention in conceptus	
	ER_m: energy retained in maternal tissues	
	$k_c = 0.50$ efficiency of ME retention in conceptus	
	$k_m = 0.77$ efficiency of ME for maternal	
ME for maintenance and effect of activity and ambient temperature	in thermoneutral conditions	
	$ME_m = 440$ kJ.BW$^{-0.75}$.d^{-1} (for 240 min.d^{-1} standing activity)	[2]
	physical activity = 0.30 KJ. kg BW$^{-0,75}$.d^{-1}.min^{-1} standing	[3]
	below lower critical temperature (LCT)	
	In individually housed sows	
	LCT = 20°C and HP increases by 18 kJ.kg BW$^{-0.75}$.d^{-1}.°C^{-1}	[4]
	In group-housed sows	
	LCT = 16°C and HP increases by 10 kJ.kg BW$^{-0.75}$.d^{-1}.°C^{-1}	[5]
Energy retention	ERc : Energy in conceptus (kJ)	
	$Ln(ERc) = 11.72 - 8.62\ e^{-0,0138\ t} + 0.0932$ Litter size	[6]
	ERm : Energy in maternal tissues (MJ)	
	$ER_m = 13.65$ BW gain + 45.94 BF gain	[7]
Nitrogen retention	NR : total N retention (g.d^{-1}),	
	NR_c: N in conceptus (g)	
	$Ln(6.25\ NR_c) = 8.090 – 8.71\ e^{-0,0149\ t} + 0.0872$ Litter size	[8]
	$NR = 0.85\ (d(NR_c)/dt – 0.4 + 45.9\ (t/100) – 105.3\ (t/100)^2 + 64.4\ (t/100)^3 + a\ (ME - ME_{mm})\ )$	[9]
	where a = f(BW at mating) and $ME_{mm} = ME_m$ at mating	
SID lysine requirement g/d	$SID\ Lys = 0.036 \times BW^{-0.75} + 6.25\ NR \times 0.065 / 0.65$	[10]

ME requirement for maintenance is calculated according to BW (eq. 2) and modulated according to physical activity (eq. 3), and ambient temperature

depending on housing conditions (eq. 4 and 5). The cumulated amount of energy retained in sow body reserves over pregnancy (ER_m) is determined according to the amount of energy in maternal body at mating and the targeted amount after farrowing. These amounts are calculated from sow BW and BF according to the equations proposed by Dourmad et al (1997) (eq. 7). The corresponding metabolizable energy (ME) requirement is calculated from ER_m and the efficiency of energy retention in maternal tissues (k_m). ME requirement for conceptus is calculated according to energy retention in conceptus (ER_c, eq. 6) and the efficiency of energy retention in conceptus (k_c).

Total nitrogen retention (eq. 9) is calculated as the sum of N retained in conceptus (eq. 8) and the nitrogen retained in maternal tissues. Standardized ileal digestible (SID) lysine requirement is the calculated assuming 6.5% lysine in retained protein (NR x 6.25) with an efficiency of retention of 65% (eq.10).

Utilisation of the decision support system (DSS)

Description of the database

A database issued from an experimental farm (Table 2) was used to simulate the utilization of the DSS. This database contains the data from 2511 gestating sows with information about their body condition at mating (i.e. body weight, BW, and backfat thickness, P2) and at farrowing. These data were used to calibrate InraPorc parameters for this phenotype. Litter size at farrowing averaged 14.1 for a mean piglet birth weight of 1.48 kg. Sows BW at mating increased from 163 to 251 kg from parity 1 to parity 8, whereas P2 tended to be higher in first and second parity and then remained rather constant.

Table 2. Description of the data base

Parity	n° sows	Average Litter size	Average Piglet weight, g	Average at mating		Average target after farrowing[2]	
				BW[1], kg	P2[1], mm	BW[1], kg	P2[1], mm
1	392	13.3	1405	163	16.9	203	18
2	389	13.5	1557	192	15.9	227	18
3	413	14.1	1523	211	15.0	243	18
4	384	14.9	1480	227	14.4	255	18
5	335	15.0	1472	234	14.1	260	18
6	253	14.8	1438	241	14.1	263	18
7	187	13.9	1445	246	14.6	265	18
8	158	13.6	1455	251	14.9	267	18
all	2511	14.1	1478	214	15.2	244	18

[1]BW sows net body weight; P2 sows backfat thickness
[2]A target of BW is calculated for each sow according to BW and age at mating. The same target of P2 is used for all sows.

Determination of energy and lysine requirement

A target of maternal BW (i.e. total BW minus uterus contents) was calculated for each sow according to her age and BW at mating (Table 2). Target of P2 at farrowing was fixed to 18 mm for all sows according to the usual recommendation for this farm.

The DSS was then used to calculate the average ME and feed requirement over pregnancy (Table 3). Average ME requirement varied according to parity, from 31 to 36.8 MJ /d, and it was highly variable between sows with a coefficient of variation of about 7%.

Table 3. Calculated ME (MJ/d) and SID lysine requirement (g/kg feed) and supplies per parity, and % of low nutrient density feed (L) and % of reduction of lysine in precision feeding (PF) compared to conventional feeding (CF) strategy.

			Av. lysine req		Lysine supply in PF strategy[1]		
Parity	ME MJ/d	Feed. kg/d	30 d	114 d	Average g/kg feed	L feed	Reduction PF vs CF,%
1	31.0	2.4	3.63	6.23	4.01	67	17%
2	34.0	2.6	3.20	5.80	3.62	78	24%
3	35.5	2.7	2.91	5.41	3.32	85	28%
4	36.4	2.8	2.68	5.14	3.09	89	30%
5	36.8	2.8	2.59	5.09	3.02	89	31%
6	36.6	2.8	2.52	4.92	2.91	91	32%
7	35.9	2.7	2.48	4.79	2.83	92	33%
8	35.7	2.7	2.44	4.72	2.77	93	33%
all	35.0	2.7	2.89	5.38	3.28	84	27%

[1]in CF feeding strategy lysine content was constant and equal to 4.8 g/kg feed

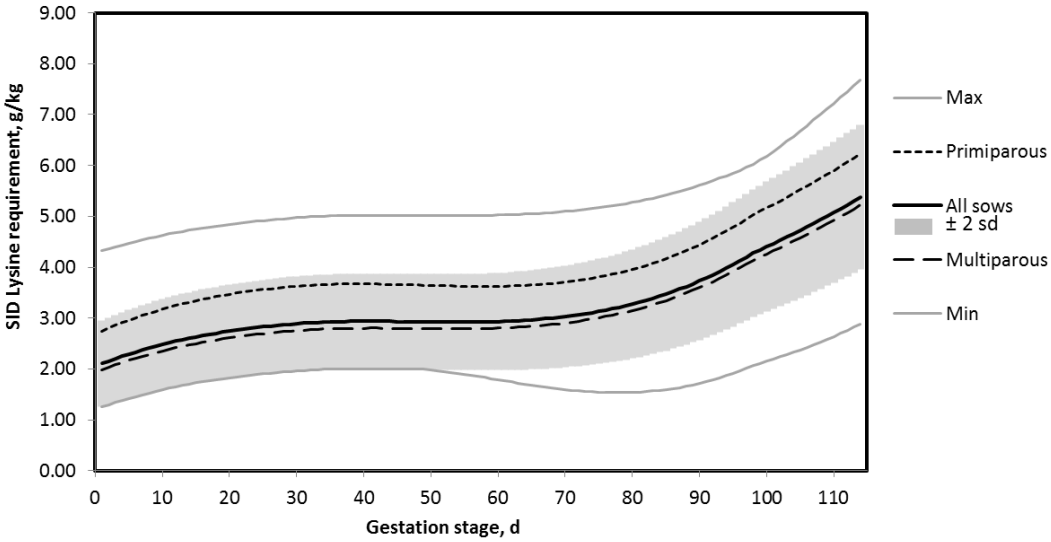


Figure 2. Evolution of SID lysine requirement (g/kg feed) of primiparous (mean), multiparous (mean) of all sows (mean ± 2sd) sows, and minimum and maximum requirement, according to gestation stage.

The dynamic of SID lysine requirement, expressed in g/kg feed, according to gestation stage is presented in Figure 2. Average SID lysine requirement increases with gestation stage with a large variability among sows, the highest value being 3-fold higher that the lowest. The requirement is also affected by sows parity with much higher values in primiparous than in multiparous sows.

Evaluation of a precision feeding strategy

These simulated data were used to evaluate the interest of precision feeding. A conventional 1-phase feeding strategy (CF) was compared to a precision feeding (PF) strategy consisting in the mixing of two diets with either a low (L) or a high (H) nutrient content. SID lysine content was assumed to 4.8, 3.0 and 6,0 g/kg feed and protein content to 14%; 9% and 16% in diets CF, L and H, respectively.

On average the level of incorporation of L diet in the PF strategy was 84%, the value being lower in first parity sow (67%). The level or incorporation of L diet decreased with gestation stage from almost 100% in the first week to less than 30% in the last week.

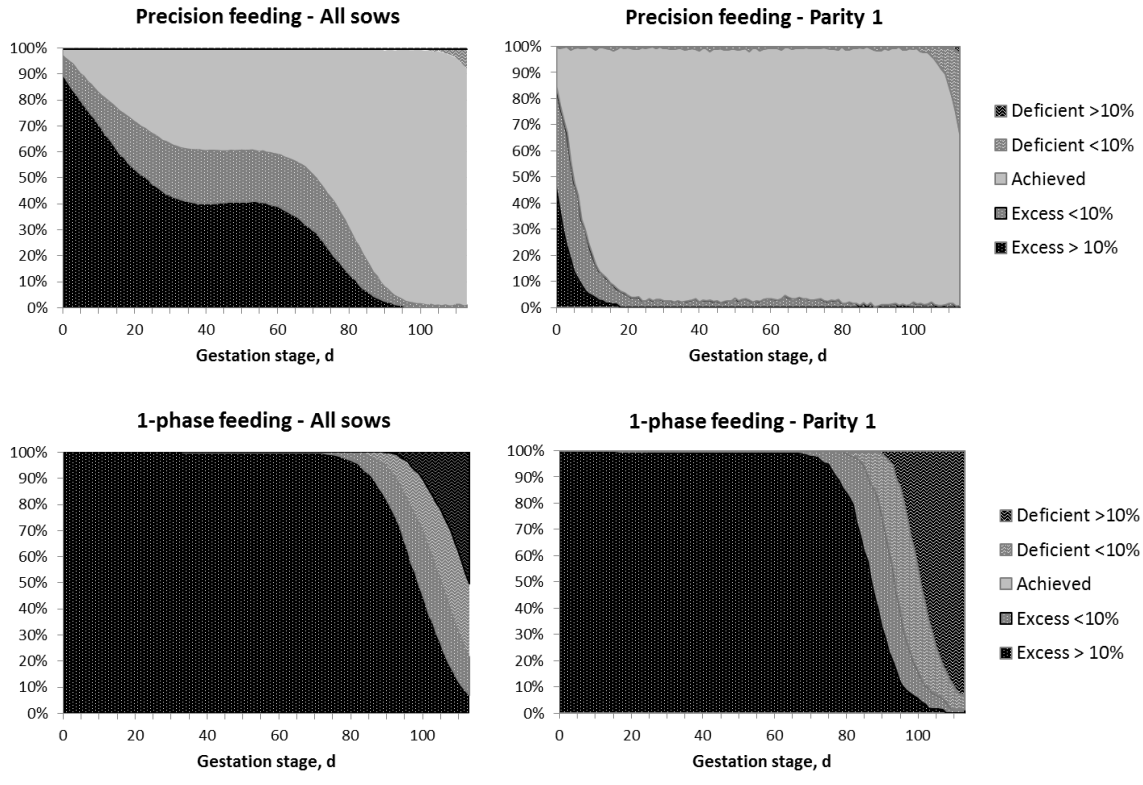


Figure 3. Effect of the feeding strategy (1-phase vs precision feeding) during gestation on the proportion of sows (among all sows or among first-parity sows) that received adequate, deficient or in excess lysine supplies.

Compared to the 1-phase strategy, PF strategy resulted in 27% decrease in total SID lysine supply and 28% decrease in total crude protein supply. Moreover, the proportion of sows that were underfed in the last two weeks of lactation decreased from more than 60% with 1CF to less than 5% with PF. For first parity sow the difference was even more marked, with almost all primiparous sows receiving deficient diets over the last 10 days of pregnancy with CF, compared to about 10% with PF (Figure 3). Conversely the proportion of sows that were overfed was drastically reduced (Figure 3).

Conclusions

The results from this study indicate that, in the same way as in fattening pigs (Pomar et al., 2009), precision feeding of gestating sows appears a win-win strategy which allows improving nutritional supplies of sows whilst reducing total protein supply and consequently reducing N excretion. The effect on

feeding cost was not evaluated but it may be expected that it will also be reduced (Dourmad et al., 2009). The DSS developed in this study allows adapting the amount and composition of feed to each sow according to her body condition at mating and expected prolificacy, and to stage pregnancy. This DSS will also allow taking account of information collected by sensors during gestation, such as BW, backfat thickness or physical activity, on the environment, such as ambient temperature.

Acknowledgements

This project has received funding from the European Union's Horizon 2020 research and innovation programme, grant agreement No 633531. The data used for the simulations were issued from a project conducted by the *Centre de Développement du Porc du Québec inc* (CDPQ) in collaboration with INRA, within the AgriInnovation Program from Agriculture and Agri-food Canada.

References

Cloutier L., Pomar C., Létourneau-Montminy M.-P., Bernier J.F., Pomar J. 2015. Evaluation of a method estimating real-time individual lysine requirements in two lines of growing-finishing pigs. *Animal 9(4)*, 561-568.

Dourmad J.Y., Etienne M., Valancogne A., Dubois S., Van Milgen J., Noblet J. 2008. InraPorc: a model and decision support tool for the nutrition of sows. *Animal Feed Science and Technology 143*, 372-386.

Dourmad J.Y., Brossard L., van Milgen J. 2009. Nutrition-Environment interaction in the sow : interest of modelling approach. in Proceeding of the 30th Western Nutrition Conference, Winnipeg, Manitoba, 182-192.

Pomar C., Hauschild L., Zhang G.-H., Pomar J., Lovatto P.A. 2009. Applying precision feeding techniques in growing-finishing pig operations. *Brazilian Journal of Animal Science 38*, 226-237.

Assessment of the dynamic growth of the fattening pigs from body weight measured daily and automatically to elaborate precision feeding strategies

N. Quiniou[1], L. Brossard[2], M. Marcon[1]
[1, 2]*Unité Mixte Technologique Ingénierie des Systèmes de Production Porcine*
[1]*IFIP-Institut du Porc, BP 35104, 35651 Le Rheu cedex, France*
[2]*INRA-Agrocampus Ouest, UMR1348 PEGASE, 35590 Saint-Gilles, France*
nathalie.quiniou@ifip.asso.fr

Abstract

Growing pigs are often fed below *ad libitum* to increase their feed efficiency and carcass leanness. When energy supply is under control, precision feeding is implemented through the amino acids (AA). As the AA requirement depends on the body weight (BW) for the maintenance part and on its daily variation (ΔBW) for the growth part, the adequacy between requirements and supplies on day D+1 depends on the adequacy of predicted BW_{D+1} and ΔBW_{D+1}. Data sets from four trials were used to forecast BW from time series analyses based either on multivariate adaptive regression splines (MARS) or double exponential smoothing (HWα) methods using the *k* latest data (8, 14 or 20). Pigs (n = 117) were group-housed and restrictively fed, and their BW was recorded daily and individually with an automatic scale (n = 11 736). With $HW_{0.6}$, the RMSEP of BW_{D+1} was the smallest one (1.21 kg) and not influenced by *k*. Linear regression on the *l* latest forecasted BW was used to assess ΔBW_{D+1}. At the beginning of the trial, ΔBW_{D+1} was more difficult to predict from BW forecasted with MARS than with $HW_{0.6}$. Descriptive statistics of individual variation of ΔBW_{D+1} based on MARS and $HW_{0.6}$ were comparable with $k = l = 20$ only after removal of the first 19 days. Compared to other methods studied, the method $HW_{0.6}$ seems to be the best compromise to forecast BW_{D+1} and ΔBW_{D+1} of restrictively fed pigs.

Keywords: Pig, precision feeding, body weight, time series, dynamic growth, modelling, nutrition

Introduction

In growing pigs, precision feeding has been implemented for around 15 years toward an improved adequacy of amino acids (AA) supply to requirements (Pomar *et al.*, 2009). The first aim is to avoid a deficiency that would decrease carcass leanness and feed efficiency and subsequently the farmer's income. The second aim is to limit the excess that increases the price of feeds and the

environmental impact of pig production through N output. More recently the need to improve the efficient use of protein-rich resources has emerged.

New devices have been developed recently that can mix different diets in specific proportions adapted to meet the daily requirement of each pig in the group. Such devices can be used either by pigs fed *ad libitum* (Pomar *et al.*, 2009) or restrictively fed (Marcon *et al.*, 2015). Requirements have to be assessed from the individual characteristics of pigs, especially its body weight (BW) or body weight gain (ΔBW) at a given age. According to the factorial approach, BW is one of the major determinant of the AA requirement for maintenance, and the AA requirement for growth depends on ΔBW. On day D+1, the supply of AA depends on BW_{D+1} and ΔBW_{D+1} forecasted from available data, i.e. from BW recorded up to day D.

Like in many other species, BW increases with age according to a S shape in pigs fed *ad libitum*. Under feed restriction, this trajectory is modified but growth rate still varies in a dynamic way. With devices equipped with an automatic weighing scale, individual BW are recorded continuously. As pigs can be weighed many times per day at different fulfillment stages of their digestive tract and udder, average daily BW can temporary drop or rocket from one day to another even after removal of outliers and without any health problem. Then, the difficulty is to extract the dynamics of growth from the short-term variations of BW. Individual and daily BW measurements performed during four trials were used to investigate different methods to forecast future BW and BW gain using different numbers of past data.

Material and methods

Data sets

Four groups of pigs were successively studied in the IFIP experimental station at Romillé (Brittany, France) during a research program on the environmental impacts of the feeding management.. At the end of the post-weaning period (around 66 days of age), 96 pigs were identified by RFID ear tags and group-housed in a single pen that is equipped with a weighing-sorting station placed on four force sensors allowing for weighing pigs individually, with a 0.1 kg accuracy. Other details on the experimental room can be found in Marcon *et al.* (2015). In each trial different feeding strategies were compared, but one of them was the reference strategy that was repeatedly studied in all trials. It corresponded to a 2-phase strategy with diets formulated at 9.75 MJ net energy (NE)/kg and 0.9 g of digestible lysine/MJ NE as long as the pigs from this group weighed less than 67 kg on average, and 0.7 g/MJ afterwards. Daily feed

allowance depended on initial BW, stage of fattening and gender: 4% of the initial BW on D1, then + 27 g/d up to 2.4 kg/d for gilts and 2.7 kg/d for barrows. Only pigs of the reference groups studied until slaughter around 110 kg were kept in the final data set, i.e. 39, 22, 25 and 31 pigs in trials 1, 2, 3 and 4, respectively (corresponding to 11 736 BW).

Forecasting methods of BW_{D+1}

Time series prediction were performed using either multivariate adaptive regression splines (MARS) or double exponential smoothing model (HWα) where α is the smoothing parameter.

MARS: This method is a nonparametric regression procedure that does not imply any assumption on the relationship between the dependent and the independent variables (StatSoft Inc., 2013). It is most often used in case of difficult data mining problems, i.e. without simple and monotone variation of the variable studied. The earth function from the earth R package was used (Milborrow, 2011).

HWα: When a lot of past BW are available, a derivative function of the Gompertz function can be used to describe the pig's growth curve. This is not possible when only few BW are available at the beginning of the fattening period. Yet it indicates that the BW time series evolves in time with a form of trend that can be taken into account in the HW model. It assigns different weights to historical data depending on how recent they are, using a smoothing parameter α. The greater α is, the greater is the influence of the last measurement; values ranging from 0.1 to 0.9 by 0.1 were studied. The HoltWinters function from stats R package was used to fit a non-seasonal HW model (R Core Team, 2016), with the trend factor determined by minimizing the squared prediction error.

The k latest data used: Based on the hypothesis that the future BW depends on the *k* latest data, different values for *k* were investigated from 8 to 20. At the beginning of the trial, the number of most recent values used was lower than *k* as long as the trial has started less than *k* days earlier:

- *k* = 8: it is the lowest number of past data required for implementing the MARS,
- *k* = 14: it takes into account data obtained on the 2 previous weeks,
- *k* = 20: the time interval between 20 and 14 is the same as between 8 and 14

Missing values: None of the forecasting methods deals with missing values. As some days some pigs were not weighed or the BW was considered as an outlier, corresponding missing data had to be fulfilled. Before D = 4, a BW gain of 0.75 kg was assumed and added to the previous BW. Later, the BW forecasted on this day, with the same model, same value of *k* and eventually same value of α, was retained.

Prediction of BW_{D+1} and ΔBW_{D+1}, and other statistics

Forecasting of BW_{D+1} was performed every day for each pig. Each forecasted value after D4 was compared to the measured BW. The residual mean square error of prediction (RMSEP) was calculated per pig and submitted to an analysis of variance (proc GLM, SAS v9.4, Inst. Inc. Cary, NC) with the forecasting method (n = 10, MARS or HWα with α ranging from 0.1 to 0.9), the value of *k* (n = 8, 14 or 20), and the batch as the main effects. Average RMSEP per method were compared.

Due to day to day variation of BW, ΔBW_{D+1} cannot be calculated as the simple difference between the forecasted BW_{D+1} and the measured BW_D. Then linear regressions (proc Reg, SAS v9.4) were performed from the forecasted BW available over the *l* latest days (ranging from 10 to 20 by 2 d increment). For each pig, variation of ΔBW with time was characterized by its descriptive statistics (proc Univariate, SAS): 5th percentile, median, range of values observed, minimum and mean.

Table 1: Average RMSEP of BW[1] and comparison of the 10 methods run with three pools of recent data (*k*)[2]

Method		MARS	$HW_{0.1}$	$HW_{0.2}$	$HW_{0.3}$	$HW_{0.4}$	$HW_{0.5}$	$HW_{0.6}$	$HW_{0.7}$	$HW_{0.8}$	$HW_{0.9}$
	8	2.39^{a}	3.29^{d}	1.82^{c}	1.84^{c}	1.48^{h}	1.27^{j}	1.21^{j}	1.23^{j}	1.34^{i}	1.56^{g}
k	14	1.97^{b}	3.35^{d}	1.72^{f}	1.56^{g}	1.37^{i}	1.26^{j}	1.21^{j}	1.23^{j}	1.34^{i}	1.56^{g}
	20	1.84^{c}	2.09^{e}	1.75^{f}	1.53^{gh}	1.37^{i}	1.26^{j}	1.21^{j}	1.23^{j}	1.34^{i}	1.56^{g}

1. Arithmetic mean of the average RMSEP per trial (n =4). 2. Across the 3 lines and 10 rows, different letters indicate a statistical difference among methods with $P < 0.05$ from the analysis of variance with the method combined with the k value (M_{30}, n = 30, $P < 0.001$), the batch (B, n = 4, $P < 0.001$) and the interaction M_{30}×B ($P < 0.001$) as main effects.

Results and discussion

Prediction of BW on day D+1

In contrast to methods $HW_{0.1 \text{ to } 0.4}$ or MARS, the average RMSEP obtained with methods $HW_{0.5 \text{ to } 0.9}$ are not significantly influenced by *k* (Table 1). With the HW model, the RMSEP significantly increases when α increases from 0.7 to 0.9 or when it decreases

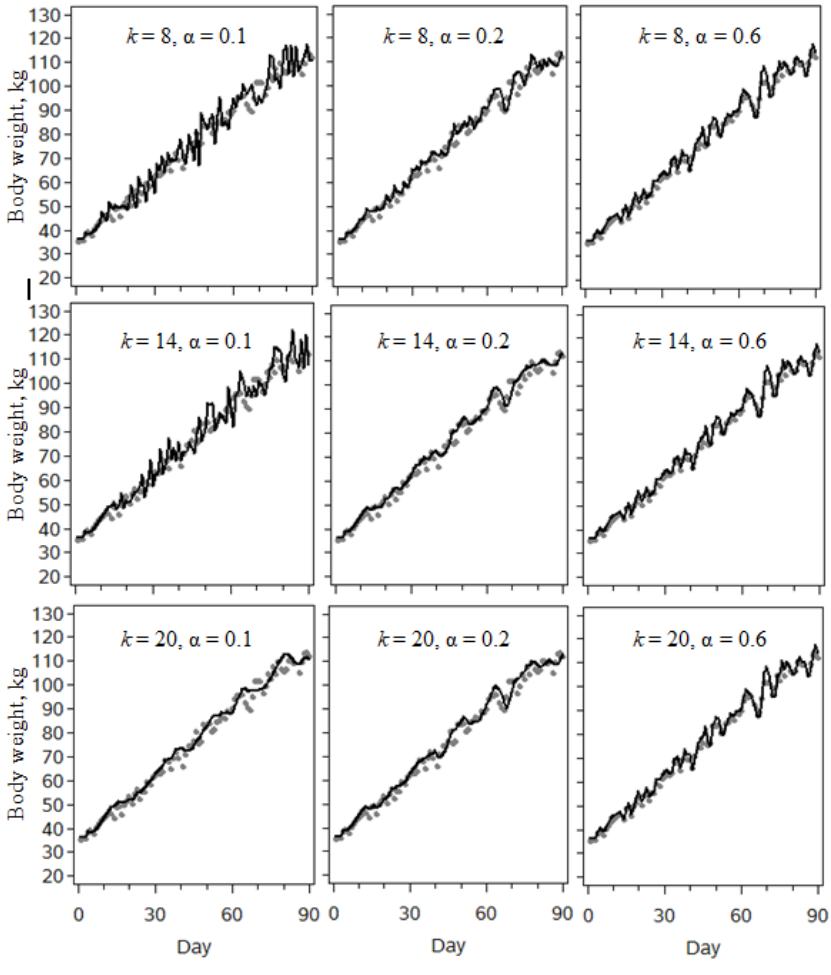


Figure 1 part 1: Example of comparison of measured (●) to forecasted (▬) BW with the HW method implemented with the 8, 14 or 20 latest values (*k)* and three values for the smoothing parameter α (pig 310 in trial 1). To be continued…

from 0.5 to 0.1 (Table 1). The lowest RMSEP is obtained with the $HW_{0.6}$ method. It does not differ significantly from those obtained with $HW_{0.5}$ and $HW_{0.7}$, but allows for the lowest difference among batches (not presented). In agreement with Hauschild *et al.* (2012), a smoother trajectory of BW is obtained

with $HW_{0.1}$ than with $HW_{0.6}$ (Figure 1), resulting in a higher RMSEP. With MARS, the RMSEP is intermediate between $HW_{0.1}$ and $HW_{0.2}$, even when the first 8 days are removed (instead of only the first 4 days). Figures 1 and 2 illustrate how the BW predicted with $HW_{0.1}$, $HW_{0.2}$, $HW_{0.6}$ and MARS fit the data for one given pig with different *k* tested.

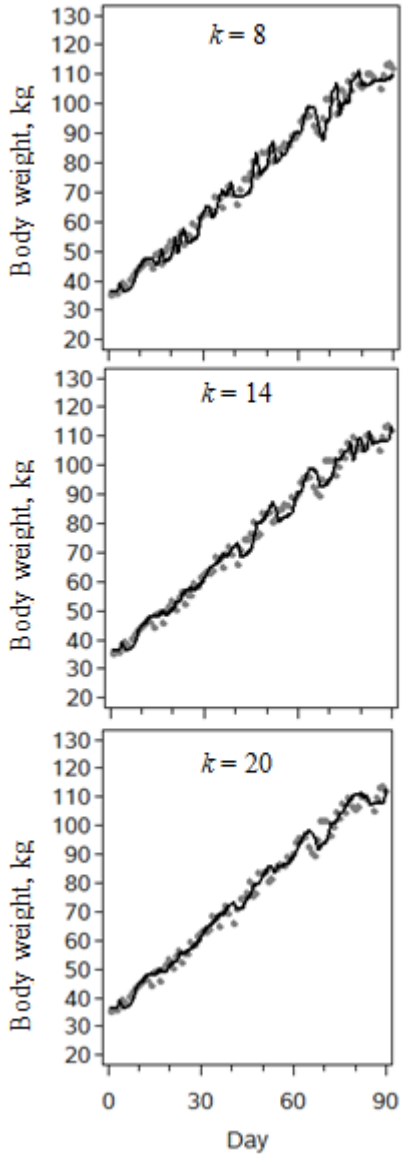
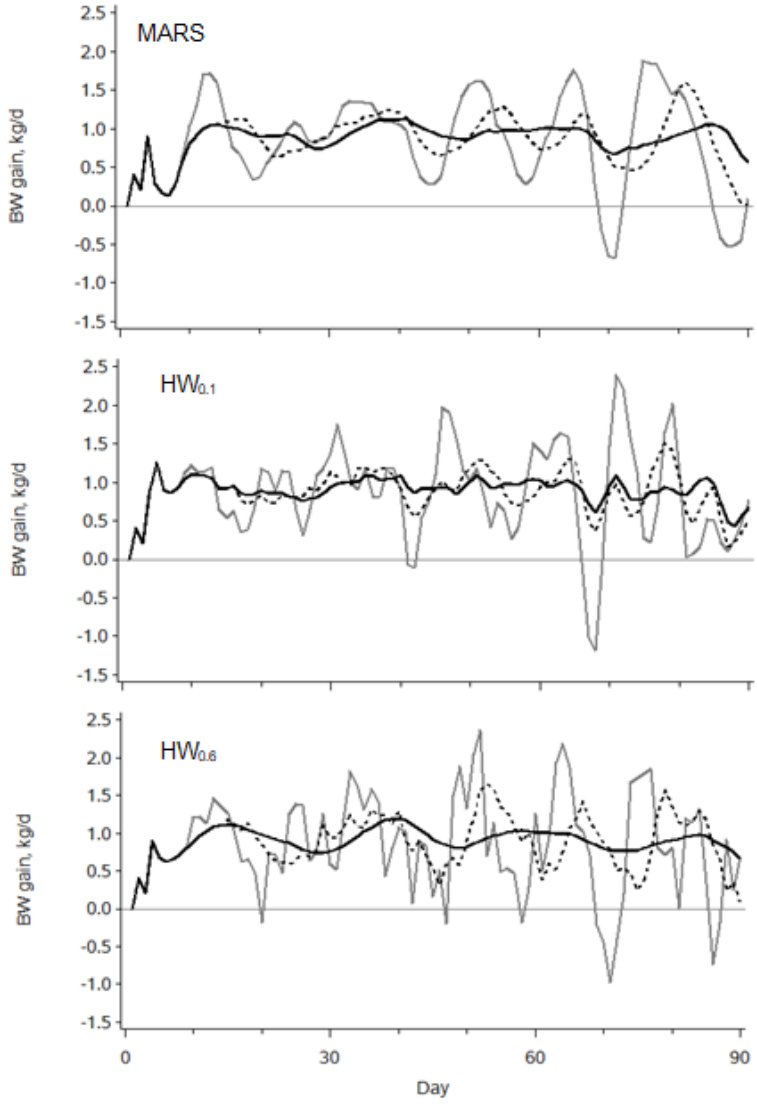


Figure 2: End of Figure 1 with the MARS method
(pig 310 in trial 1)

Prediction of ΔBW on day D+1

Based on results presented above, prediction of ΔBW was investigated from BW forecasted with $HW_{0.6}$, $HW_{0.1}$ and MARS. When daily ΔBW is assessed by regression over the *l* latest days, the smaller the *l* value, the more erratic is the variation of ΔBW whichever the method considered (MARS, $HW_{0.1}$ or $HW_{0.6}$ with k = 20). It can even be negative on certain days for some pigs (Figure 3).



W gain assessed from BW predicted with methods MARS, $HW_{0.1}$ and $HW_{0.6}$ by linear regression with k = 20 and l = 8 (▬), 14 (---) or 20 (▬) (pig 310 in trial 1)

As illustrated for one pig in Figure 3, the prediction of ΔBW is very difficult at the beginning of the trial when only few data are available. Therefore, descriptive statistics of daily variation of ΔBW were calculated for each pig after removal of the ΔBW assessed on the 4 first days (see paragraph "*Missing values*") or on the 20 first days (allowing regression on the 20 latest data when l = 20). Descriptive statistics were obtained for ΔBW assessed from the forecasted BW: with methods MARS, $HW_{0.1}$ or $HW_{0.6}$ with k = 20 and l = 20, or with $HW_{0.6}$ with k = 20 and l ranging between 10 and 20 by 2. From individual criteria per pig, an average per batch was calculated (proc Means, SAS) and results were pooled by an arithmetic mean in Table 2.

Table 2: Descriptive statistics[1] on ΔBW (g) obtained by linear regressions based on forecasted BW with different methods and number of available data

Method (k = 20)	$HW_{0.6}$						$HW_{0.1}$	MARS
l value[2]	10	12	14	16	18	20	20	20
Day D ≥ 5								
5th percentile	238	339	410	452	484	510	291	361
25th percentile	621	653	676	690	700	706	674	683
Median	816	812	811	811	811	807	816	801
Range	1608	1311	1093	974	909	858	1363	1020
Minimum	-128	48	165	229	265	292	-3	42
Mean	792	792	791	791	791	789	787	764
Day D ≥ 21								
5th percentile	251	372	465	511	550	554	481	534
25th percentile	642	680	702	720	730	736	706	733
Median	841	837	832	830	827	822	826	825
Range	1516	1180	905	743	640	546	705	559
Minimum	-56	143	295	386	447	503	420	500
Mean	812	813	813	813	813	812	812	814

1. Proc Univariate (SAS, v9.4) on variation of ΔBW per pig; arithmetic mean of average results per trial.
2. Number of previous forecasted BW with methods $HW_{0.1}$, $HW_{0.6}$ or MARS used to assess ΔBW on day D by linear regression.

In agreement with what could be expected from Figure 3, differences among methods are more important when only the first 4 predicted values are removed from the analysis, compared to removal of the first 20 ones (Table 2). In this last case, when regressions are performed from the 20 available BW ($k = l = 20$), descriptive statistics of ΔBW based on MARS and $HW_{0.6}$ are comparable and not so different from those obtained with $HW_{0.1}$. Additionally, means and medians are comparable for the three methods, but $HW_{0.6}$ results in higher values for the minimum ΔBW and the 5th percentile and a reduced range of variation. In other words, ΔBW obtained from BW forecasted with $HW_{0.6}$ seems secured.

Using less than 20 past data to predict ΔBW from forecasted BW with $HW_{0.6}$ has little influence on the mean and the median but impacts more the other criteria when less than 16 past BW are used. With $l = 16$ or 18, values of the 5th and 25th percentiles remain rather high. But with a value of l below 16, the range of values increases markedly and the average minimum decreases so that ΔBW can punctually reach negative values for some pigs. These results agree those published by Zumbach *et al.* (2010). These authors obtained similar average daily gain when it was calculated over different time intervals (1, 7 or 14 days) but reducing the time interval increased the variability.

Conclusion

Combined with a linear regression from the last 16 to 20 forecasted BW, the method $HW_{0.6}$ seems to be the most interesting one to predict BW_{D+1} and ΔBW_{D+1} in restrictively fed pigs. Compared to other forecasting methods investigated in this study, it presents a low sensitivity to the number of k latest values used. It allows for a secured prediction of BW soon after the beginning of the growing phase, which contributes to the low residual mean square error of prediction of BW and to smooth variations of predicted ΔBW.

Funding and acknowledgement

The original data sets have been obtained during a research program funded by ADEME, from which data obtained on pigs fed with the same feeding strategy across trials were extracted. The data analyses presented in the present paper were performed in the Feed a Gene project, which has received funding from the European Union's Horizon 2020 research and innovation program under grant N° 633531. The authors acknowledge I. Taoussi and O. Delcourt for their contribution to the development of the R and SAS codes.

References

Hauschild, L., Lovatto, P.A., Pomar, J., Pomar, C. 2012. Development of sustainable precision farming systems for swine: Estimating real-time individual amino acid requirements in growing-finishing pigs. *Journal of Animal Science* **90** 2255-2263.

Marcon, M., Brossard, L., Quiniou, N. 2015. Precision feeding based on individual daily body weight of pigs with an automatic feeder developed to allow for restricting feed allowance. In: *Proc. of the 7th European conference on Precision Livestock Farming*, Guarine M. and Berckmans D. (Ed), Milan, Italy, 592-602.

Milborrow, S. 2011. Earth: multivariate adaptive regression spline models. R package version 4.4.9.1. URL http://CRAN.R-project.org/package=earth

Pomar, C., Hauschildt, L., Zhang, G.H., Pomar, J., Lovatto, P.A. 2009. Applying precision feeding techniques in growing-finishing pig operations. *Revista Brasileira de Zootecnia* **38** 226-237 (suppl. special).

R Core Team (2016). *R: A language and environment for statistical computing.* R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/.

StatSoft Inc. 2013. Electronic statistics textbook. Tulsa, OK: StatSoft. WEB: http://www.statsoft.com/textbook/

Zumbach, B., Misztal, I., Chen, C.Y., Tsuruta, S., Lukaszewicz, M., Herring, W.O., Culbertson, M. 2010. Use of serial pig body weights for genetic evaluation of daily gain. *Journal of Animal Breeding and Genetics* **121** 93-99.

Session 17

RFID and pigs

Behaviour and activity monitoring of growing-finishing pigs with UHF-RFID

A. Kapun[1], F. Adrion[1] and E. Gallmann[1]
[1]*Livestock Systems Engineering (440b), Institute of Agricultural Engineering, University of Hohenheim, 70593 Stuttgart, Germany*
Anita.Kapun@uni-hohenheim.de

Abstract

The objective of this paper is to monitor the behaviour of grow-finishing pigs throughout the fattening period with an ultra-high frequency radio frequency identification system (UHF-RFID). The RFID system can identify and register the pigs' visits at the trough, the drinkers and a playing device. It is therefore possible to monitor a large part of the behaviour repertoire of each individual pig. Due to the strong connection of behaviour to the health status, different approaches to detect illnesses, focusing on lameness, through the behavioural data of the UHF-RFID system were tested. Along with the daily duration at the different hotspots, the possible ranking order and the social network of the pigs was examined. Results show changings in the feeding behaviour and social relationships of lame pigs, but also the difficulties due to the high intra- and inter-animal variability of the behaviour and the interaction of different parameters.

Keywords: UHF-RFID, behaviour, activity, growing-finishing pigs, feeding, lameness

Introduction

Health monitoring on the level of the individual animal has become a growing challenge in modern pig husbandry due to increasing herd sizes. Additionally, the level of interest in animal welfare, product traceability and transparency of production methods on the consumer side is rising. Hence, systems for automatic health and activity monitoring of individual pigs are demanded and would support the farmer in management issues. An individual identification of the animals is the basis of all monitoring applications (Adrion *et al.*, 2015). By using RFID (Radio Frequency Identification) for electronic animal identification, the pigs' visits at different hotspots in the pen (e.g. at the trough) can be registered (Brown-Brandl *et al.*, 2013; Maselyne *et al.*, 2014; Maselyne *et al.*, 2016a). With UHF-RFID technology (ultra-high frequency RFID) a simultaneous identification of several pigs is possible without separating the individual animals and with a relatively high reading range (Adrion *et al.*, 2015; Barge *et al.*, 2013).

By recording the duration and frequency of visits at a specific hotspot the behaviour of the animals can be partly concluded. For example, a pig detected at the trough for a specific time was most likely feeding. Due to the strong connection of behaviour to different kinds of illnesses, analysing a pig's behaviour may lead to conclusions on the animal's health (Matthews *et al.*, 2016; Weary *et al.*, 2009).

The aim of this research is to develop an automatic health and activity monitoring system based on UHF-RFID by analysing the visiting events of growing-finishing pigs at the trough, the drinkers and a playing device. In this article, different approaches to distinguish sick animals from healthy ones are pointed out. The focus lies on the detection of lame pigs by analysing social parameters like ranking order and social relationships.

Material and Methods

Research barn, animals and technical equipment

The study was carried out in a conventional fattening pig barn at the Agricultural Sciences Experimental Station of the University of Hohenheim, Germany, from August 30th to December 6th, 2016, with a preceding validation phase of about 10 days to determine the right settings for the UHF-RFID system. Each of the four identically constructed pens had a total size of 3.30 m × 7.80 m. Every pen was equipped with a slatted floor in the defecation area (about one-third of the pen) and a concrete floor with reduced perforation in the lying area in the rest of the pen. There were three nipple drinkers in every pen as well as a metal trough (1.50 m × 0.37 m) with a sensor-controlled liquid feeding system. There was also a playing device ("Porky Play", Zimmermann Stalltechnik GmbH, Oberessendorf, Germany), which consisted of a trough, a straw-filled metal container and a free-hanging wooden beam.

Four mixed-gender groups of finishing pigs (25 per pen, 100 in total) were tagged with UHF-RFID transponder ear tags. The ear tags were developed within a previous research project. The transponders were equipped with an Impinj Monza 4® chip and had a PIF antenna design (Planar Inverted f-Shaped Antenna; Adrion *et al.*, 2015). They were grouted into a flexible plastic ear tag (Primaflex®, Caisley International GmbH, Bocholt, Germany). The pigs (German Landrace × Pietrain) had an average weight of about 50 kg at the beginning of the trial and were fattened to a total weight of about 120 kg.

In each of the four pens, the hotspots feeding area (trough), drinking areas (drinkers) and playing area (playing device) were equipped with UHF antennas (Figure 1). Along the length of the trough, a cable antenna with an active length of 2 m was installed in a plastic pipe (Locfield®, Cavea Identification GmbH, Olching, Germany). Cable antennas in plastic pipes were also mounted vertically

to the right of the drinkers (Locfield® with 0.35 m active length, Cavea Identification GmbH). At the Porky Play hotspot, a mid-range antenna was located at the top (MIRA-100, Kathrein Sachsen GmbH, Stephanskirchen, Germany).
The readers used were functional models (deister electronic GmbH, agrident GmbH, Barsinghausen, Germany) with a multiplexer for four antennas, a maximum output power of 29 dBm and an operation frequency of 865.7 MHz. The communication between reader and transponder followed EPC class 1, generation 2, specifications defined by ISO 18000-6C. Each antenna was switched on for 250 ms per second in the multiplexing process. The transponder ear tags could be read by the antennas approximately once per second. Simultaneous reading of multiple transponders was enabled by using anti-collision procedures, which allow the reader to coordinate the points in time at which the transponders send their data.

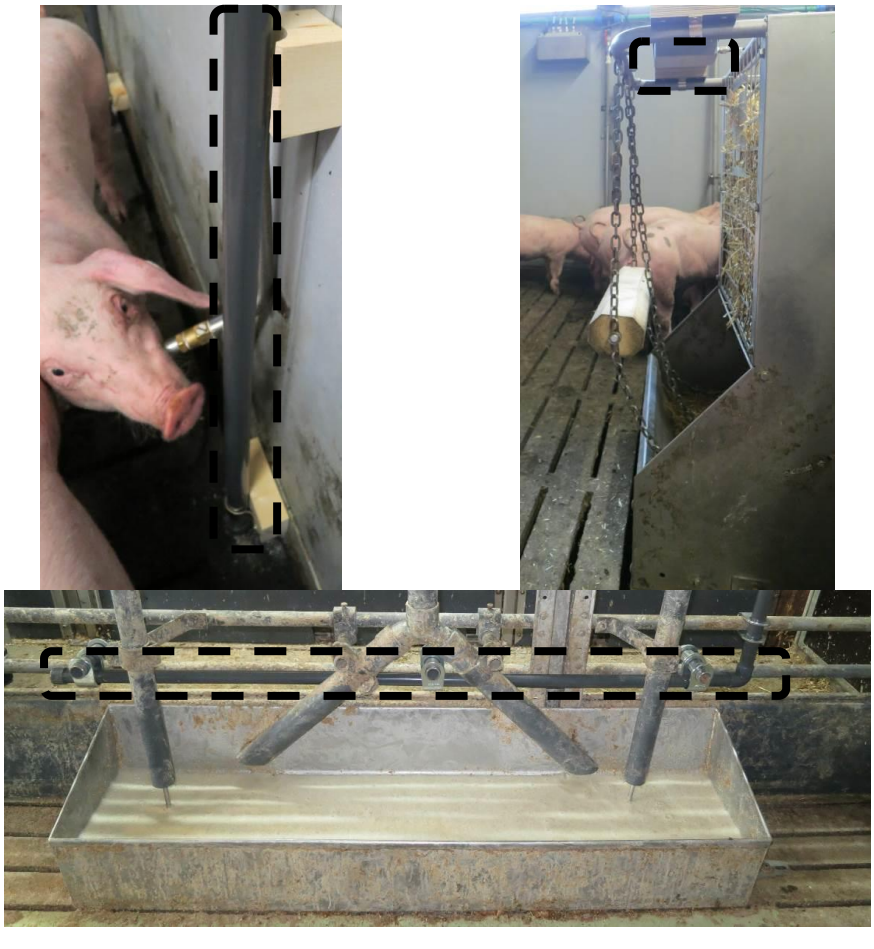


Figure 1: Drinker, playing device and feeding trough equipped with UHF-RFID antennas (antennas marked)

The main study ran for about 12 weeks. During this period the UHF-RFID system consisting of UHF ear tags, UHF antennas, readers and a monitoring software (Phenobyte GmbH, Ludwigsburg, Germany), which recorded occurring RFID registration, ran constantly. The software can aggregate the RFID registrations using a minimum duration and a bout criterion to create visits out of the raw data. These visits were used in the validation phase. For the results of the main study, the single RFID registrations were analysed. The temperature and humidity inside the compartments were permanently logged by dataloggers (testo 175H, Testo AG Lenzkirch, Germany). Twice a week, the health status of the individual pigs was observed including lameness, skin lesions (number of scratches) and soiling (scale from 0 to 3), tail lesions (scale from 0 to 2), diarrhoea (binary scale), coughing (number per pig) and sneezing (number per pen). Lameness was of particular interest for this analysis. The severity of lameness was determined by a 0 to 3 scale, the Locomotion Score (LS) (ZINPRO Feet First®). A score of 0 was assigned to pigs without any sings of lameness, whereas a score of 3 was assigned to pigs with a strong reluctance to walk and bear weight on one or more legs. Additionally, the weights of the pigs were measured every four weeks.

Validation phase

A validation of the UHF-RFID system was carried out with 10 focal pigs before the start of the monitoring period. For each hotspot, a target reading area was defined. A focal pig was scored as “in the target area” when its whole head, including both ears, was inside the defined area around each hotspot. Four different settings of antenna output power were each tested from 11:00 to 22:00 on one of four consecutive test days. In this way, the reading area could be adjusted to detect the pigs only when they were visiting the different hotspots. In parallel, the hotspots were observed with video cameras for recording of reference data. The video data was analysed continuously (event sampling) to record the pigs’ visits at each hotspot. Sensitivity (true positive rate), specificity (true negative rate), precision (positive predictive value) and accuracy were calculated by comparing video and RFID data to the split second according to common definitions (e.g. Maselyne *et al.*, 2016b). Table 1 shows the results of the validation for all three hotspots.

Table 1: Sensitivity, specificity, precision and accuracy for the chosen antenna output power for all three hotspots

Hotspot	Antenna output power (dBm)	Sensitivity (%)	Specificity (%)	Precision (%)	Accuracy (%)
Trough	27	79.2	98.9	76.6	98.0
Drinkers	27	60.2	99.9	21.5	99.8
Playing device	24	78.4	98.5	41.3	98.2

Data analysis

The daily duration at the different hotspots was calculated for every pig on every day during the trial out of the time, where there was an actual reading at the respective antenna.

The group structure of the pigs in a pen was examined more closely. For example, the ranking order was determined based on the visiting order at the trough. In this analysis, the RFID-readings at the trough were examined after the first feeding time at 6 a.m. Readings were counted as a visit, only if the total visit lasted at least one minute with readings not more than 30 seconds apart. For pigs with visible health issues like signs of lameness, the ranking order was regarded throughout the trial period with focus on possible changes.

Another closer look was taken at the social network. The network type of the pigs in a pen can be categorized as a unipartite, directed network with valued ties. *Unipartite* refers to networks with only one type of actor, in this case, the pigs (Grunspan *et al.*, 2014). *Directed* means that the ties between the actors are not bidirectional (Grunspan *et al.*, 2014). For example, a pig can spend all of its time at the trough with a special other pig, but for the other pig it is just a fraction of its time spent at the trough. The ties are *valued*, because they include a quantitative information about the relation (Grunspan *et al.*, 2014).

Sociomatrices were created for every pen and every day per hotspot and for all hotspots together. A sociomatrix is containing the relational data in a social network (Grunspan *et al.*, 2014). In this study, the sociomatrices were created on the base of the seconds a pig was registered at a specific hotspot together with a certain other pig in relation to the total number of seconds the pig was registered there at all. With the mean values (mv) and the standard deviation (sd) over the complete trial period, the relationship between the pigs was rated as “acquaintance” (threshold value: mv) or “friendship” (threshold value: mv + sd) for the different hotspots and for all hotspots together. For example, if pig A spent more than 6.7 % of its daily time at the trough with pig B, pig B would be a “feeding acquaintance” of pig A for this day. If pig C would spent more than 13.1 % of pig A’s feeding time at the trough, it would count as a “feeding

friendship" (directed). With this, the number of acquaintances and friends for every pig could be calculated for each test day.

Results and Discussion

During the trial period, signs of lameness were the most frequently observed health issue. In total, 26 out of 100 pigs had a locomotion score of 0 throughout the whole trial period. That means that 74 pigs showed signs of lameness at least once. Ten of these pigs were rated with an LS 2 or higher at least five times. By analysing the data of these severely lame pigs and by comparing it to the data of the pigs that did not show any signs of lameness, an approach to detect indications of lameness in advance could be possible. The following analysis were intended to fulfil this task.

Daily mean values

The overall mean of the visiting time of all pigs at the trough throughout all days in the trial was 23.3 ± 14.6 min (mean ± sd). The mean duration and standard deviation at the drinkers were 2.9 min ± 3.4 min and at the playing device 14.5 min ± 15.6 min. In table 2, the average daily mean values are shown grouped by test day (over all pigs) and by pig (over all test days). These mean values are similar to the ungrouped ones. Looking at the minima and maxima, it is clearly visible that there is a high variability between the different test days and between the individual pigs. Hence, regarding mean values only is insufficient and far more detailed analyses are necessary.

Table 2: Daily mean values of duration at the trough, the drinkers and the playing device (Porky Play) with the average, minimum and maximum value of all pigs per day and per pig over all days

		Trough		Drinkers		Playing device	
		Duration (min:sec)	Day or pig	Duration (min:sec)	Day or pig	Duration (min:sec)	Day or pig
Per day (over all pigs)	Mean	24:34	-	02:38	-	16:40	-
	Min.	17:21	Sep 8th	00:35	Nov 24th	08:03	Sep 13th
	Max.	39:44	Nov 22nd	06:44	Sep 13th	54:03	Dec 1st
Per pig (over all days)	Mean	22:58	-	02:57	-	14:15	-
	Min.	07:44	Pig 22	00:45	Pig 42	02:08	Pig 20
	Max.	64:12	Pig 94	09:46	Pig 86	37:12	Pig 54

Social structure

Alterations of the daily first visit at the trough and the number of acquaintances and friends over the whole period of the trial could indicate health issues. One example for this could be pig 20. Figures 2 and 3 show the number of feeding acquaintances and friends as well as the time of the first visit at the trough of pig 20 after 6 a.m. for all test days. The locomotion scores in this period are shown as reference data. Between September 11 and September 22, no RFID-readings could be recorded due to technical errors.

The time of the first visit of pig 20 at the trough seems to be around 6 and 6:30 a.m. every day. Apparently, starting at September 28, the first feeding visit was delayed regularly. This may be connected to the occurring lameness at about the same time around October 6. In October, the daily weight gain of this pig also decreased from about 980 g/d over the previous two months to 780 g/d, which is probably related to the changes in feeding behaviour.

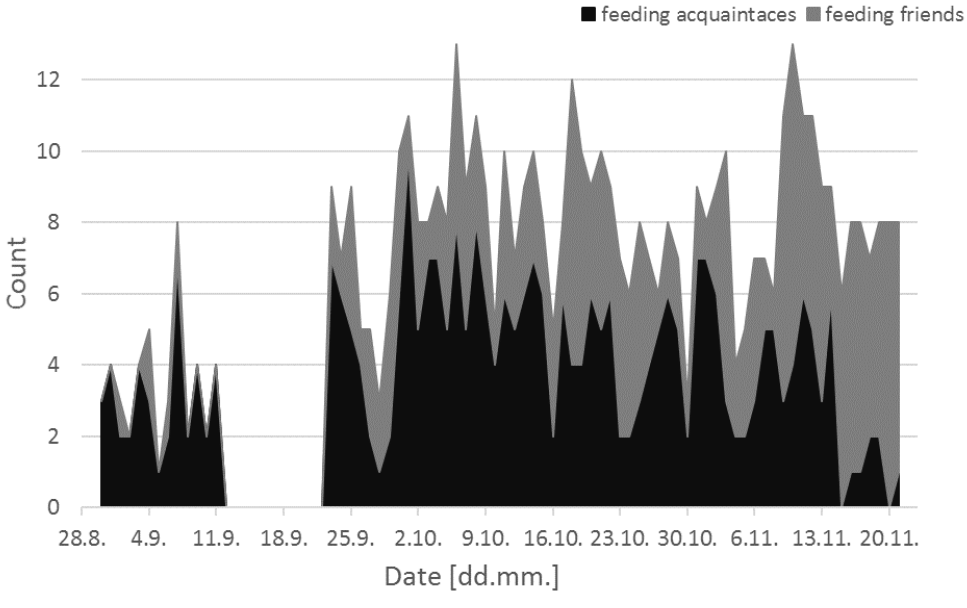


Figure 2: Number of “feeding acquaintances” and “feeding friends” (stacked) of pig 20 over all test days

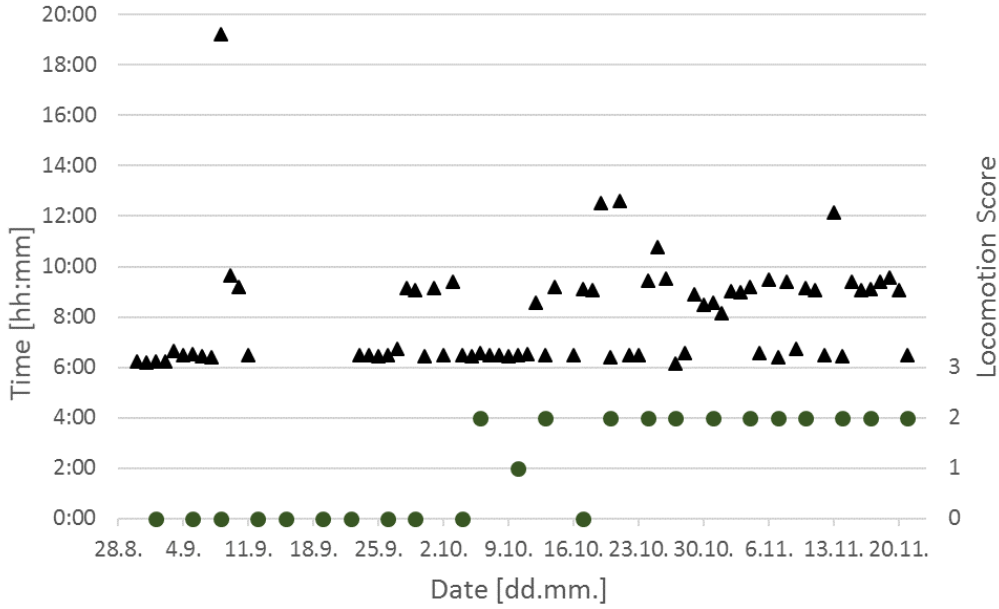


Figure 3: First visit at the trough (triangles, no data between September 11 and September 22) and lameness scoring (locomotion score, dots) of pig 20 over all test days

Around September 28, there is also a drop in the number of feeding acquaintances and friends which is also possibly related to the beginning lameness. Other irregularities like the delayed trough visit between September 8 and September 10 or the increase in number of feeding friends could not be connected to any visible health issues. To develop an early detection of health impacts, it is crucial to include several parameters into the analysis, because they are likely to mutually influence each other. For example, looking at social structures in combination with diurnal rhythms of feeding behaviour, frequency of feeder and drinker visits and also playing behaviour could result in a more reliable prediction of illness.

Conclusions

With a UHF-RFID system observing different hotspots in a pen certain parts of the behaviour of pigs can be monitored continuously. The results of this study show that the analysis of the pigs' behaviour has a promising potential for monitoring of the health status or automatic detection of possible health issues. However, because of the high intra- and inter-animal variability of the behaviour this remains a difficult task. Possible approaches to complete this task were provided together with first data analyses in this article. The amount of data collected in this trial is not yet sufficient to obtain results that can be statistically

investigated to confirm the assumptions made. Hence, more data will be collected and thoroughly analysed in at least two further trial periods.

References

Adrion, F., Hammer, N., Eckert, F., Götz, S., and Gallmann, E. 2015. Adjustment of a UHF-RFID system for hotspot monitoring of fattening pigs. In: *Precision Livestock Farming '15. Papers presented at the 7th European Conference on Precision Livestock Farming.* Guarino, M., and Berckmans, D., Milan, Italy, 573-582.

Barge, P., Gay, P., Merlino, V., and Tortia, C. 2013. Radio frequency identification technologies for livestock management and meat supply chain traceability. *Canadian Journal of Animal Science* **93**(1) 23-33.

Brown-Brandl, T.M., Rohrer, G.A., and Eigenberg, R.A. 2013. Analysis of feeding behavior of group housed growing-finishing pigs. *Computers and Electronics in Agriculture* **96** 246-252.

Grunspan, D.Z., Wiggins, B.L., and Goodreau, S.M. 2014. Understanding Classrooms through Social Network Analysis: A Primer for Social Network Analysis in Education Research. *CBE – Life Sciences Education* **13** 167-178.

Maselyne, J., Saeys, W., De Ketelaere, B., Mertens, K., Vangeyte, J., Hessel, E.F., Millet, S., and Van Nuffel, A. 2014. Validation of a High Frequency Radio Frequency Identification (HF RFID) system for registering feeding patterns of growing-finishing pigs. *Computers and Electronics in Agriculture* **102** 10-18.

Maselyne, J., Adriaens, I., Huybrechts, T., De Ketelaere, B., Millet, S., Vangeyte, J., Van Nuffel, A., and Saeys, W. 2016a. Measuring the drinking behaviour of individual pigs housed in group using radio frequency identification (RFID). *Animal* **10**(9) 1557-1566.

Maselyne, J., Saeys, W., Briene, P., Mertens, K., Vangeyte, J., De Ketelaere, B., Hessel, E.F., Sonck, B., van Nuffel, A. 2016b. Methods to construct feeding visits from RFID registrations of growing-finishing pigs at the feed trough. *Computers and Electronics in Agriculture* **128** 9-19.

Matthews, S.G., Miller, A.L., Clapp, J., Plötz, T., and Kyriazakis, I. 2016. Early detection of health and welfare compromises through automated detection of behavioural changes in pigs. *The Veterinary Journal* **217** 43-51.

Weary, D.M., Huzzey, J.M., and von Keyserlingk, M.A.G. 2009. Board-invited review: Using behavior to predict and identify ill health in animals. *Journal of animal science* **87**(2) 770-777.

Deployment and Evaluation of an Active RFID Tracking System for Finishing Pigs

Brian L. Barnes[1], Deepak R. Keshwani[1] Tami M. Brown-Brandl[2]
[1]*University of Nebraska—Lincoln. 223 L. W. Chase Hall, P. O. Box 830726, Lincoln, NE 68583-0726.*
[2]*USDA, ARS, U.S. Meat Animal Research Center. P. O. Box 166, Clay Center, NE 68933.*
tami.brownbrandl@ars.usda.gov

Abstract

Modern swine facilities were developed mainly based on logistics of feeding and moving animals. In recent years, the public has become increasingly concerned about animal care and well-being. A better understanding of the animal space utilization in current facilities could lead to improved facility design and better animal well-being. This study was conducted to determine whether an active RFID tag tracking system could accurately provide animal locomotion data on an individual animal basis. The system is composed of four sensors, located in the corners of a swine pen, and compact tags, which attach to the animals and transmit a signal. The sensors use the tag signals to determine 3-D positions in real-time. A data acquisition system was developed to capture raw data from the system software into a database for analysis. A single-location test was performed with 34 tags placed in close proximity to a known location, followed by three trials of a second test with 34 tags randomly arranged in a 1-meter by 1-meter grid across the pen. Results from the single-location test were relatively consistent with the manufacturer's claim of 15-cm accuracy. Error was higher in the grid test, particularly in the Z-direction. The system was used to track four pigs for a period of two days, with visual data analysis showing 84.4% tracking accuracy. Further work revealed that the system is prone to generate large, random jumps in the data that need to be filtered if the desired use is for instantaneous measurements.

Keywords: Precision Livestock Farming, Precision Livestock Management, Swine, RFID, Ubisense

Introduction

The livestock production industry is facing increased pressure from multiple sources. Improving animal welfare has become a major hurdle for sustainable livestock production (Berckmans, 2014). With the rapid expansion of the industry, the labor force has struggled to produce enough employees well trained in animal husbandry, making it increasingly difficult to track health parameters and provide care on an individual animal basis. To remain economically competitive, farmers must address this challenge while continuing to lower overhead and improve production efficiencies.

Active radio-frequency identification (RFID) technology is a powerful tool for tracking the location of objects in real time. In an active RFID system, battery-powered tags are attached to the objects to be tracked and sensors are placed around the tracking area. The tags emit a signal at a specified time interval, which is received by the sensors and used to calculate the 3-dimensional position of the tags. Therefore, the objective of this study was to deploy and evaluate an active RFID system within a swine facility to determine positional accuracy and ability to track individual animal movement.

Materials and Methods

Site and Equipment Setup

The active RFID tag tracking system (Real-Time Location System, Ubisense Inc., Denver, CO) was deployed in a swine pen in a finishing facility at the USDA U.S. Meat Animal Research Center in Clay Center, Nebraska. The pen had dimensions 6.33 m (W) × 5.09 m (L) with 1-m high fences and contained one five-hole feeder, four nipple drinkers, and a spray cooling system. A diagram of the swine pen, including key elements, is shown in Figure 1. The Real-Time Location System (RTLS) was composed of two hardware elements: sensors (Series 7000 Sensor, Ubisense Inc., Denver, CO) and tags (Series 7000 Compact Tag, Ubisense Inc., Denver, CO), shown in Figure 2.

For this study, four sensors were mounted in the corners of the pen at a height of 2.2 m and oriented toward the center of the pen, angled downward at 30 degrees. The sensors were connected to each other by cat6e Ethernet cables for the calculation of the difference in signal arrival time between each sensor. The sensors were also connected by cat6e Ethernet cables to a power-over-Ethernet (PoE) switch, for transmitting power and data to a computer.

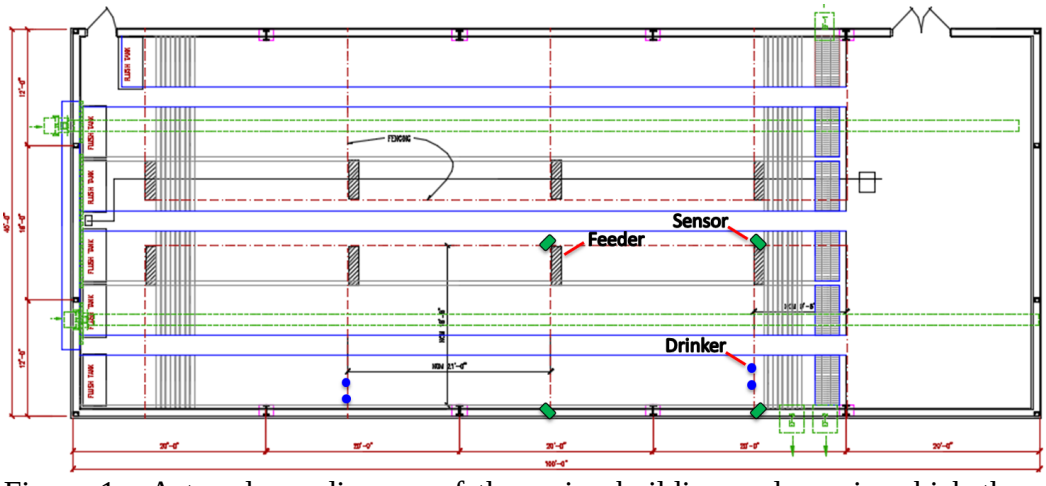


Figure 1. A top-down diagram of the swine building and pen in which the Ubisense system is located. The locations of the feeder, nipple drinkers, and four sensors are also shown.

Stationary Tag Tests

Two tests were performed to evaluate the ability of the system to accurately locate stationary tags in the pen. Each pen holds a maximum of 40 animals, therefore 34 tags were used for tracking. For the first test, all tags were grouped together in a 6×7 array, and was set at a height of 0.39 m. The tags were centered on a single known location within the pen, and data were collected for 1 hour with tags updating positions every 15 seconds.

The second test was conducted as a grid test. Tags were place in a 1m x 1m grid across the pen at a height of 0.39 m. The second test was performed three times to test the location x tag effects. Each trial was performed with tag locations updating every 15 seconds for 24 hours.

The absolute error and standard deviation of the error of measured tag locations in the x, y, and z directions was calculated. Absolute error was calculated by subtracting the actual position from each measured position, and taking the absolute value. The Euclidean distance for each measured position was calculated using the formula:

$$E_{dist} = \sqrt{{X_{err}}^2 + {Y_{err}}^2 + {Z_{err}}^2} \qquad \text{(Eq. 1)}$$

Where E_{dist} is the Euclidean distance, X_{err} is the error in the X direction, Y_{err} is the error in the Y direction, and Z_{err} is the error in the Z direction. For this application, the Euclidean distance was a linear distance by which the measured tag position was displaced from the actual tag position. During analysis of the first test, the actual location of each tag was adjusted by the distance of the tag from the center of the array.

Mobile Tag Test

Four finishing gilts (24 weeks of age) were moved into the pen for the purposes of testing the system. All animal procedures were performed in compliance with federal and institutional regulations regarding proper animal care practices (FASS, 2010). In order to place the tags on the animals, a custom ear tag was designed. This ear tag was a hollow tag enclosures which was 3D printed using NinjaFlex (NinjaTek, Manheim, PA), a thermoplastic elastomer. NinjaFlex was chosen for the combination of flexibility and durability. To test the ability of the system to locate the animals in the pen, the gilts were tagged and tracked over two days. During the test, cameras were programmed to take pictures along the X axis and Y axis of the pen once per minute, and the pigs were marked with distinct patterns for visual identification (Figure 2). Colored tape was used to mark off 1 m intervals on the railings or wall in the foreground and background of images along the X and Y axis. This process established thirty 1 m × 1 m zones in the XY plane, with columns labeled A through F and rows 1 through 5. Three sets of images per hour were selected where each pig was clearly visible in a zone, at times when the pigs appeared to be stationary. The corresponding location data at the time of each image were then compared to the images for verification of accurate tracking.

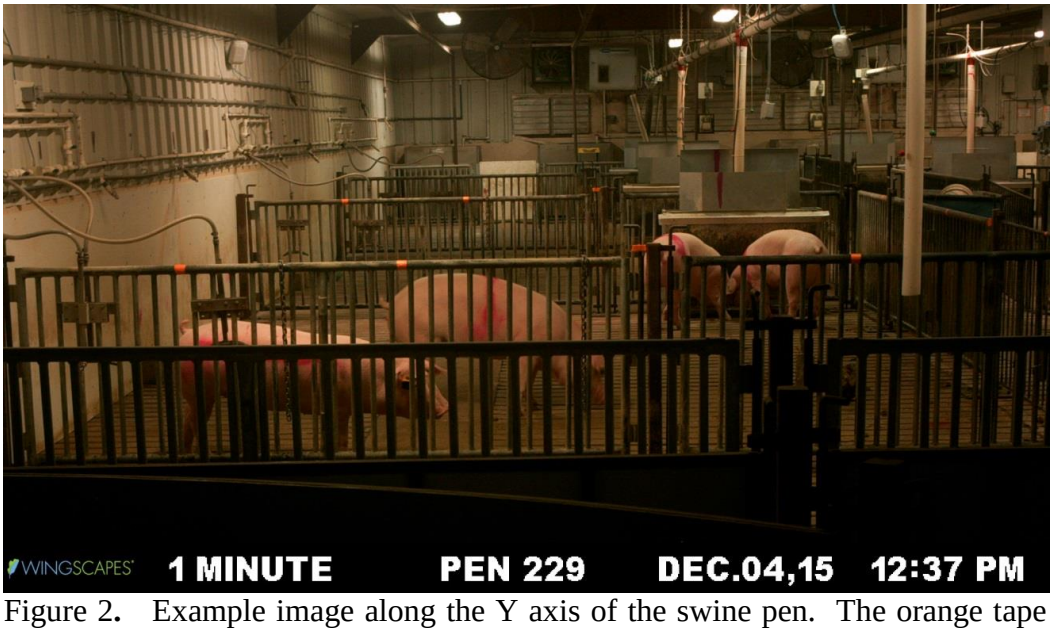


Figure 2. Example image along the Y axis of the swine pen. The orange tape marking 1- m intervals can be seen on the railings in the foreground and background.

Results and Discussion

Stationary tag tests

The stationary tag test was conducted with 34 tags at a known location for one hour. The average X, Y, and Z errors and the Euclidean distance for the 34 tags is displayed in Table 2. For this test, the errors in both the X and Y direction were roughly twice as large as the error in the Z direction.

The grid test was conducted 3 times and used 34 tags randomized in a 1m x 1m grid. The average X, Y, and Z errors and the Euclidean distances for all three trials are presented in Table 2. We found that the average of the X and Y errors were roughly doubled in each trial when compared to the single location test. The average Z error showed the largest increase between the single location and grid test, rising between four- and five-fold in each trial.

Table 2. Average X, Y, and Z errors and average Euclidean distance for all tags during stationary tag testing

Measurement (in meters)	Single Location Test	Grid Tests		
		1	2	3
Avg X error	0.101 (0.086)	0.213 (0.288)	0.182 (0.189)	0.214 (0.261)
Avg Y error	0.093 (0.08)	0.171 (0.171)	0.147 (0.143)	0.17 (0.157)
Avg Z error	0.058 (0.05)	0.26 (0.431)	0.197 (0.344)	0.255 (0.406)
Avg Euclidean Distance	0.166 (0.105)	0.424 (0.509)	0.346 (0.386)	0.413 (0.476)

The manufacturer estimates the accuracy of 15 cm. Results from the single location test matched these results. However, results from the grid tests indicate that the system tracked tags at a higher accuracy in some locations within the pen than others. As shown above, the largest change in tracking error was in the Z direction. As noted earlier, if more sensors have a clear line of sight to a tag, the calculated position will be more robust to errors. However, the Z direction was not of significant importance for the purpose of this paper, as the head height is not indicative of pig movement and therefore was not used. Therefore, the mobile tag test involved analysis of data in only the X and Y directions.

Mobile tag test

To verify that the system could track moving objects accurately, the pen was divided into a 1m × 1m grid and checked their measured positions against a series of images taken during the trial. The system accurately predicted the zone a given tag was in on 162 out of 192 observations (84.4%). Recent research in precision livestock farming has focused primarily on establishing and evaluating sensor-based data collection techniques on livestock operations. With an accuracy of 84.4%, the results of our initial evaluation of the active RFID system are consistent with other work in the field of PLF. Top-down image processing techniques have been used in swine research to automatically determine

individual animal identity with 88.7% accuracy (Kashiha *et al.*, 2013). Kashiha *et al*. (2013) were able to use the information to track each individual's appearances in the feeding, drinking, resting, and defecating zones within the pen. Aggressive interactions between finishing pigs in confinement have also been analyzed using top-down video recordings (Oczak *et al.*, 2013 and Viazzi, 2014). Oczak *et al*. (2013) used a human observer to manually label the phases of aggressive interactions with the goal of the eventual creation of a program that could recognize these interactions. Viazzi continued this work, using image analysis techniques to detect aggressive interactions with 89.0% accuracy. The primary advantage of the active RFID system is that once it is properly calibrated, the data do not need post processing by image or video analysis. The data is stored in a simple format that could be directly fed into a decision making model.

Animal Movement Data Analysis

Fifteen pigs were tracked for five days, and the resulting data were analyzed each day for total distance, average speed when moving, and the number of direction changes. Sample results for one day are presented in Table 3. As the parameters for the trig method of calculating direction changes became more restrictive, the number of direction changes observed decreased, as expected. The system also tracked feeding and drinking events, which were analyzed each day for the total number of events, total time at the feeder or drinker, and average event duration. Sample results for one day of event data are presented in Table 4.

Table 3. Analysis of one full day of location data for baseline movement parameters.

		Avg Speed	# of Direction Changes				
		When Moving	θ<135	θ<90	θ<90, D1-3 and	θ<60	θ<60, D1-3 and
Tag #	Total Dist (m)	(m/s)	D2-3>0.5m	D2-3>0.5m	D2-3>0.5m	D2-3>0.5m	D2-3>0.5m
3	4591.385	0.414	3271	1626	664	383	150
19	4544.865	0.422	3472	1619	553	388	109
20	3212.561	0.408	2565	1173	388	274	77
21	6070.713	0.466	4696	2321	977	547	199
22	5033.686	0.407	4000	1889	609	400	110
23	5869.558	0.408	4766	2278	895	563	199
24	3313.296	0.434	2402	1087	381	271	86
25	4744.079	0.429	3637	1715	614	414	136
26	4641.012	0.429	3538	1723	605	376	120
27	4864.727	0.417	3841	1834	617	451	139
28	4883.412	0.415	3751	1782	681	418	132
29	5261.605	0.428	3975	1915	704	457	165
30	2437.409	0.411	1835	924	393	189	68
31	3593.978	0.374	2559	1185	554	294	132
32	3005.459	0.417	2267	1067	354	238	64

Table 4. Analysis of one full day of event data for baseline movement parameters.

	Feeding events			Drinking events		
Tag #	# of events	Total time (h:mm:ss)	Avg duration (h:mm:ss)	# of events	Total time (h:mm:ss)	Avg duration (h:mm:ss)
3	274	0:51:42	0:00:11	118	0:21:12	0:00:11
19	124	0:21:21	0:00:10	100	0:19:17	0:00:12
20	185	0:47:02	0:00:15	42	0:21:47	0:00:31
21	320	0:59:36	0:00:11	130	0:22:10	0:00:10
22	235	0:45:30	0:00:12	313	1:59:40	0:00:23
23	426	2:12:16	0:00:19	277	1:14:39	0:00:16
24	69	0:42:31	0:00:37	50	0:57:27	0:01:09
25	387	1:26:31	0:00:13	114	0:28:29	0:00:15
26	311	1:05:31	0:00:13	89	0:25:52	0:00:17
27	210	1:03:14	0:00:18	49	0:09:49	0:00:12
28	348	1:30:27	0:00:16	145	0:37:34	0:00:16
29	139	0:48:02	0:00:21	260	1:12:57	0:00:17
30	100	0:38:28	0:00:23	122	0:45:22	0:00:22
31	114	0:37:25	0:00:20	103	0:27:12	0:00:16
32	47	0:51:21	0:01:06	101	1:14:41	0:00:44

It is worth noting that the total number of events and the average event duration for the feeding and drinking event data is likely not an accurate representation of the true number of visits to either zone or the average duration of an event in either zone. It is very likely that the tags pass into and out of a zone multiple times during an actual visit to the feeder or nipple drinker. For example, an animal may be standing near the edge of the established feeder zone, and even slight movements of the head would generate repeated entry and exit events. Likewise, simply walking past the feeder or nipple drinker may generate one or more entry and exit events. The overall effect of these false events is to drive up the total number of feeder or drinker events, resulting in a decrease in average event time. In the short term, this effect could be solved offline by importing the data to MATLAB or a similar program, which would give greater control over the establishment of zone boundaries than is possible within the Ubisense software. However, a software application running in parallel with the data collection process could perform precise calculations of feeding and drinking events, distance traveled, average speed when moving, and number of direction changes much closer to real-time.

Conclusions

In conclusion, this study shows that an active RFID tracking system is capable of providing accurate location data in a finishing swine pen. The data generated could be used to map feeding behaviors, drinking behaviors, access to cooling systems, and animal interactions. Most importantly, the system could be combined with other biological sensors to provide more complete individual animal health profiles.

Acknowledgements

This research was funded jointly by the University of Nebraska Institute of Agriculture and Natural Resources (Lincoln, NE, USA) and the USDA, ARS, U.S. Meat Animal Research Center (Clay Center, NE, USA).

References

Berckmans, D. 2014. Precision livestock farming technologies for welfare management in intensive livestock systems. *Revue Scientifique Et Technique-Office International Des Epizooties 33*(1), 189-196.

FAO. 2009. How to feed the world in 2050. *High Level Expert Forum*, Rome, Italy. 2.

Federation of Animal Science Societies. 2010. *Guide for the care and use of agricultural animals in research and teaching*. 3rd edition. FASS, Champaign, IL, USA.

Kashiha, M., Bahr, C., Ott, S., Moons, C.P.H., Niewold, T.A., Ödberg, F.O., and Berckmans, D. 2013. Automatic identification of marked pigs in a pen using image pattern recognition. *Computers and Electronics in Agriculture* **93;** 111-120. doi: http://dx.doi.org/10.1016/j.compag.2013.01.013

Oczak, M., Ismayilova, G., Costa, A., Viazzi, S., Sonoda, L. T., Fels, M., Bahr, C., Hartung, J., Guarino, M., Berckmans, D.,Vranken, E. (2013). Analysis of aggressive behaviours of pigs by automatic video recordings. *Computers and Electronics in Agriculture* **99;** 209-217. doi:http://dx.doi.org/10.1016/j.compag.2013.09.015

Ubisense Limited. 2014. Ubisense RTLS Training-Overview [PowerPoint Slides].Ubisense, Inc., Denver, CO, USA.

Viazzi, S., Ismayilove, G., Oczak, M., Sonoda, L.T., Fels, M. Guarino, M., Vranken, E., Hartung, J., Bahr, C., Berckmans, D. 2014. Image feature extraction for classification of aggressive interactions among pigs. *Computers and Electronics in Agriculture* **104** 57-62.

Comparing three different passive RFID systems for behaviour monitoring in grow-finish pigs

T. M. Brown-Brandl[1], J. Maselyne[2], F. Adrion[3], A. Kapun[3], E. F. Hessel[4], W. Saeys[5], A. Van Nuffel[2], E. Gallmann[3]
[1]*USDA, ARS, U.S. Meat Animal Research Center, P.O. Box 166, Clay Center, NE, USA*
[2]*ILVO (Flanders research institute for agriculture, fisheries and food), Technology and Food Science Unit - Agricultural engineering, Burg. Van Gansberghelaan 115 bus 1, 9820 Merelbeke, Belgium*
[3]*University of Hohenheim, Institute of Agricultural Engineering, Livestock Systems Engineering (440b), Garbenstrasse 9, 70593 Stuttgart, Germany*
[4]*Georg-August University of Göttingen, Department of Animal Sciences, Gutenbergstr. 33, 37075 Göttingen*
[5]*KU Leuven, Department of Biosystems, MeBioS, Kasteelpark Arenberg 30, 3001 Leuven, Belgium*
Tami.BrownBrandl@ars.usda.gov

Abstract

Animal facilities are increasing in size making it difficult for animal caretakers to ensure the health and well-being of all animals under their care. Radio Frequency Identification (RFID) systems have been successfully used in animal facilities and research has identified potential applications in behaviour monitoring for automated problem detection. Low Frequency (LF), High Frequency (HF), and Ultra-High Frequency (UHF) are the three frequency ranges most commonly used. The objective of this paper is to compare and evaluate the application of these three different RFID systems within grow-finish swine facilities in terms of hardware characteristics, system design, and data processing and usage. Differences in tag construction, availability and cost are evident, but also basic differences in reader and antenna function, such as physics of data exchange, speed of detection, and anti-collision procedures exist. The systems can have significant differences in read ranges and also showed varying influence of materials, especially water and metal, on the performance of the systems. However, the data streams as well as methods of data processing and the creation of events (e.g. visits to a feeder) are similar for all systems. The characteristics mentioned do not necessarily identify an ideal RFID technology, but reveal positive and negative aspects of each system. The three different RFID systems have been successfully applied in pig facilities. Current research is focussed on the utilisation of the RFID data in prediction and decision models for illness, animal welfare and management actions.

Keywords: radio frequency identification, behaviour monitoring, grow-finish pigs, frequency ranges, ear tag, transponder

Introduction

Radio frequency identification (RFID) is a technology including tags or transponders and readers that can be used to identify and track individual items. It uses electromagnetic fields to interrogate the tags, which contain a worldwide unique identification code. Radio-frequency identification (RFID) systems continue to improve animal management and care through identification and tracking. Basic RFID systems for animals include a reader and an electronic identification tag. Tags of various sizes, form factors, and weights have been developed, including ear tags, injectable capsules, and rumen boluses (Rossing, 1999). These systems have been applied to animals ranging from pets to livestock. Their components are reliable, lightweight, rugged, and have a long life due to the lack of battery (in case of passive RFID), as long as the tag electronics are protected.

While the animal industry mainly uses low-frequency (LF) technology (Artmann, 1999), alternative frequencies are continuing to be developed. Low-frequency tags are not very sensitive to radio wave interference and water and are not impacted by metal in the environment making them a good choice for animal facilities (HID, 2014). However, LF systems have some disadvantages including a limited ability to identify multiple tags at the same time (anti-collision), read distances which can be too limiting for some applications, and slower read speed. For monitoring animal behaviour, the three main frequency bands LF, high-frequency (HF) and ultra-high-frequency (UHF) are currently being used by the different research groups (Adrion et al., 2015a; Brown-Brandl and Eigenberg, 2011; Maselyne et al., 2014a).

The objective of this paper is to compare and discuss the application of these three different RFID-technologies within grow-finish swine facilities. Aspects of hardware characteristics, system design, data processing and usage will be discussed.

Hardware and system design

RFID systems exist in countless variations, several types of techniques exist and within each technique several types of formats and housing of tags and designs of readers exist as well. Some distinctions can be made based on features of the system however, of which the operating frequency is the most important. The focus of this paper is on passive RFID technology (passive transponders carry no battery) only.

Low-Frequency RFID

Low frequency tags have two different reading protocols, Half Duplex (HDX) and Full Duplex (FDX). Readers for both HDX and FDX livestock tags operate on 134.2 kHz RF. Half duplex readers operate using a power and a listen mode, while FDX readers generate a continuous magnetic field. The magnetic field from the reader is "collected" by the antenna in the tag transponder and provides power for the tag to respond (inductive coupling). Both FDX and HDX tags are commercial available and used by the livestock industry, according to ISO 11784 and 11785 (Jansen and Eradus, 1999).

Tags designed for LF come in many different form factors. Generally for the livestock industry, the tags are designed as an eartag. However, a bolus can be used in the cattle and a small capsule placed under the skin is commonly used in the pet industry (Fig. 1).

High-Frequency RFID

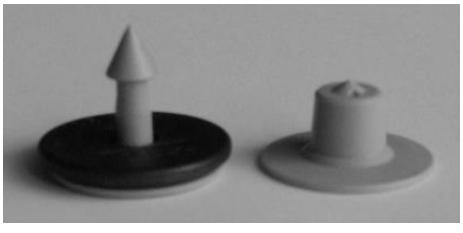
Both LF and HF RFID systems are remote coupling systems that can have reading ranges range between 1 cm (close-coupling), 15 cm (proximity coupling) and up to 1-1.5 m (vicinity coupling) (Finkenzeller, 2010; Ruiz-Garcia and Lunadei, 2011; Sattlegger and Denk, 2014). HF RFID also works on the inductive coupling principle in most cases. The main difference with HF RFID is the faster data transmission and the anti-collision mechanisms that are used. While in LF RFID systems, only one transponder in range of the reader can be read (multiple tags create data collision and a loss of data), multiple tags can be read by HF RFID systems.

Figure 1: Various form factors of low-frequency RFID tags for animals. The round tags are to be applied as an ear tag, the large white cylindrical capsule is a bolus to be placed in the rumen of cattle, and the small capsule is to be placed under the skin.

For use in livestock monitoring systems, HF RFID tags of ISO 15693 have been used (Maselyne et al., 2014). No HF RFID ear tags are standard on the market,

the tags generally have the same form factors but are flatter than LF RFID tags, so the same possibilities exist. Tags can also be found that fit onto standard pig ear tags and are protected against the barn environment (Fig 2.).

Figure 2: The IN Tag 300 I-Code SLI tag (HID Global) fits over a standard pig ear tag.



Ultra-High-Frequency RFID

In contrast to LF and HF RFID, UHF RFID systems are mostly working as long-range systems with a very flexibly adjustable read range up to 12 m for passive transponders. The high read range implies that UHF RFID is based on backscatter coupling instead of inductive coupling (Finkenzeller, 2010). The transponder gains its energy from the electromagnetic waves of the reader and communicates by reflecting part of the radiation back to the reader (Nikitin and Rao, 2006). The high operating frequency facilitates fast data transmission and very efficient use of anti-collision protocols, but the influence of materials, especially water, by absorption of radiation and reflections on electrically conducting surfaces is also high in this frequency range (Kern, 2007; Lorenzo et al, 2011).

There are some UHF ear tags on the market for use with cattle and sheep, but there is still a need for further development to make transponders less sensitive to the surrounding ear tissue (Adrion et al., 2015b). Similar to LF and HF RFID, there are various form factors of UHF transponders (mostly labels) on the market so that differently formed ear tags can be designed (Fig. 3).

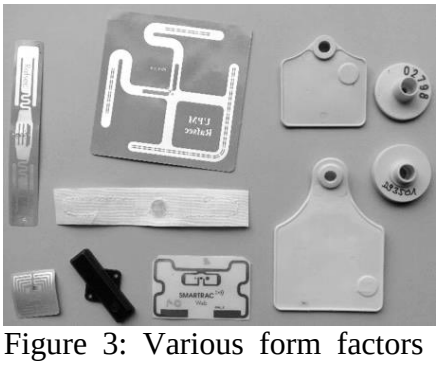


Figure 3: Various form factors of UHF RFID transponders and ear tags for livestock.

Choosing the right frequency

In general, with all three RFID technologies the monitoring of animals at certain locations in the barn is possible, but for some applications one of the three technologies may fit better than the others. For example, LF RFID offers a high reliability of reading due to little influence of ear tissue, but on the other hand, multiple antennas are needed to read more than one animal at the same time and location (Brown-Brandl and Eigenberg, 2011). With HF RFID simultaneous detection is possible but still in a limited read range (Maselyne et al., 2014a). The specific reading range that can be achieved with a certain RFID system depends on the combination of tags and readers (and antennas), and their relative position and orientation (Adrion et al., 2015c; Maselyne et al., 2014b). However, observation of large areas or long troughs with only one antenna will only be possible with UHF RFID. Table 1 gives a summary of the decisive characteristics of all three RFID systems.

Table 1: Overview of different properties of the three RFID systems LF, HF and UHF

	Low Frequency	High Frequency	Ultra High Frequency
Typical frequency used in Livestock	134.2 kHz	13.56 MHz	866-868 MHz (EU), 915 MHz (US)
Read range	0-80 cm	10 cm to 1 m	up to 12 m
Tags Available for livestock	Yes	As add-on to an ear tag	Yes, but limited variety
Anti-collision protocol	No	Yes	Yes
Data rate	4 to 8 kbps[1]	6.7 to 848 kbps[1]	20 to 300 kbps
Tags read per second	<10	>10	>100
Water Interference	No	Low	Strong
Metal Interference[2]	High	High	Reflections and interferences

[1]Sattlegger and Denk (2014)
[2]Kern (2007)

Data processing

Despite the different frequency ranges, the data processing for use in livestock is similar for any RFID system. A typical RFID registration consists of a timestamp, ID of the tag and the antenna or location where it was identified.

When using RFID for monitoring animal behaviour, such as feeding and drinking behaviour, data processing is needed to extract feeding and drinking visits from the raw RFID data. RFID registrations are not continuous during one behavioural event, but have irregular gaps between them created on the one hand due to the use of multiplexers to connect multiple antennas to one reader and on the other hand due to the movement of the pigs.

Constructing feeding and drinking visits can be done using a combination of appropriate visit criteria: 1) a bout criterion to fill gaps between registrations below a certain threshold; 2) minimum duration criterion to remove too short visit; 3) maximum duration criterion to remove too long visits. Figure 4 shows an example, using visit criteria feeding visits (or drinking, playing) can be constructed from the RFID registrations (Adrion et al., 2015a; Maselyne et al., 2015a; Maselyne et al., 2016).

Also the construction of meals (cluster of feeding visits) is possible, different methods to determine meals are known in literature (Brown-Brandl and Eigenberg, 2015; Maselyne et al., 2015; Tolkamp et al, 1998).

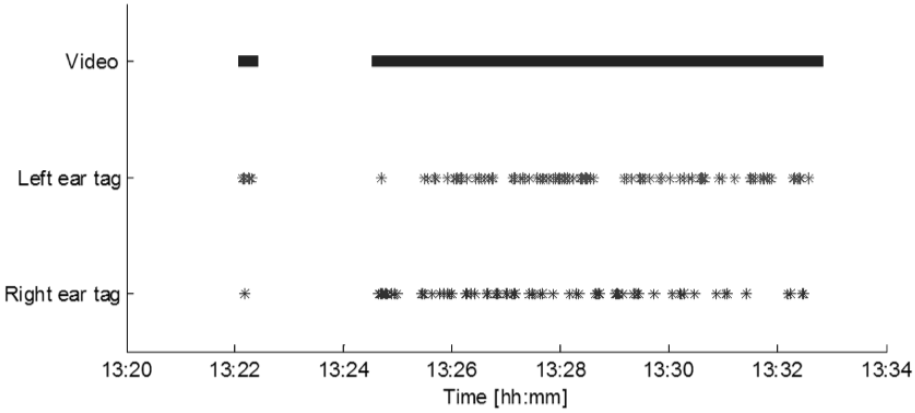


Figure 4: Overview of typical RFID registrations of a pig (in this case of a pig with a tag in each ear) at a RFID feeder (in this case at the HF RFID feeding system), and the corresponding feeding visit as determined via video observation.

Application example

As an application example, a LF RFID system developed for pig feeders is presented (Brown-Brandl and Eigenberg, 2011). The core of the feeding behaviour monitoring system includes an RFID system that was designed around a commercial available reader. The antennas for this application were designed to provide sufficient range, to be rugged and relatively inexpensive, and to fit within the cavity on the face of the feeders for swine. Additionally, the antennas were tuned to be resonant at the reader operating frequency so that adequate

energy was coupled to energize the ID tags. The design of the antenna and the tuning components were based on design criteria (Texas Instruments, 2003; Malik, 2015). The dimensions of the antennas were determined by the physical constraints of the installation. Antenna assembly involved constructing a form that fit within the feeder systems, and then precisely constructing antenna coils to achieve the correct inductance. Tuning the antennas was accomplished by adding a combination of an inductors and/or capacitors to achieve antenna resonance.

In order to collect animal feeding behaviour data using a LF system, an antenna per feeding space is required. One challenge with such was to distribute the RF signals to the appropriate antennas frequently enough to determine when and where animals are eating. The antenna distribution system used fairly conventional concepts and devices to allow fast development, a robust design, and traditional maintenance methods. Multiplexers (MPXs) were employed to function as multiple (four/eight positions) switches connecting the signal from the RA-RFM to the correct antenna. Figure 5 shows a block diagram of the system. An input to the MPX can be directed to any of four/eight outputs. Multiplexer switching was controlled by a four-wire system (three control lines and a ground).

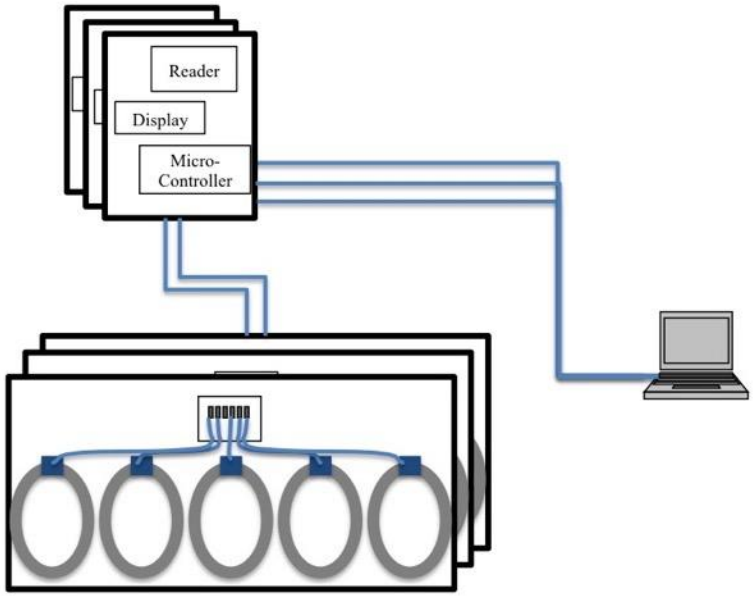


Figure 5: Schematic of the Low Frequency Feeding behaviour system. Five antennas and a multiplexer are place on a panel mounted to the feeder, the reader module, a micro-controller and a small display are placed in a box above each feeder.

Data from any of the different RFID systems can be used to collect feeding or drinking behaviour data. This information can be used for several specific

applications. First, the data can be used to understand the feeding behaviour of the animals within the pen environment (Brown-Brandl et al., 2011) and how changes in the environment will impact the feeding behaviour (Cross et al., 2017). Second, feeding behaviour can be used as an early indication of illness (Brown-Brandl et al., 2011; Brown-Brandl et al., 2016, Kapun et al., 2016). Animal breeding companies can utilize feeding behaviour of individual animals as a selection tool (Rohrer et al., 2013).

Conclusion

The three different RFID technologies presented here all offer various possibilities for behaviour monitoring of grow-finish pigs. However, each of the technologies can be advantageous in a certain application. Further research has to be conducted, especially in HF and UHF RFID, to adapt the technology for regular use in livestock. Furthermore, the behaviour data recorded should be used for creating prediction models for animal health and welfare, as well as for comparisons of the influence of different housing systems on animal behaviour and for genetic evaluation.

References

Adrion, F., Hammer, N., Eckert, F., Goetz, S., and Gallmann, E. 2015a. Adjustment of a UHF-RFID system for hotspot monitoring of fattening pigs. In: *Precision Livestock Farming '15. Papers presented at the 7th Conference on Precision Livestock Farming*. Guarino, M., and Berckmans, D., Milan, Italy, 573-582.

Adrion, F., Hammer, N., Loeb, P., and Gallmann, E. 2015b. Measurement of the influence of pig's ears and tissue imitations on detection area and signal strength of UHF-RFID ear tags. In: *12th Conference: Construction, Engineering and Environment in Livestock Farming.* Association for Technology and Constructions in Agriculture e. V., Darmstadt, Germany, 98-103.

Adrion, F., Hammer, N., Rößler, B., Jezierny, D., Kapun, A., and Gallmann, E. 2015c. Development, function and test of a static test bench for UHF-RFID ear tags. *Landtechnik* **70**(3), 46-66.

Artmann, R. 1999. Electronic identification systems: state of the art and their further development. *Computers and Electronics in Agriculture* **24**, 5-26.

Brown-Brandl, T. M., and Eigenberg, R. A. 2011. Development of a livestock feeding behavior monitoring system. *Transactions of the ASABE* **54**, 1913-1920.

Brown-Brandl, T. M., and Eigenberg, R. A. 2015. Determination of Minimum Meal Interval and Analysis of Feeding Behavior in Shaded and Open-Lot Feedlot Heifers. T*ransactions of the ASABE* **58**(6), 1833-1839.

Brown-Brandl, T.M., Jones, D.D., and Eigenberg, R.A. 2016. Modeling Feeding Behavior of Swine to Detect Illness. International Conference on Agricultural Engineering, CIGR – AgEng 2016, *June 26-29, Aarhus, Denmark.*

Cross, A.J., Brown-Brandl, T.M., and Rohrer, G.A. 2017. Impacts of genetic line, gender, and season on feeding behaviour of grow-finish swine. *13th Conference: Construction, Engineering and Environment in Livestock Farming*, September 18-20, Stuttgart, Germany.

Finkenzeller, K. 2010. *RFID Handbook: Fundamentals and Applications in Contactless Smart Cards, Radio Frequency Identification and Near-Field Communication*. 3rd Ed. John Wiley & Sons Ltd, West Sussex, United Kingdom.

HID Global Corporation 2014. Top 7 consideration to choose the right RFID Tag. White paper, HID Global Corporation/ASSA ABLOY AB.

Jansen, M. B., and Eradus, W. 1999. Future developments on devices for animal radiofrequency identification. *Computers and Electronics in Agriculture* **24**, 109-117.

Kapun, A., Adrion, F., Schmid, L.A., Staiger, M., Holland, E.M., Gallmann, E., and Jungbluth, T. 2016. Test of a UHF-RFID system for health monitoring of finishing pigs. *International Conference on Agricultural Engineering, CIGR – AgEng 2016, June 26-29, Aarhus, Denmark.*

Kern, C.J. 2007. *Anwendung von RFID-Systemen*. 2nd Ed. Springer Verlag, Berlin, Heidelberg, New York.

Lorenzo, J., Girbau, D., Lázaro, A., and Villarino, R. 2011. Read range reduction in UHF RFID due to antenna detuning and gain penalty. *Microwave and Optical Technology Letters* **53**(1), 144-148.

Malik, W. 2015. Low Frequency Reader and Antenna Design Using RFID. *Universal Journal of Electrical and Electronic Engineering* **3**(1),1-5.

Maselyne, J., Adriaens, I., Huybrechts, T., De Ketelaere, B., Millet, S., Vangeyte, J., Van Nuffel, A., and Saeys, W. 2015a. Measuring the drinking behaviour of individual pigs housed in group using radio frequency identification (RFID). *Animal* **10**, 1557-1566.

Maselyne, J., Saeys, W., Briene, P., Mertens, K. C., Vangeyte, J., De Ketelaere, B., Hessel, E. F., Sonck, B., and Van Nuffel, A. 2016. Methods to construct feeding visits from RFID registrations of growing-finishing pigs at the feed trough. *Computers and Electronics in Agriculture* **128**, 9-19.

Maselyne, J., Saeys, W., De Ketelaere, B., Mertens, K., Vangeyte, J., Hessel, E. F., Millet, S., and Van Nuffel, A. 2014a. Validation of a High Frequency Radio Frequency Identification (HF RFID) system for registering feeding patterns of growing-finishing pigs. *Computers and Electronics in Agriculture* **102**, 10-18.

Maselyne, J., Saeys, W., and Van Nuffel, A. 2015b. Review: Quantifying animal feeding behaviour with a focus on pigs. *Physiology & Behavior* **138**, 37-51.

Maselyne, J., Van Nuffel, A., De Ketelaere, B., Vangeyte, J., Hessel, E. F., Sonck, B., and Saeys, W. 2014b. Range measurements of a High Frequency Radio Frequency Identification (HF RFID) system for registering feeding patterns of growing-finishing pigs. *Computers and Electronics in Agriculture* **108**, 209-220.

Nikitin, P.V., and Rao, K. 2006. Theory and measurement of backscattering from RFID tags. *IEEE Antennas and Propagation Magazine* **48**(6), 212-218.

Rohrer, G.A., Brown-Brandl, T.M., Rempel, L.A., Schneider, J.F., Holl, J. 2013. Genetic analysis of behaviour traits in swine production. Livestock Science **157**, 28-37.

Rossing, W. 1999. Animal identification: introduction and history, In: Rossing, W. (Ed.). *Electronic Animal Identification. Computers and Electronics in Agriculture*, vol. 24. Elsevier Science, Amsterdam, 1-4.

Ruiz-Garcia, L., and Lunadei, L. 2011. The role of RFID in agriculture: Applications, limitations and challenges. *Computers and Electronics in Agriculture* **79**, 42-50.

Sattleger, K., and Denk, U. 2014. Navigating your way through the RFID jungle. White paper, Texas Instruments.

Texas Instruments. 2003. Series 2000 LF Antenna Design Guide: Application Guide. Lit. Number: 11-06-21-068.

Tolkamp, B. J., Allcroft, D. J., Austin, E. J., Nielsen, B. L., and Kyriazakis, I. 1998. Satiety splits feeding behaviour into bouts. Journal of Theoretical Biology **194**, 235-250.

Session 18

Pigs/Sows

Automatic estimation of number of piglets in a pen during farrowing, using image analysis

M. Oczak[1,2], K. Maschat[1], D. Berckmans[2], E. Vranken[2] and J. Baumgartner[1]
[1]*Institute of Animal Husbandry and Animal Welfare, University of Veterinary Medicine Vienna (Vetmeduni Vienna), Veterinärplatz 1, A-1210 Vienna, Austria*
[2]*M3-BIORES: Measure, Model, Manage Bioresponses, Katholieke Universiteit Leuven, Kasteelpark Arenberg 30, B-3001 Leuven, Belgium*
Maciej.Oczak@vetmeduni.ac.at

Abstract

The objective was to develop a camera based monitoring system of the farrowing process in sows. The system, when used in practical farm conditions, should support the farm staff in reducing the problems of mortality in piglets due to perinatal asphyxia and crushing. The experiments took place in the research farm of the University of Veterinary Medicine Vienna, using a herd of 120 Large White sows. Data were collected from sows housed in farrowing pens with possibility of temporary crating. The farrowing process of 8 sows was video recorded and labelled for a period of 6 hours (h) before the start of farrowing until the end of farrowing. Timestamps of births of all piglets in the litter were labelled. Images obtained during the experiment were segmented with focus on piglet detection. Three parameters were extracted from segmented images: number of objects detected, area and perimeter of all objects. On the basis of the parameters, a Transfer Function (TF) model was estimated with output variable defined as number of piglets in the pen. The developed model explained 82 % (R^2) variability in the training set composed of 5 sows and 81 % (R^2) in the validation set composed of 3 sows. Number of piglets in the pen was estimated with a standard error of 1.73 piglets in the training set and 1.72 in the validation set. The potential application of the developed technique is monitoring of start of farrowing, perinatal asphyxia and crushing in piglets.

Keywords: farrowing monitoring; piglet counter; automated image processing; Transfer Function modelling

Introduction

Farrowing in sows mostly does not last longer than several hours (Fraser et al., 1997). This relatively short process, which is a culmination of nearly 4 months of gestation, is critical from welfare and economical point of view. Losses from the start until the end of farrowing can account on average for up to a dozen percent

of a litter (Dyck and Swierstra, 1987; Leenhouwers et al., 2003) and their significance can only be compared to losses that occur in the first few days after farrowing is finished (Weber et al., 2007). The losses from the start until the end of farrowing are predominantly a result of perinatal asphyxia experienced in utero or during delivery (Randall, 1977). Perinatal asphyxia results in stillborn piglets and also in reduced viability (Randall, 1971), reduced early postnatal vitality and decreased growth and survival rates until the age of 10 days of piglets born live (Herpin et al., 1996). The risk of perinatal asphyxia is higher when farrowing lasts longer, number of piglets born in the litter is higher or when a piglet is born later in comparison to the other piglets in the litter (Herpin et al., 1996).

Besides perinatal asphyxia, a second important cause of mortality of piglets, during farrowing is crushing (Weber et al., 2007). During farrowing sows can change their postures rapidly. Fast lying down or a transition from a vertical lying position (prone) to a lateral position (on the side) can lead to piglet crushing (Andersen et al., 2005). These sudden changes in postures of sows impose major risks for the piglets (Damm et al., 2005; Wechsler and Hegglin, 1997). Furthermore, piglets are predisposed to being crushed by a failure to achieve regular and adequate intake of food. Piglets that do not get enough food spend more time in proximity to the sow and are hence more at risk (Weary et al., 1996).

Recent developments in Precision Livestock Farming (PLF) techniques could offer new possibilities to support farm staff in reducing the problems of mortality in piglets during farrowing. Important causes of piglet mortality during farrowing (perinatal asphyxia and crushing) are associated with factors that could be potentially monitored with camera technology and image analysis. Location of piglets in a pen is an important factor related to piglet crushing (Weary et al., 1996) and it has been already estimated in fattening pens for a purpose of locomotion monitoring on individual (Lind et al., 2005) and group level (Kashiha et al., 2014). Automated detection of a sudden decrease in number of piglets in camera view in farrowing pen could suggest that some piglets are crushed by the sow’s body. Finding and counting piglets in a pen could also help in estimation of duration of farrowing, place of piglets in birth order and determine the total number of piglets born in a litter; all factors closely connected with perinatal asphyxia (Herpin et al., 1996).

The objective of this research was to develop a camera based monitoring system of farrowing process in sows. The system, when used in practical farm conditions, should support the farm staff in reducing the problems of perinatal asphyxia and crushing of piglets.

Materials and methods

Animals and housing

Experiments were conducted between June 2014 and March 2015 at the experimental farm of the University of Veterinary Medicine, Vienna. In total 8 Austrian Large White sows were included in the experiments. The sows were kept in farrowing pens with possibility of temporary crating of the animals.

The farrowing pens had an area of 5.5 square metres (m^2). The floor of the pens consisted of slatted plastic and solid concrete floor elements. The pens had solid concrete flooring in the piglet area. The sows were introduced to the farrowing pens five days before the expected due date of farrowing. The experimental period was from 6 h before the first piglet was born in a litter of a sow until the last piglet was born in that litter. The experimental pens were located in a test unit of the farm which had an automatic ventilation system. The average temperature in the unit was 22 degree Celsius (°C). The sows were fed twice a day in the experimental period. Water was provided permanently in the troughs either via a nipple drinker or an automatic water-level system.

Video recording

Behaviour of sows was video recorded from introduction to the farrowing pens until weaning with 2D cameras in order to create a data set that could be labelled. Each pen was equipped with one internet protocol (IP) camera (GV-BX 1300-KV, Geovision, Taipei, Taiwan) locked in protective housing (HEB32K1, Videotec, Schio, Italy) hanging 3 metres (m) above the pen, giving an overhead view. Additionally, infrared spotlights (IR-LED294S-90, Microlight, Bad Nauheim, Germany) were installed in order to allow night recording. The images were recorded with 1280 × 720 pixel resolution, in Moving Picture Experts Group - 4 (MPEG-4) format, at 30 frames per second (fps). Recordings were stored on exchangeable, external 2 and 3 terabytes (TB) hard drives.

Data labelling

Recorded videos were manually labelled in order to create a reference data set on the basis of which an algorithm for automatic monitoring of the progress of farrowing could be developed. In the first step of the labelling process, the time of the beginning of farrowing of each individual sow was labelled. In the second step, timestamps of moments of births of all remaining piglets in the litter were labelled. Finally, the end of the farrowing was labelled for each sow. The end of farrowing was defined as the point in time when the body of the last piglet born dropped on the floor. In order to add recordings in which only the sow and no piglets are present in the pen, period of 6 h before the start of farrowing for each sow was added to the labelled data set. Labelling software Interact (version 9 and

14, Mangold International GmbH, Arnstorf, Germany) was used to label the images.

Segmentation

In order to extract the parameters from image, on the basis of which number of piglets in the pen could be estimated the following segmentation procedure was executed. In the first step original recording frame rate of 30 fps was reduced to 1 frame per minute (fpm). The frame rate was reduced to improve the speed of image processing and make it visible to use the developed technique in real time (Fig. 1). In the next step the original red, green, blue colour model (RGB) images were converted to grayscale and the central area of the pen in which the farrowing was occurring was manually selected as the zone of interest. In order to eliminate background from the images binarisation procedure had to be performed. In order to make it possible to eliminate the background successfully, the zone of interest was divided into two areas. To remove small objects such as slat edges and side bars from the image, dilation followed by erosion was performed. The morphological element used for the operation was a disk of size 9 × 15 pixels (Gonzales et al., 2004). In the next step greyscale image were converted to binary with two threshold levels for two area of the pen - one with plastic and second with concrete floor. This step was followed by merging of two areas into one image. Merging the areas allowed the use of Watershed algorithm for finding boundaries between piglets and between piglet and a sow (Meyer, 1994). In the final step exterior boundaries of objects were traced in the binary image with limit in size of objects to a range of 800 to 20,000 pixels (Gonzales et al., 2004) (Fig. 2). Introduction of the range in size of the objects allowed eliminating very small objects (i.e. floor elements) and a sow. The result of performing the segmentation was certain number of objects extracted in each frame of the video.

Figure 1. Original image in RGB

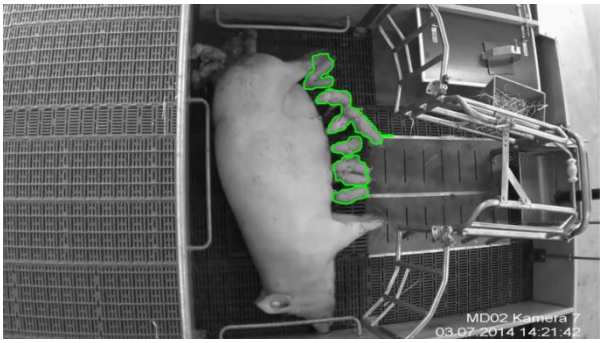


Figure 2. Grayscale image with objects traced of size 800 to 20000 pixels.

Parameters

In order to estimate the number of piglets in the pen, in the next step, parameter(s) were calculated, which could be used as inputs to the model. Beside the most obvious parameter, the number of objects detected in an image, two additional parameters were calculated:

Area – sum of pixels in all extracted objects.

Perimeter – sum of distances around the boundaries of all extracted objects.

The reason for calculating the two additional parameters was that the segmentation procedure often resulted in group of piglets being identified as one object (Fig. 2). These two parameters proved to be useful previously for estimation of thermal comfort in pigs (Shao et al., 1998).

Estimation of number of piglets in a pen using TF model

In order to estimate a number of piglets in a pen on the basis of the three calculated parameters TF model was used. TF model type was multiple-input single-output (MISO) (Young, 2011). The Captain toolbox in Matlab 2014b (Mathworks, Natick, MA, USA) was used in order to estimate model variables with refined instrumental variable approach (Young, 2011). Different combinations of model variables were used in order to estimate the MISO model with three input parameters. The optimal model was selected on the basis of value of coefficient of determination (R^2). R^2explained how well the model fitted into the data and had a value from 0 to 1 (Young and Lees, 1993).

The model was estimated, in the first step, on the training set, which was composed of 5 sows randomly selected from 8 sows included in the experiments. In the second step validation was performed on data set collected on 3 remaining sows. The model performance in the validation set was evaluated on the basis of R^2.

Results and Discussion

In total, the behaviour of 8 sows was labelled to create a reference data set for algorithm development. Sows assigned to training set (5) gave birth to a total number of 55 piglets, while 3 sows assigned to validation set to 34 piglets. Total duration of farrowing of sows in the training set was 18.9 h, whereas sows in the validation set was 12.3 h.

On the basis of three parameters calculated: area, perimeter and number of objects, the following TF model with highest $R^2$was selected.

$$P(t) = \frac{0.00000039 \cdot Z^{-1}}{1 - 1.93 \cdot Z^{-1} + 0.93 \cdot Z^{-2}} A_1(t-2) + \frac{-0.00001 \cdot Z^{-1}}{1 - 1.93 \cdot Z^{-1} + 0.93 \cdot Z^{-2}} A_2(t-2) + \frac{0.087 \cdot Z^{-1} - 0.086 \cdot Z^{-2}}{1 - 1.93 \cdot Z^{-1} + 0.93 \cdot Z^{-2}} A_3(t-1)$$

R^2 of selected TF model was 0.82 in the training set, with standard error of 1.73 piglets. Estimated order of denominator of TF model was 2. Orders of nominators of three parameters were 1 of area, 1 of perimeter and 2 of number of objects. Estimated delays were 2 of area, 2 of perimeter and 1 of number of objects. Validation of the estimated TF model on remaining 3 sows resulted in accuracy (R^2) of 0.81, with a standard error (SE) of 1.72 piglets.

In the training set the estimated standard error was the lowest for sow number 147,045 (1.34). The highest standard error in the training set was estimated for sow 147,102 (2.02). In the validation set the highest estimated standard error was in sow 147,127 (1.76), while the lowest was estimated in sow 147,149 (1.61) (Fig. 3).

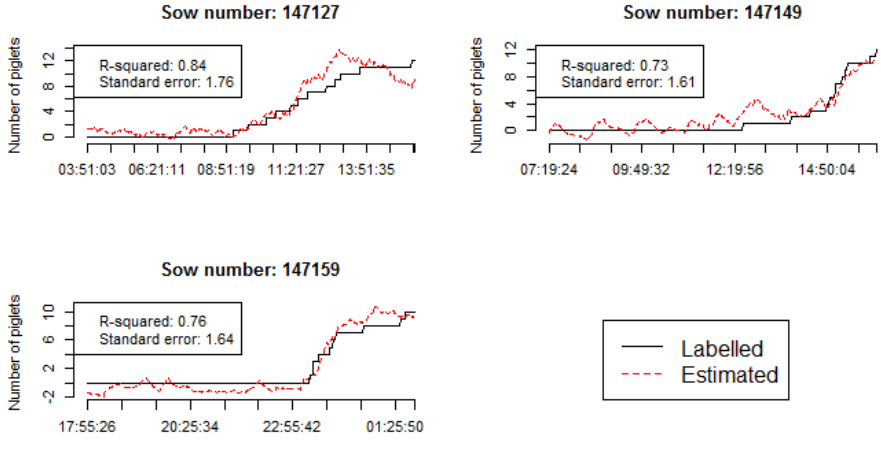


Figure 3. Validation set results

There are several potential applications of the developed piglet counter in practical farm conditions. Firstly, by using the automatic counting of piglets in an image it should be possible to detect the start of farrowing. So far there have been several approaches to predict the start of farrowing in sows on the basis of accelerometer sensors (Cornou et al., 2011; Oczak et al., 2015; Pastell et al., 2013) light barriers (Manteuffel et al., 2015) and a combination of monitoring water intake, a camera and photocell sensors (Aparna et al., 2014). The best prediction accuracy obtained in the above research was ±4 h (Manteuffel et al., 2015) in crated sows and ±4.6 h in loose housed sows (Aparna et al., 2014). However, these predictions were based only on behavioural changes in a sow related to nest-building (i.e. activity increase) which occurs just before the start of farrowing. By utilising the developed method it is possible to automatically detect when piglets are actually born. This should provide much more precise information about the time of the start of farrowing than prediction methods.

The next possible application of the developed method could be to support farm staff in the process of supervised farrowing, with the aim to reduce the problem of perinatal asphyxia. Because stillborn piglets are delivered after significantly longer birth intervals than live born (Dijk et al., 2005), current practice of farm staff is, in the first stage, to assess how much time has passed since the last piglet was born. This is done by looking at state of wetness of piglet's skin and also by counting number of piglets in the pen. In the second stage, when farm staff asses the time as being too long, obstetric intervention is performed. Obstetric intervention determines if there is a piglet present in the uterus and, if so, what is its position. During obstetric intervention it is possible to support the farrowing process by changing the orientation of a piglet in the uterus and reducing the time needed for its expulsion (Jackson and Cockcroft, 2007). These practices can reduce the risk of piglets suffocating during farrowing. Using the automated piglet counter should make evaluation of the time that passed since the last piglet was born more reliable. Thus, an alarm could be generated when too much time has passed since the last piglet was born by a certain sow, indicating that this sow should be examined. It is important to consider that, although total litter size is a risk factor for stillborn piglets, it is unknown before farrowing. Therefore, constant farrowing supervision, which an automated cameras system offers, could be important management tool to help to reduce the risk of stillborn piglets (Lucia et al., 2002).

An additional advantage of using an automated system that counts piglets is that farm staff could have an overview on the situation in the pen when they are not directly observing the pen. This potentially could reduce stress during farrowing and improve productivity especially in fearful sows as high levels of fear of humans by sows may affect the survival of their piglets (Hemsworth et al., 1999). Automated monitoring of the progress of farrowing should allow for the

more efficient allocation of manpower on the farm. Farm staff could invest less time in observing the animals and more in executing obstetric interventions when needed and other duties.

A system which allows counting piglets during farrowing should help reducing the problem of piglet crushing. Piglet crushing is a major welfare and economic problem in the pig industry. In order to reduce the risk of piglet crushing, in practical farm conditions, farm staff monitor pens visually. If piglets are located in a dangerous area of the pen when a sow changes its posture, or if piglets are trapped under the sow, farm staff move the piglets to safe location in the pen (Vasdal et al., 2011). In the experiment performed by Weary et al. (1996) out of 84 piglets caught under a sow, 80 survived when duration of time spent under a sow was < 1 min. However, only eight out of 24 piglets survived when being trapped for ≥ 4 min. This result suggests that if crushing could be detected, and intervention applied within one minute from the beginning of crushing, then most of the piglets at risk could be saved. In this context application of an automated piglet counter based on camera technology could play an important role in reduction of the problem of piglet crushing. The practical application of the system could be to detect sudden drops of number of piglets in a pen. The drops could indicate that piglets previously detected in a pen are covered by the body of a sow. Finally, the data related to the progress of farrowing for each sow (i.e. duration of breaks between piglet expulsions) and to crushing events, could be stored and used for litter analysis. This could allow predicting problems in the future farrowing as well as determining the ratio of stillborn piglets and discovering if the number of piglets crushed is consistent between litters (Jarvis et al., 2005).

Conclusions

Image analysis and TF model was used in order to estimate number of piglets in a farrowing pen, during farrowing. The developed model explained 82% (R^2) variability in the training set composed of 5 sows and 81% (R^2) in the validation set composed of 3 sows. The number of piglets in the pen was estimated with a standard error of 1.73 piglets in the training set and 1.72 in the validation set. A potential application of the developed technique is the monitoring of start of farrowing and perinatal mortality in piglets. The technique could also be applied to helping estimate the duration of farrowing, placing piglets in birth order and the total number of piglets born in a litter.

Acknowledgements

Project ‘PIGwatch’ fundet by Provincial Government of Niederösterreich (K3-F-149/003-2013).

References

Andersen, I.L., Berg, S., Bøe, K.E., 2005. Crushing of piglets by the mother sow (Sus scrofa)—purely accidental or a poor mother? Applied Animal Behaviour Science 93, 229-243.

Aparna, U., Pedersen, L.J., Jørgensen, E., 2014. Hidden phase-type Markov model for the prediction of onset of farrowing for loose-housed sows. Computers and Electronics in Agriculture 108, 135-147.

Cornou, C., Lundbye-Christensen, S., Bono, C., Kristensen, A.R., 2011. Monitoring individual sows’ activity & detecting the onset of parturition, In: EAAP 2011. 62th Annual Meeting of the European Association for Animal Production.

Damm, B.I., Forkman, B., Pedersen, L.J., 2005. Lying down and rolling behaviour in sows in relation to piglet crushing. Applied Animal Behaviour Science 90, 3-20.

Dijk, A.J.v., Rens, B.T.v., Lende, T.v.d., Taverne, M.A., 2005. Factors affecting duration of the expulsive stage of parturition and piglet birth intervals in sows with uncomplicated, spontaneous farrowings. Theriogenology 64, 1573-1590.

Dyck, G., Swierstra, E., 1987. Causes of piglet death from birth to weaning. Canadian Journal of Animal Science 67, 543-547.

Fraser, D., Phillips, P., Thompson, B., 1997. Farrowing behaviour and stillbirth in two environments: an evaluation of the restraint-stillbirth hypothesis. Applied Animal Behaviour Science 55, 51-66.

Gonzales, R.C., Woods, R.E., Eddins, S.L., 2004. Digital image processing using MATLAB. Pearson Prentice Hall.

Hemsworth, P., Pedersen, V., Cox, M., Cronin, G., Coleman, G., 1999. A note on the relationship between the behavioural response of lactating sows to humans and the survival of their piglets. Applied Animal Behaviour Science 65, 43-52.

Herpin, P., Le Dividich, J., Hulin, J.C., Fillaut, M., De Marco, F., Bertin, R., 1996. Effects of the level of asphyxia during delivery on viability at birth and early postnatal vitality of newborn pigs. Journal of animal science 74, 2067-2075.

Jackson, P.G., Cockcroft, P.D., 2007. Handbook of pig medicine. Elsevier Health Sciences.

Jarvis, S., D'Eath, R., Fujita, K., 2005. Consistency of piglet crushing by sows. Animal Welfare 14, 43-51.

Kashiha, M., Bahr, C., Ott, S., Moons, C.P., Niewold, T.A., Tuyttens, F., Berckmans, D., 2014. Automatic monitoring of pig locomotion using image analysis. Livestock Science 159, 141-148.

Leenhouwers, J., Wissink, P., Van der Lende, T., Paridaans, H., Knol, E., 2003. Stillbirth in the pig in relation to genetic merit for farrowing survival. Journal of animal science 81, 2419-2424.

Lind, N.M., Vinther, M., Hemmingsen, R.P., Hansen, A.K., 2005. Validation of a digital video tracking system for recording pig locomotor behaviour. Journal of neuroscience methods 143, 123-132.

Lucia, T., Corrêa, M.N., Deschamps, J.C., Bianchi, I., Donin, M.A., Machado, A.C., Meincke, W., Matheus, J.E., 2002. Risk factors for stillbirths in two swine farms in the south of Brazil. Preventive veterinary medicine 53, 285-292.

Manteuffel, C., Hartung, E., Schmidt, M., Hoffmann, G., Schön, P.C., 2015. Individual quantitative prediction of the onset of parturition in sows based on light barriers.

Meyer, F., 1994. Topographic distance and watershed lines. Signal processing 38, 113-125.

Oczak, M., Maschat, K., Berckmans, D., Vranken, E., Baumgartner, J., 2015. Classification of nest-building behaviour in non-crated farrowing sows on the basis of accelerometer data. Biosystems Engineering 140, 48-58.

Pastell, M., Hietaoja, J., Yun, J., Tiusanen, J., Valros, A., 2013. Predicting farrowing based on accelerometer data. Precision Livestock Farming 13, 243-252.

Randall, G.C.B., 1971. The relationship of arterial blood pH and pCO2 to the viability of the newborn piglet. Canadian Journal of Comparative Medicine 35, 141.

Randall, G.C.B., 1977. Perinatal mortality: some problems of adaptation at birth. Advances in veterinary science and comparative medicine 22, 53-81.

Shao, J., Xin, H., Harmon, J., 1998. Comparison of image feature extraction for classification of swine thermal comfort behavior. Computers and electronics in agriculture 19, 223-232.

Vasdal, G., Østensen, I., Melišová, M., Bozděchová, B., Illmann, G., Andersen, I.L., 2011. Management routines at the time of farrowing—effects on teat success and postnatal piglet mortality from loose housed sows. Livestock Science 136, 225-231.

Weary, D.M., Pajor, E.A., Thompson, B.K., Fraser, D., 1996. The relationship between piglet body condition and proximity to the sow: a trade-off between feeding and the risk of mortality by maternal crushing. Anim. Behav 51, 619-624.

Weber, R., Keil, N., Fehr, M., Horat, R., 2007. Piglet mortality on farms using farrowing systems with or without crates. Animal Welfare 16, 277-279.

Wechsler, B., Hegglin, D., 1997. Individual differences in the behaviour of sows at the nest-site and the crushing of piglets. Applied Animal Behaviour Science 51, 39-49.

Young, P.C., 2011. Recursive estimation and time-series analysis: An introduction for the student and practitioner. Springer Science & Business Media.

Young, P.C., Lees, M.J., 1993. The active mixing volume: a new concept in modelling environmental systems. Statistics for the Environment 2, 3-46.

Monitoring of the individual drinking behaviour of healthy weaned piglets and pregnant sows

Y. Rousselière, A. Hémonic, M. Marcon
IFIP-Institut du Porc, BP 35104, 35651 Le Rheu cedex, France
yvonnick.rousseliere@ifip.asso.fr

Abstract

Trials were conducted at the Ifip experimental station in Romillé (Brittany, France) to assess the individual drinking behaviour of healthy weaned piglets and pregnant sows. A special connected drinker was developed to collect this type of data. It is composed of an anti-wastage bowl drinker surrounded by shoulder partitions, a precision water meter (± 0.01 l for piglets and ± 0.1 l for sows) and a RFID (Radio Frequency IDentification) antenna to detect animals near the drinker by means of the individual electronic ear tag on each pig. Observations on animals were carried out twice a week to evaluate their health status. This study only focuses on healthy animals. Weaned piglets were bred in pens of 19 animals. The individual water consumption was 10.7% of body weight on average. Sows were bred in a dynamic group equipped with 6 connected drinkers and automatic feeders. On average, the daily water consumption was 8.2 l/day (1.6 l during the meal and 6.6 l directly at the bowl drinker). For the two types of animal, there is large inter- and intra-individual variability in terms of water consumption (more than 30%). Thus, it appears to be difficult to determine the health status of piglets or sows on the basis of drinking behaviour only. The next step is to combine this information with other data (feeding system, automatic weighing station, accelerometer, etc.) to identify a behavioural pattern in healthy animals.

Keywords
Drinking behaviour, connected drinker, water consumption, pig, monitoring, healthy

Introduction

Drinking behaviour and water consumption of pigs seem to be an interesting indicator which may provide a good understanding of their health status. Indeed, several authors have found that an animal may modify its feeding and/or drinking behaviour at the onset of disease (Pijpers *et al.*, 1991; Andersen *et al.*, 2014). This modification may occur a few hours before the start of the first

clinical symptoms observed by an operator (Madsen and Kirstensen, 2005; Brumm, 2006).

Early prediction of disease may be an innovative way of reducing antibiotic usage, by treating sick animals more promptly in order to reduce the transmission of pathogens to others or by treating only sick animals instead of the whole group. For more effective early prediction of disease, it is essential to collect individual data because collective drinking behaviour can hide a large amount of variability.

Thus, one of the goals of this study was to develop and validate a technology which was capable of recording the individual drinking behaviour of weaned piglets or pregnant sows. It would be used to determine the water consumption patterns of healthy pigs.

Materials and methods

Trial periods

The trial using weaned piglets took place from 4th June to 16th July 2015. The first few days of the trial were used to design and test connected drinkers, which is why the results relate only to the last 22 days of post-weaning (from the 47th to the 69th day of age). The trial using sows took place over 58 days, from 4th May 2016 to 30th June 2016.

Connected bowl drinker

An automatic system was developed with a French firm specialising in animal livestock housing (Asserva) in order to isolate and identify pigs in front of the drinker then to record their individual drinking behaviour. This automatic system, known as Aqualab, is composed of an anti-wastage bowl drinker surrounded by shoulder partitions, a precision water meter (± 0.01 l for piglets and ± 0.1 l for sows) and a RFID (Radio Frequency IDentification) antenna to detect animals near the drinker by means of the individual electronic ear tag on each pig (Figures 1 and 2). This automatic system was connected to a computer which recorded water quantity used and duration of each visit. The amount of water recorded included actual consumption by the pig and water wastage, this latter being considered a part of the natural drinking behaviour of the pig.

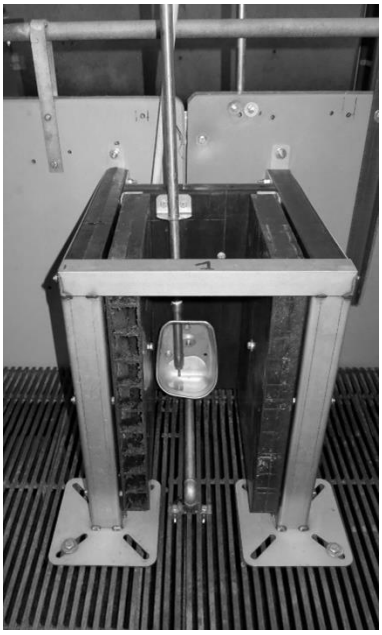


Figure 1: Connected drinker pregnant sow

Figure 2: Connected drinkerfor for piglet

Housing conditions

Tests were carried out at the Ifip experimental station in Romillé (Brittany, France).

- Weaned piglets: After weaning, 228 piglets, 28 days old, were allocated to 12 pens of 19 animals. Three weight groups were created with four pens each (heavy, medium and light with a mean weight of 11.1 kg, 9.1 kg and 7.0 kg, respectively). Piglets were individually weighed every 14 days. As shown in Figure 3, six pens had a traditional bowl drinker and the others had a connected drinker (Aqualab). The water flow was set to 1 l/minute and checked every 14 days. The daily water consumption of the twelve pens was recorded. Pens were heated to 28°C at the start of post-weaning and the temperature was gradually reduced to 24°C by the end of the trial.
- Pregnant sows: 83 sows (3 different batches with 3 different gestation periods) were housed in a dynamic group. They were fed individually with automatic feeders by means of their electronic ear tags. They were given dry food but some water (0.5 litre / kilogram of feed) was automatically added inside the trough to meet the needs of the capacitive sensor which detects the remaining level of food. Sows were weighed every day by an automatic weighing station located at the exits from the

feeders. Six connected drinkers were installed (Figure 4). The water flow was set to 3 l/minute and checked every 14 days. The temperature in the pen was maintained at around 21 °C throughout the trial.

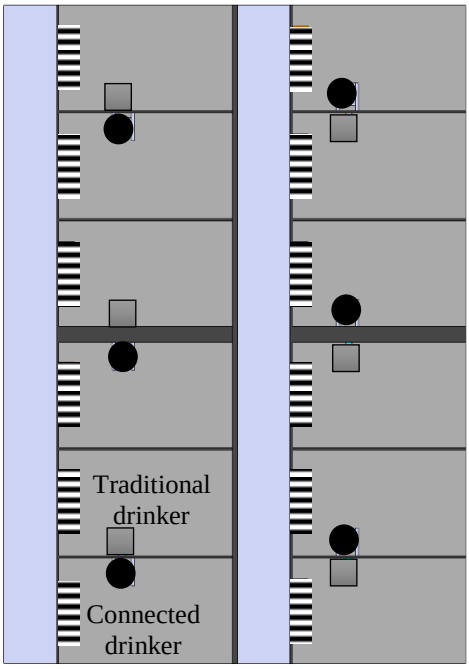


Figure 3: Housing conditions of piglets (black horizontal lines for feeding system, circle for connected drinker and square for traditional drinker)

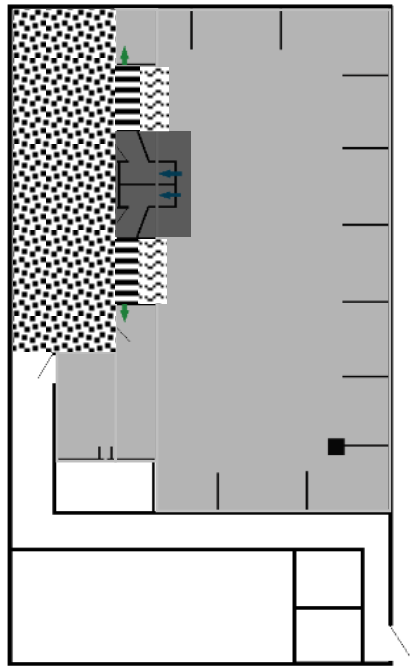


Figure 4: Housing conditions of sows (grey for living area, dot for selected area, black wavy lines for connected drinker, black for automatic feeder and black horizontal lines for weighing station)

Health status of the animals

Each day, animals were observed by the staff of the station to assess their health status. Specific attention was paid to the most frequent diseases observed in pig barns: locomotor and urinary disorders for sows and digestive and respiratory disorders for piglets. In addition, observations of the general health status were carried out by an external operator on each animal, once a week for sows and twice a week for piglets. This evaluation was based on a rating grid inspired by the Welfare Quality approach. All remarks relating to the health of the animals were recorded (pathology, severity, date, operator, veterinary intervention if necessary). For sows, individual urine test strips were used at the end of the pregnancy.

Statistical analyses

Data analysis by descriptive statistics was carried out under R version 3.3.1. The comparison of water consumption between pens according to their drinker type (traditional bowl drinker vs connected drinker) was carried out using a non-parametric test (Kruskal-Wallis).

Results

All the results related only to animals which were observed as being healthy. Data for sick animals were deleted from the database: (i) for locomotor, digestive or respiratory disorders, we kept the animal in the database but deleted all the data around the day concerned (ii) for urinary disorders; we deleted all the data for the animal.

Weaned piglets

At the end of the trial, data for 95 animals (from 114) were retained. On 22 days, the average water consumption did not differ significantly according to the drinking equipment (traditional bowl drinker vs connected drinker). Therefore, the automatic system did not seem to interfere with piglets' access to the drinker. The daily individual water consumption by piglets is, as an average for all animals, 10.7% of the body weight in kilograms (BW). Table 1 shows great inter-individual variability since the coefficient of variation (CV) calculated from the average of the individual average values obtained per piglet is 33.6%. At the intra-individual scale, the daily consumption expressed per kilogram of BW is also very variable, the coefficient of variation of the individual measurements being on average 31.5% (± 9.9).

Table 1 : Mean and variability of the daily water consumption of weaned piglets

Scale	Parameters	Values
Inter-individual	Mean, l/kg of body weight (BW)	0.104
	Standard deviation	0.035
	Coefficient of variation (CV), %	33.6
Intra-individual	Mean CV, %	31.5
	Standard deviation of CV	9.9

With the connected drinker, it was possible to track the daily water consumption of each piglet over several days. As an example, Figure 5 shows the individual consumption profiles of three piglets compared to the average profile obtained from 95 piglets.

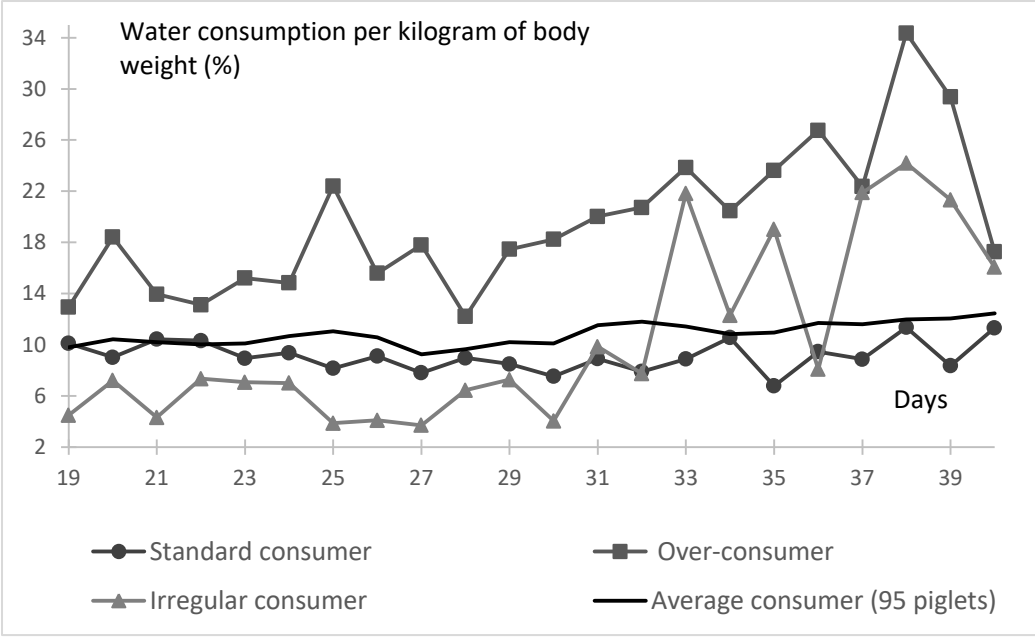


Figure 5: Contrasted examples of drinking behaviour of weaned piglets

- The profile named "Standard Consumer" matches with a piglet consuming a quantity of water between 7 and 11% of BW. Its profile is regular and relatively close to the consumption profile of the average piglet.
- The profile named "Irregular Consumer" matches with a piglet whose consumption of water from one day to the next can be very different (variation of 13.8 % of BW between the 36th (8.1% BW) and 37th day (21.9% BW)).
- The profile named "Over-consumer" corresponds to consumption which is higher than the average consumption of the average piglet. It varies from 13 to 34% of BW.

Most of the remaining 92 piglets did not have such specific and contrasting profiles as these three examples: they pass from one to the other over time, which is even more difficult to interpret and predict.

There is also great variability in the drinking behaviour of piglets. At each visit, the average amount of water consumed per piglet was 104 ml (SD 133). The number of visits to the drinker was around 27.2 (SD 12.3) per day.

Pregnant sows

At the end of the trial, the database held 4814 data records (1 data record is equivalent to the drinking behaviour of one sow on one day). We removed the data relating to sows with locomotor disorders and all the data for two sows: one with a urinary disorder and one because of aberrant data. Indeed, we identified an atypical sow whose average water consumption was 41.7 l / day, i.e. more than four times the water consumption of the average sow. This sow also represented 14.8% of the inter-individual variability in daily average water consumption.

The final database is composed of 81 sows and 3900 data records.

On average, sows weighed 252 kg and consumed 8.2 l of water per day, divided into: (i) 1.6 l consumed during the meal (water added in automatic feeder) and (ii) 6.6 l consumed spontaneously at connected drinkers.

For water consumption, Table 2 shows great variability on two levels. On the one hand, a very high inter-individual variability: the coefficient of variation (CV) calculated from the average of the average values obtained per sow is 50.0%. On the other hand, the intra-individual variability is also significant: the average individual CV for daily water consumption is 37.9% ± 10.2.

Table 2 : Mean and variability of the daily water consumption of pregnant sows

Scale	Parameter	Value
Inter-individual	Mean, ml/kg of body weight (BW)	33.2
	Standard deviation	16.5
	Coefficient of variation (CV), %	50.0
Intra-individual	Mean CV %	37.9
	Standard deviation of CV, %	10.2

As shown in Figure 6, the litter rank of sows was significantly linked to water consumption. The drinking behaviour of primiparous sows was completely different. Their water consumption was 49.2 ml/kg BW (± 46.9). Consumption by older sows (litter rank higher than 6) was lower than the first group at around 18.9 ml/kg BW. This concerned only a small percentage of the population (8 sows out of 81) so this result is subject to some reservations. Sows with a litter rank of 0, 2, 4 and 5 seemed to have the same water consumption at around 34.0 ml/kg BW.

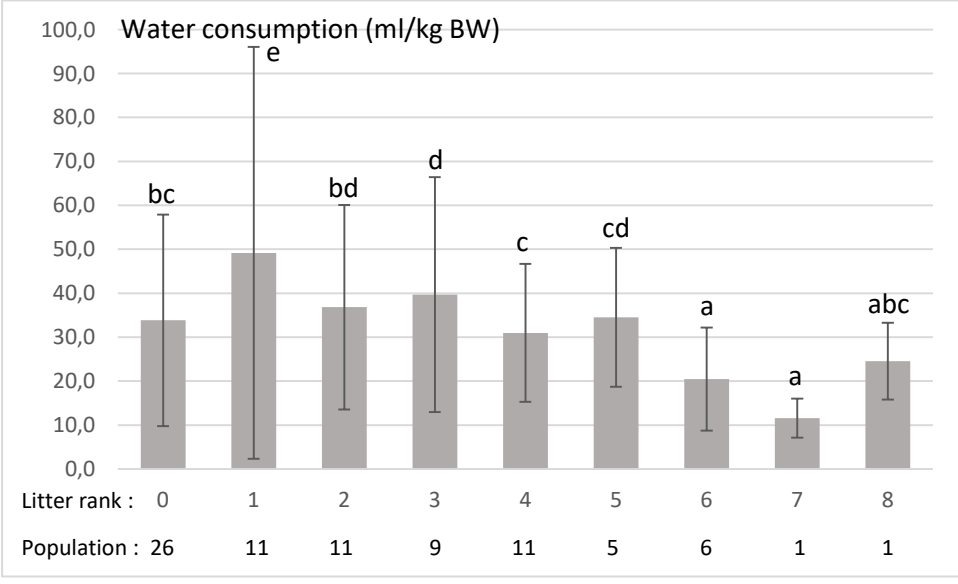


Figure 6: Water consumption and litter rank of pregnant sows.

The batch effect is correlated with the stage of gestation and there were significant differences. Sows at the start of the gestation (from the 28th to the 85th days of gestation) had a water consumption of 34.9 ml/kg BW. Sows in the middle of gestation (from 41 to 98 days) consumed around 45.0 ml/kg BW. Finally, sows at the end of gestation (from 62 to 110 days) consumed around 25.8 ml/kg BW.
These differences are not due solely to the litter rank of sows in each batch because we found the same type of results when we studied the interaction between batch and litter rank, and it was also significant.

Throughout the trial, the daily mean temperature of the pen remained at around 22.0°C (±1). Only one day was hotter, with a mean temperature of 26.9°C. The temperature had no effect on water consumption.

There was also no statistical link between water distributed through the feeding system and water consumption, probably because the main water consumption is through the bowl drinkers.

Discussion

The water consumption observed in weaned piglets (around 10% of BW) is very close to data already presented in the bibliography (Ward and McKague, 2007).

We did not observe an effect of the ambient air temperature, but piglets remained in their thermal comfort zone throughout the trial (between 24°C and 28°C).
Among the sows we also found that ambient air temperature had no effect on water consumption. It will probably be easier to show this effect in the month of July or August.
The global water consumption of sows was relatively close to the results presented by Klopfenstein *et al.* (1996) who found an average water daily consumption of between 5 and 9 litres per sow (dry feed and individual trough). Cerneau *et al.* (1997) reported an individual daily water consumption of 20 litres/sow (group of four animals with liquid feed distribution). With liquid feed distribution, water consumption is generally higher than in dry systems because most of the water intake is determined by the dilution rate.
Kruse *et al.* (2011) showed, with a connected drinker equivalent to ours, a link between water consumption, litter rank of sows and day of gestation. They worked with water consumption and not with water consumption divided by body weight. Nulliparous sows had the lowest consumption (around 12 litres/day) and multiparous the highest (around 22 litres/day). This result is probably due to the difference in weight between sows (around 160 kg for nulliparous and 270 kg for multiparous). Working with water consumption divided by body weight, we obtained less contrasted results and the water consumption per kilogram of BW seems to be lower for multiparous than for nulliparous sows. Kruse *et al.* did not find atypical results for primiparous sows, in contrast to this study where their drinking behaviour was very variable.
Kruse *et al.* showed an increase in water intake during the gestation which was related to weight gain of the sows. If this weight gain is taken into account, water intake per kilogram of BW seems to increase from the beginning to the middle of the gestation and then to decrease.
In the future, it would be interesting to measure water wastage in order to better understand the water consumption of a few sows and interpret this data in relation to ambient air temperature or behavioural disorders.
It could also be useful to study litter size in order to understand some of the variability in sows' water consumption. We can suppose that the larger the litter size, the higher the physiological water intake of sows.

Conclusion

There is significant inter and intra-individual variability in water consumption by healthy weaned piglets and pregnant sows, so it seems appropriate to work at an individual scale in order to study the link between drinking behaviour and the detection of pathologies. The connected drinker could therefore be an interesting means of achieving this. The next step is to use this data on water consumption

of healthy pigs as a reference to understand and interpret variations when pigs begin to be sick. The final goal is to create a tool which is capable of generating relevant alerts in real time in connection with potential early deterioration in the health status of piglets or sows (diarrhoea, hyperthermia, lameness, etc..) or with problems in the drinking system (water leakage, obstruction). The huge variability observed is one of the main issues, so we will probably need to combine water consumption with other data from automatic systems or sensors (automatic feeder, automatic weighing station, accelerometers, etc.) in order to develop an efficient animal health alert system. Other studies are already in progress in this area and could create new opportunities for monitoring animal health status.

Funding and acknowledgement

The data were obtained during a research programme funded by CASDAR for the sows and by FAM for the piglets. The authors acknowledge D. Pilorget, K. Rocher, A. Debroise, R. Richard, D. Loiseau and P. Rocher for monitoring the trials, G. Melot for his contribution to the development of the database and Asserva for the technical support.

References

Andersen HM., Dybkjaer L., Herskin MS., 2014. Growing pigs' drinking behavior: number of visits, duration, water intake and diurnal variation. Animal, 1-8.

Brumm M., 2006. Patterns of drinking water use in pork production facilities. Nebraska Swine Reports. Paper 221.

Klopfenstein C., Bigras- Poulin M., Martineau G.P., 1996. La truie potomane, une réalité physiologique. Journées Rech. Porcine, 28, 319-324.

Kruse S., Stamer E., Traulsen I. and Krieter J., 2011. Relationship between feed, water intake, and body weight in gestating sows. Livestock Science 137, 37-41.

Madsen TN., Kristensen AR., 2005. A model for monitoring the condition of young pigs by their drinking behavior. Computers and Electronics in Agriculture 48, 138-154.

Pijpers A., Schoevers EJ., Van Gogh H., Van Leengoed LA., Visser IJ., Van Miert AS., Verheijden JH., 1991. The influence of disease on feed and water consumption and on pharmacokinetics of orally administered oxytetracycline in pigs. J ANIM SCI 1991, 69, 2947-2954.

Ward D., McKague K., 2007.Water Requirements of Livestock. OMAFRA Factsheet, Order No. 07-023, 8p.

Monitoring body temperature and activity in sows using a sensor-based telemetric system

E. van Erp-van der Kooij[1], J. B. Roelofs[1], J. S. Johnson[2], D. Hovden[3], L. P.J.J. Noldus[4]
[1]*HAS University of Applied Sciences, Onderwijsboulevard 221, 5223 DE 's Hertogenbosch, the Netherlands;*
[2]*USDA-ARS Livestock Research Unit, 125 South Russell Street, IN47907, West Lafayette, USA;*
[3]*Telemetronics Biomedical, Nieuwe Kanaal 5, 6709 PA Wageningen, the Netherlands;*
[4]*Noldus IT, Nieuwe Kanaal 5, 6709 PA Wageningen, the Netherlands.*
l.verp@has.nl

Abstract

Improving estrus detection accuracy could improve sow conception rates, leading to higher production efficiency. Current observation-based estrus detection practices are labor intensive and less accurate. Around estrus, body temperature and activity change. Therefore in this study a telemetric monitoring system for body temperature and activity was tested. Firstly Templant2 sensors (TeleMetronics) were validated under lab conditions for temperatures from 35°C to 45°C, using a water basin with a Julabo heater and a P600 thermometer. Activity measurements were validated with the sensors attached to a stick, simulating sow movements. Secondly, sensors were attached externally to 4 gilts and 4 sows for 30 minutes, testing functionality. Thirdly, activity of sows was recorded manually for 3 days around estrus. Results showed that under lab conditions temperature results of sensors, heater and thermometer were highly correlated (linear regression, R^2=0,96; slope 1,1). Simulated activities corresponded consistently with peaks in sensor values. Activity was measured reliably with the sensor attached externally to the sows. On the farm, sows showed more activity (manual observations, $P<0.05$ for standing up, lying down, sitting down and walking) the day before insemination. We conclude that monitoring activity and body temperature is a promising tool for estrous detection in sows.

Keywords: pigs, estrus detection, temperature, activity

Introduction

Estrus detection in sows is important in pig husbandry. Financial losses due to non-productive days can be high, and estrus detection is taking up approximately 30% of the overall labor input. (Freson et al., 1998). Failure to accurately detect estrus has the greatest impact on farrowing rate and litter size (Kraeling and Webel, 2015). In current European and American practice, sows are artificially inseminated and estrus detection is done manually (Knox, 2016). The primary estrus detection method is the Back Pressure Test (BPT, Willemse and Boeder, 1966), where sow movement is assessed by the producer or animal caretaker when pressure is applied to the back and sides. The sow is considered in estrus when she shows a full standing reflex, meaning that the sow is immobile in response to back pressure (Cornou, 2006).

Precision Livestock Farming technology may improve estrus detection accuracy and increase sow conception rates, leading to higher production efficiency and less labor. Different techniques have been tested so far, based on monitoring physical activity or temperature (Cornou, 2006). Mean daily activity of sows peaks just before standing estrus (Freson et al., 1998, Cornou, 2006). The activity of sows kept in individual sow pens can be measured by using infrared sensors mounted on the pen, in front of the sow. For group housed sows, automated recording of visits to the boar pen with a 'ticket window', or a separate detection area where the sow can have nose contact with a boar and the number of visits is scored automatically, is possible. Another possibility to measure activity, is using an accelerometer on the back of the sow (Cornou, 2006; Ostersen, 2010). Sensitivity of the tested systems varied from 53% to 87%, while sensitivity of manual estrus detection is reported to be 93% (Cornou, 2006). Body temperature of sows deviates around estrus. This physiological trait can be measured automatically with a sensor implanted in the ear base or inserted in the vagina, or by infrared thermography of the vulvar area. Ear base temperature seems to rise before standing estrus (approx. +1 °C), while vaginal temperature seems to drop (appr. -0.5 °C) (Cornou, 2006). Vulvar temperature seems to rise before estrus (Simões et al., 2014) and drop before ovulation (-1.5 °C) (Scolari et al., 2011). However, results from different studies show conflicting results (Cornou et al., 2006; Soede et al., 1997).

Assuming that around estrus, body temperature and activity of sows change, in this study a sensor-based telemetric system that monitors both body temperature and activity was tested. We hypothesized that combining activity and temperature measurements will improve sensitivity of automated estrus detection in sows. The aim of this study was twofold: first, to test whether Templant2, a telemetric monitoring system for body temperature and activity, functioned reliably under lab and farm conditions, and second, to study changes in behavior

around estrus in sows kept in cubicles. This pilot study was the first step in developing an automated estrus detection system for sows based on temperature and activity.

Material and methods

In this study, Templant2 sensors (TeleMetronics Biomedical[1], Wageningen, The Netherlands) were used, containing an NTCS0603E3104FXT Thermistor temperature-sensitive resistor (VISHAY), a BMA250 accelerometer (Bosch), a PIC18LF14K22 controller (Microchip), a 40 MHz crystal (LFIQXC42) radio transmitter and a 170 mAh battery (Varta). Five levels of sensitivity of the activity sensor could be set (S001 to S005), with a trigger level ranging from 7.82 mg (S001) to 23.46 mg (S005). Every exceedance of the trigger level was recorded as one count for activity. Sampling interval was set to 15 seconds.
In Phase 1, the temperature measurements of the sensors were validated under lab conditions, using a water basin with a Julabo heater and a validated P600 thermometer. Temperature was recorded in degrees Celsius. A constant temperature was tested as well as rising temperatures, roughly around the biological range of the sow's body temperature, starting at 35 °C and increasing to 45 °C. The validation test with the Templant2 sensor was performed twice, with slightly different time periods used for the increase in temperature (Table 1). Temperature results of the sensors and the validated thermometer were compared using a linear regression analysis.
Activity measurements of the sensors were validated by attaching the sensor to a stick and simulating sow movements by moving the stick with the sensor: Walking (moving the sensor slowly backward or forward), Standing up (moving the sensor upward), Lying down or Sitting down (moving the sensor downward), Standing, Sitting or Lying (holding the sensor in the same position) (Table 1). Activity was recorded in counts/second. All five levels of sensitivity were tested (S001 to S005). All tests were performed twice, with two similar sensors. Linear regression was used to test whether active behaviors showed higher counts than holding the sensor stationary, and to test the influence of sensitivity level.

Table 1: Measurement protocols of Templant2 temperature and activity sensors under lab conditions

Temperature sensor Test 1		**Temperature sensor Test 2**		**Activity sensor**	
Temperature (°C)	Time (Min)	Temperature	Time (Min)	Time (Min:Sec)	Simulated activity

[1] In March 2017, the activities of TeleMetronics Biomedical have been taken over by Noldus Information Technology.

From	*To*		*From*	*To*			
						0:00	Lie down
20	35	15	20	35	15	0:15	Lie
35	35	5	35	35	5	0:30	Lie
35	38.8	15	35	38.8	15	0:45	Lie
38.8	38.9	10	38.8	39.6	15	1:00	Lie
38.9	39.0	10	39.6	38.8	15	1:15	Sit down
39.0	39.1	10	38.8	40.5	15	1:30	Sit
39.1	39.2	10	40.5	42	15	1:45	Stand up
39.2	39.3	10	42	45	15	2:00	Stand
39.3	39.4	10	45	45	5	2:15	Stand
39.4	39.5	10				2:30	Walk forward
39.5	39.6	10				2:45	Stand
39.6	38.8	15				3:00	Stand
38.8	40.5	15				3:15	Walk backward
40.5	42	15				3:30	Stand
42	45	15				3:45	Sit down
45	45	5				4:00	Lie down
						4:15	Lie
						4:30	Lie
						4:45	Stand up
						5:00	Lie down

In Phase 2, sensors were attached to a neck collar or taped to the back of 3 sows for 30 minutes. Activity was measured with the sensor and recorded manually using an ethogram containing the following behaviors: Sit down, Sit, Lie down, Lie, Stand up, Stand, Head movement, Walk, Unrest. Different sensitivities were tested to determine which sensitivity would reflect movements of the sow most accurately. A total of 12 tests were performed with 4 similar sensors. Sow 1 had the sensor attached to neck and back with sensitivities S004 and S005 (4 tests); sow 2 had the sensor attached to neck and back with sensitivity S003 (2 tests) and sow 3 had the sensor attached to neck and back with sensitivity S003, S004 and S005 (6 tests). Univariate Analysis of Variance was used to determine whether active behaviors were related to higher sensor counts and influenced by sow number and sensor location.

Activity for 3 days around estrus was recorded manually for 4 gilts and 4 sows using video analysis with The ObserverXT (Noldus Information Technology). The following behaviors were recorded: Stand up, Lie down, Sit down, Walk forward and Walk backward. From each 24 hours, 2 hours during the day and 2 hours during the night were scored, with a total of 12 hours per sow. Time periods were chosen outside feeding times and when no personnel was around and were categorized in 1) the day before insemination, 2) the day of insemination and 3) no estrus (>1 day before or after insemination). Insemination

dates were recorded by the farm personnel. Activity on the non-estrus day was compared to the day before estrus with a 1-sided paired T-test.
The Templant2 sensors were not yet robust enough in this phase to record and transfer data for three days in a row, so manual observations of activity and sensor measurements were not yet combined in this pilot study.

Results and Discussion

Temperature results of sensors, heater and thermometer correlated highly under lab conditions in both tests (Figure 1a and 1b). Results from the linear regression showed an R^2 of 0.96 and 0.97 and a slope of 1.09 and 1.07 in both tests.

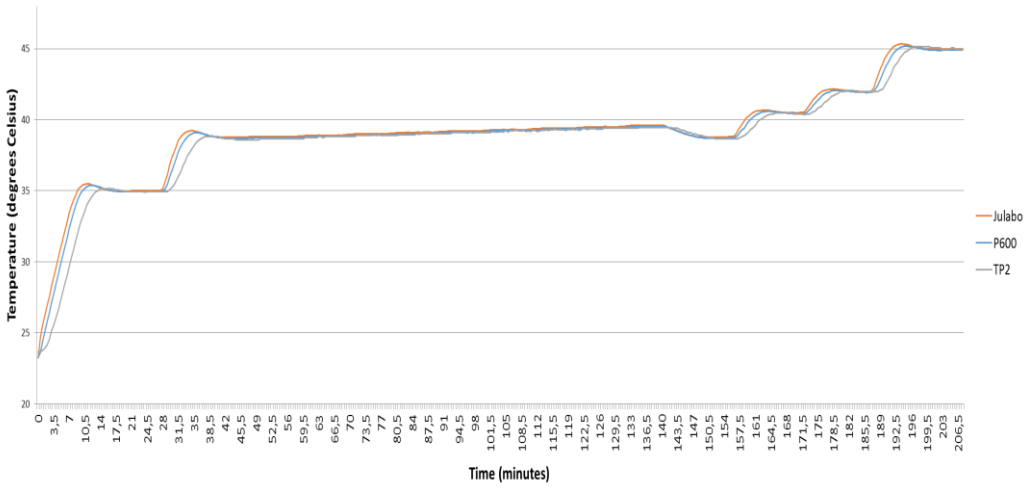


Figure 1a: Validation test of Templant2 temperature sensor under lab condition, test 1.

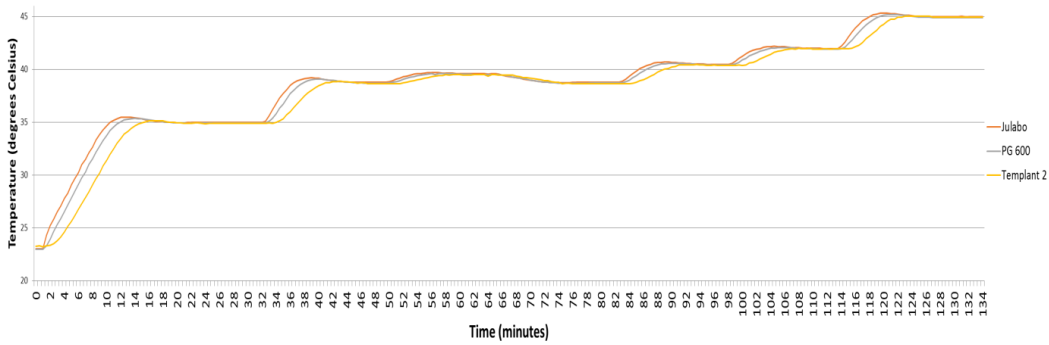


Figure 1b: Validation test of Templant2 temperature sensor under lab condition, test 2.

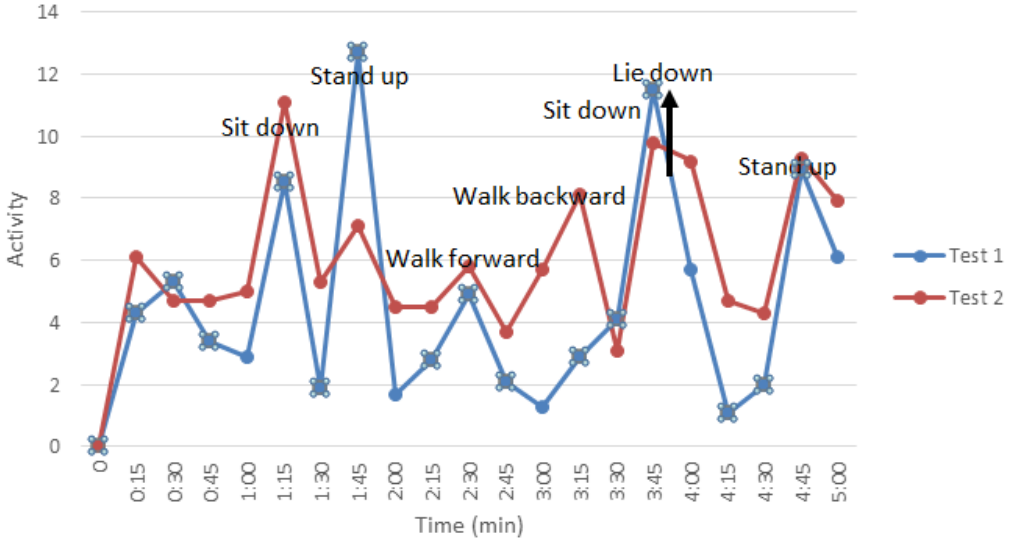
To test the activity sensor, sow movement was simulated with the sensor on a stick and sensitivities S001, S002, S003, S004 and S005. Sensor activity counts when the stick was moved, simulating the active behaviors Sit down, Stand up, Walk, Lie down, were higher than when the sensor was stationary, simulating the inactive behaviors Lie, Sit, Stand (P=0.010). Sensitivity influenced mean results (P=0.027), with the highest mean counts and standard deviations for S001 and S005 (Table 2).

Table 2: Simulating sow behaviors (active/inactive) with the sensor on a stick: activity counts for different sensitivities S001 to S005

Sensitivity	**Sensor count overall (mean ± stdev)**	**Sensor count, inactive (mean ± stdev)**	**Sensor count, active (mean ± stdev)**
S001	17.7 ± 7.9	14.6 ± 6.9	25.4 ± 4.2
S002	8.6 ± 4.6	6.4 ± 3.4	12.9 ± 3.4
S003	5.2 ± 3.1	3.7 ± 1.9	8.3 ± 2.7
S004	3.4 ± 3.7	2.1 ± 3.0	6.1 ± 3.7
S005	14.5 ± 50.0	9.4 ± 46.9	24.8 ± 56.2

An example of the test simulating the sow movements with the sensor on a stick is shown in Figure 2.

Figure 2: Simulated sow movements and activity measured with Templant2 sensor on a stick, sensitivity S003; active movements are noted in the graph.



Under farm conditions, sow activity was measured for 30 minutes by attaching the sensor to the back and the neck of three sows in a series of tests with different sensitivities set in the sensor.

For sensitivity S003, the sensor was attached to the neck and back of sows 2 and 3, in 4 tests. Mean activity was 145.0 ± 75.8 when the sensor was attached to the back of the sow, and 265.1 ± 194.1 when attached to the neck. When the sow was actively moving (Walk,Stand up, Lie down, Unrest, Head movement), mean activity for the sensor on the back was 184.5 ± 84.2 and for the sensor on the neck 333.5 ± 207.5; when the sow was not moving (Lie, Stand), mean activity for the sensor on the back was 116.4 ± 54.0 and for the sensor on the neck 146.1 ± 79.9. With this sensitivity, all sow movements gave a sensor count.

For sensitivity S004, the sensor was attached to the neck and back of sows 1 and 3, in 4 tests. Mean activity was 50.5 ± 69.2 when the sensor was attached to the back of the sow, and 253.5 ± 400.9 when attached to the neck. When the sow was actively moving, mean activity for the sensor on the back was 78.2 ± 100.6 and for the sensor on the neck 269.3 ± 268.2; when the sow was not moving, mean activity for the sensor on the back was 34.7 ± 35.8 and for the sensor on the neck 216.0 ± 627.7. With this sensitivity, 4 of 15 events (Lie down or Stand up) did not give any sensor count (0).

For sensitivity S005, the sensor was also attached to the neck and back of sows 1 and 3, in 4 tests. Mean activity was 21.5 ± 42.2 when the sensor was attached to the back of the sow, and 96.0 ± 159.9 when attached to the neck. When the sow was actively moving, mean activity for the sensor on the back was 40.7 ± 57.7 and for the sensor on the neck 135.5 ± 184.6; when the sow was not moving, mean activity for the sensor on the back was 6.1 ± 7.2 and for the sensor on the neck 23.9 ± 52.0. With this sensitivity, 6 of 15 events (Lie down or Stand up) did not give any sensor count (0).

For all tests, the sensors showed higher activity counts for active than for inactive behaviors (P=0.000 for S003, P=0.042 for S004 and P=0.000 for S005; overall P=0.000). Sow number did influence sensor results, with sow nr 1 showing the lowest mean count of 66.8 ± 118.5, sow nr 2 showing a mean count of 155.2 ± 95.5 and sow nr 3 showing the highest mean count of 210,9 ± 277.4. This means that sows vary in individual activity levels. As a consequence, for an activity based estrus detection system, the sow's own mean (or predicted) activity levels should be taken as standard and not the mean activity level of the herd. Sensitivity settings influenced mean count as well (P=0.016), with S003 showing the highest and S005 showing the lowest mean count. All sensitivity levels showed a clear difference between active and inactive behavior, but it seems that level S003 is the most reliable, with low standard deviations and no missed events.

An example of sensor results with the sensor attached to the neck of sow nr 3, with sensitivity S003, is shown in Figure 3.

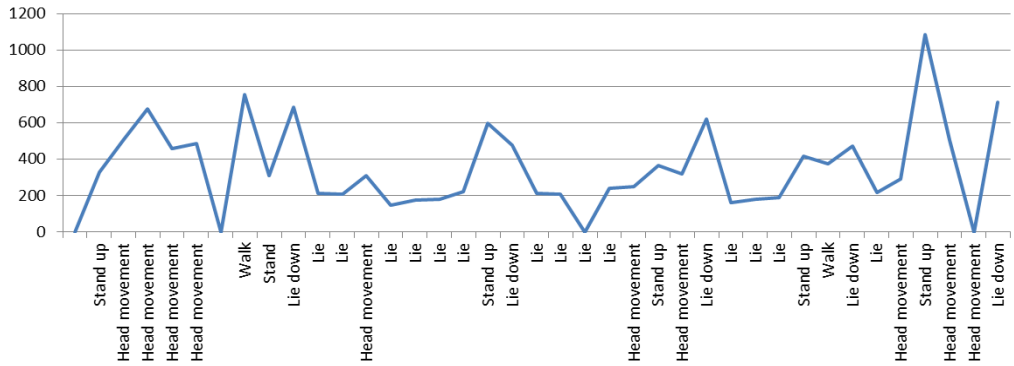


Figure 3: Movements recorded for 30 minutes with the Templant2 sensor attached to the neck of a sow (sensitivity S003).

During the manual observations (4 hours/day), sows showed more activity on the day before insemination ($P<0.05$ for standing up, lying down, sitting down and walking backward). All sows and gilts showed an increase in activity on the day before estrus, which makes activity a good predictor for estrus (Figure 4). The increase in activity from no estrus to the day before estrus was 2.4 ± 2.6 for Standing up ($P=0.03$), 4.6 ± 4.4 for Lying down ($P=0.02$), 3.3 ± 3.7 for Sitting down ($P=0.03$), 4.7 ± 4.9 for Walking backward ($P=0.02$) and 2.6 ± 3.8 for Walking forward ($P=0.06$).

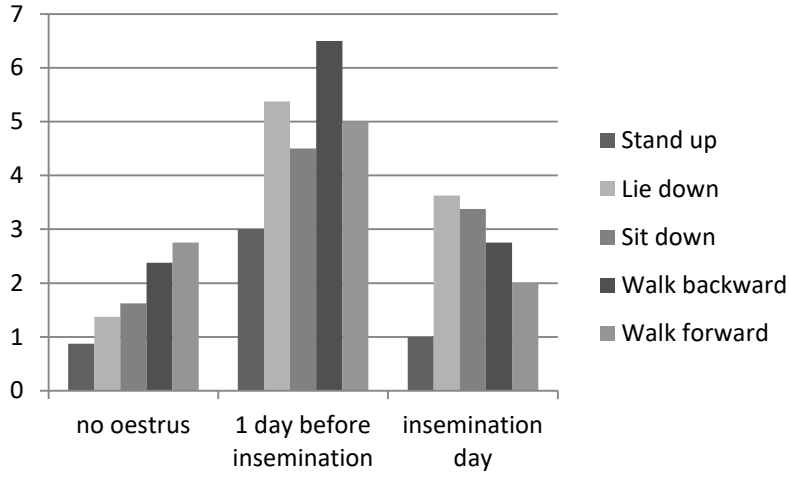


Figure 4: Mean activity around estrus for 4 sows and 4 gilts

In this study we could not yet use the Templant2 sensors internally, so we could only test activity in sows and not the combination of activity and temperature. In a follow-up study (Johnson and Shade, 2017) with an improved version of the Templant2 sensors used intra-vaginally in 12 gilts, temperature decreased (-0.26°C) and activity increased (+38%) significantly at the onset of estrus, with both parameters measured reliably with the sensors. This is a promising development for an estrus detection system based on activity and temperature combined.

Conclusions

Temperature could be measured reliably with the Templant2 sensor under lab conditions, and activity could be measured reliably under lab as well as under farm conditions. Templant2 activity sensors functioned best with sensitivity S003; with that sensitivity, no events (i.e. movements of the sow) were missed and the standard deviation was low. Sensor counts were significantly higher during active behaviors; a marked increase in sensor count was shown every time the sow moves, especially when standing up or lying down. Sows in cubicles showed more activity the day before insemination, which is at the start of the estrus period. This increase in activity consists mainly in more standups and more times lying down; as mentioned above, these are the same activities that Templant2 can measure reliably. We conclude that monitoring activity with Templant2 is a promising tool for estrus detection in sows. In future research, combining automated activity and temperature measurements in one system will be validated for estrus detection in sows.

Acknowledgements

We thank Marijn Tiemissen and Teun Nabuurs for performing the practical studies with sensors and sows.

References

Cornou, C. 2006. Automated estrus detection methods in group housed sows: Review of the current methods and perspectives for development. *Livestock Science* **105** 1-11.

Freson., L., Godrie, S., Bos, N., Jourquin, J., and Geers, R. 1998. Validation of an infra-red sensor for estrus detection of individually housed sows. *Computers and Electronics in Agriculture* **20** 21-29.

Johnson, J.S., and Shade, K.A. 2017. Characterizing body temperature and activity changes at the onset of estrus in replacement gilts. *Livestock Science* **199** 22-24.

Knox, R.V. 2016. Artificial inseminations in pigs today. *Theriogenology* **85** (1) 83-93.

Kraeling, R.R., and Webel, S.K. 2015. Current strategies for reproductive management of gilts and sows in North America. *Journal of Animal Science and Biotechnology* **6**(1) 3.

Ostersen, T., Cornou, C., and Kristensen, A.R. 2010. Detecting estrus by monitoring sows' visits to a boar. *Computers and Electronics in Agriculture*. **74** 51-58.

Scolari, S.C., Clark, S.G., Knox, R.V., and Tamassia, M.A. 2011. Vulvar skin temperature changes significantily during estrus in swine as determined by digital infrared thermofraphy. *Journal of Wine Health and Production* **19**(3) 151-155.

Simões, V.G., Lyazrhi, F., Picard-Hagen, N., Gayrard, V., Martineau, G.P., and Waret-Szkuta, A. 2014. Variations in the vulvar temperature of sows during proestrus and estrus as determined by infrared thermography and its relation to ovulation.

Theriogenology **82**(8) 1080-1085.Soede, N.M., Hazeleger, W., Broos, J., and Kemp, B. 1997. Vaginal temperature is not related to the time of ovulation in sows. *Animal Reproduction Science* **47** 245-252.

Accelerometer technology to perform precision feeding of pregnant sows and follow their health status

M. Marcon[1], M.C. Meunier-Salaün[2], M. Le Mer[3], Y. Rousselière[1]
[1, 2]*Unité Mixte Technologique Ingénierie des Systèmes de Production Porcine*
[1]*IFIP-Institut du Porc, BP 35104, 35651 Le Rheu cedex, France*
[2]*INRA-Agrocampus Ouest, UMR1348 PEGASE, 35590 Saint-Gilles, France*
[3]*RF-Track, Espace Gallium, 80 Av des Buttes de Coësmes, 35700 Rennes, France*
michel.marcon@ifip.asso.fr

Abstract

Two trials were conducted at experimental stations of IFIP, located in Romillé (France, Trial 1), and INRA, located in Saint Gilles (France, Trial 2), on pregnant sows equipped with individual ear tag accelerometers to record their activity level: duration of lying, standing and moving sequences. The first trial involved 72 sows penned on a slatted floor in a dynamic group with connected drinkers and automatic feeders, whereas the second trial was carried out on 4 small groups of 6 sows penned on a concrete floor with straw and fed in individual stalls. Firstly, an algorithm was built from video recordings of 24 sows on the slatted floor (2 x 2 h sequences per sow, 96 h). Secondly, the accuracy of the algorithm was assessed by recording and sequencing 96 h and 109 h, respectively, on the slatted floor and concrete floor with straw. The respective sensitivities of the lying, standing and moving behaviours on the slatted floor were 94.4%, 66.9% and 68.4%. With straw, lower sensitivity values were found: 93.65% for lying, 68.35% for standing and 38.83% for moving, linked to more investigative behaviours using the head. The final step was to use these data to improve the feeding practices of pregnant sows, taking their activity level into account. The strong inter- and intra-individual variability shown in the physical activity is a limiting factor for detection of health problems, such as lameness, through the accelerometers. Thus we need additional information, especially the behaviour data generated by identified drinkers and automatic feeders.

Keywords: Sow, precision feeding, physical activity, accelerometer, sensor

Introduction

The individual level of sow activity affects their body condition and food needs, and may be a good health indicator (Noblet et al., 1993, 1994; Quiniou, 2016).

Noblet et al. (1994) showed that the energy used by a standing sow is twice that used in a lying position. Thus, if the physical activity level of a sow can be assessed, it becomes feasible to adjust the feeding plan to compensate for the energy expended by each sow and to achieve better homogeneity of back fat thickness in the herd. Several studies have shown that accelerometer sensors can be a good tool for measuring the activity of a sow (Ringgenberg et al., 2010, Cornou et al., 2011, Ramonet and Bertin, 2015). However, the sensor must be robust and accessibility must be low to circumvent the high motivation of pigs to investigate any substrate available in the pen or conspecific (Studnitz et al, 2007). The positioning of the sensor on the neck or leg could be a limiting factor for widespread use in pig barns. A possible position is the sow's ear where the sensor is more protected. This position was chosen for the accelerometer to measure animal activity. The aim of this paper is to (i) create an algorithm which is capable of determining three sow states (lying, standing and moving) and (ii) evaluate the quality of measurement under two conditions (dynamic group of sows penned on a fully slatted floor and small groups of 6 sows penned on straw).

Materials and methods

Animals and housing conditions

To meet the objectives of the project, three trials were established. The first (Trial 1) focused on algorithm development, and the other two were carried out to evaluate the accuracy of the sensor for sows in two flooring conditions: on a fully slatted floor (Trial 2) and on a concrete floor with a thin straw layer (Trial 3).

Trial 1 took place at the IFIP experimental station in Romillé, (France) using Landrace x Large White crossbreed sows, with erect or drooping ears. The pregnant sows were housed in a large dynamic group of 72 sows (three batches), in a pen measuring 226 m^2 and equipped with two automatic feeders (AF) and 6 connected drinkers (CD). Six groups of four sows are selected randomly from the 72 sows in order to build the algorithm.

Trial 2 also took place at Romillé using 10 sows with a similar breed and housing conditions as those in trial 1. They were chosen according to different litter rank and activity level defined by the number of visits to the AF and/or CD.

Trial 3 was conducted on 24 Large-White X Landrace crossbred sows, penned in 4 groups of six and fitted with accelerometers on the ears as in trials 1 and 2. Each group was penned in an area measuring 18 m^2, on a concrete floor with straw and equipped with 6 feeding stalls which only opened during the two daily meals. Every morning the pens were cleaned and fresh straw supplied while sows were fed in the feeding stalls.

Animal activity assessment

To build the algorithm (trial 1), 24 sows at mid-gestation were simultaneously equipped with accelerometers and video recorded (cameras: National Electronics and a video tape recorder: Geutebrück) twice during a two-hour period (10:00-12:00 and 14:00-16:00). Ninety-six hours of video were considered, and in order to observe a variety of behaviours, especially investigative behaviours such as playing with a chain or exploring on the floor, the selected sows were introduced into a new area equipped with chains. The posture of the animals was continuously recorded with reference to four states: lying down, sitting, standing up, and moving (standing up in motion). The activities associated with each state were not recorded. As a result, a standing sow chewing a chain was not "moving" as long as its legs were not displaced. The start and end time of each state was noted.

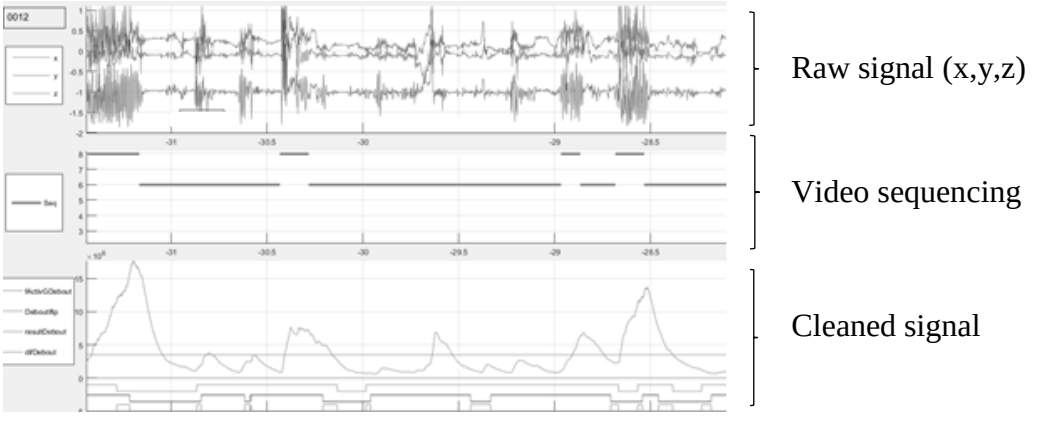
To assess the accuracy of the algorithm in trial 2, two video recording sessions (18-31 March 2016 and 11 April-9 May 2016) provided 96 additional hours of video acquired on 10 sows (different from the sows in trial 1). Video recordings were taken using five cameras for monitoring sows all over the room with continuous recordings during diurnal periods. The video sequencing related to the same four states as in trial 1 and took place over four 1h time periods: 8:30-9:30; 11:30-12:30; 14:30-15:30; 17h30:18h30, which were chosen to be representative of the main diurnal activity of sows.

For the assessment of accuracy in trial 3 on small groups of sows penned on a concrete floor with straw, 12 sows at mid-gestation were chosen (3 per group) according to their behavioural activity, exhibited at a high level during three hours (9-11h, 14-15h) and representative of high physical activity within groups. A total of 103 hours were considered for the analysis.

Accelerometer sensors

Two types of accelerometer were used. In the first trial, the accelerometer data logger (RF-Track, Rennes) prototype recorded acceleration levels on three axes in space with a frequency of 16 Hertz. The raw data were stored on a micro SD card. A second version double accelerometer datalogger was used in trials 2 and 3, including a device with radiofrequency (RF) transmission of processed data by the embedded algorithm in a microcontroller. Ultimately, we obtained three types of signal: the first was the acceleration within the 3 axes (x,y,z), the second the video sequencing and the third a cleaned raw signal (Fig.1).

Figure 1: Signal analysis methodology



These prototype sensors were autonomous and battery powered. The accelerometers were fixed on an identification ring using a plastic self-locking collar (Fig. 2). The new tags equipped with accelerometers were attached to the sow's ear, assuming that the accelerometer was positioned on the inner face of the ear.

Figure 2: Location of the experimental prototype accelerometer

In order to synchronise accelerometer data with video recording, the operator rotated the sensor three times in front of one of the five cameras before attaching it to the animal.

Accuracy of algorithm assessment:

The quality of the algorithm was evaluated separately for the different states, analysing the correspondence between the state indicated by the algorithm and the state observed by real-time video analysis. To do this, we used the binary classification test with sensitivity and specificity calculation. Sensitivity is the

true positive rate which measures the proportion of positives correctly identified (Fig. 3). The specificity, or true negative rate, measures the proportion of negatives that are correctly identified. Finally, the accuracy measures the global exactitude.

Figure 3: Confusion matrix

		Predicted condition (n second predicted by sensor)	
	Total population	Prediction positive	Prediction negative
True condition (n second given by video)	positive condition	True positive (TP)	False negative (FN)
	negative condition	False positive (FP)	True negative (TN)

Sensitivity = $\frac{TP}{TP+FP}$; Specificity = $\frac{TN}{TN+FN}$; Accuracy = $\frac{TN+TP}{TP+FP+TN+FN}$

To achieve good sensitivity and specificity, we needed to have perfect synchronisation between the accelerometer data and the video sequences. Indeed, we worked on a time base expressed in seconds. So the total population for a trial lasting 96 hours was 345 600 (96 hours * 3 600 seconds).

Results

Recordings of sows

Of the 96 hours and 109 hours of sequential video recordings and accelerometer data from trial 2 and 3, respectively, we excluded the sitting behaviour from the analysis. This posture was rarely observed (Trial 2: 1.6% and Trial 3: 2.45% of the recorded time, Table 1) and the algorithm did not allow recognition of this type of behaviour which is intermediate between the lying or standing position and thus generates confusing data. Therefore, to perform our analysis, we used 94 hours and 27 minutes of data for trial 2 and 87 hours and 48 minutes for trial 3.

Table 1: Relative share of different states over trial 2 and 3 (% of recorded time)

States	***Time proportion trial 2***	***Time proportion trial 3***
Lying	66.57	22.69
Standing	28.21	68.92
Moving	3.61	5.94
Sitting	1.61	2.45

Algorithm accuracy

The algorithm was able to predict the lying position (sensitivity 94.3% and 89.1%, respectively, for trials 2 and 3) with very high accuracy (Table 2). Specificity analysis confirmed these results with values of more than 83% for the slatted floor and 96% for sows penned with straw. For the standing state, the results were limited, as shown in Table 2; standing sensitivity was around 67% in both trials but the specificity remained good with 94.1% and 75.9% in trials 2 and 3, respectively. For the moving state, there was a large difference between the slatted floor and straw. In the second trial, sensitivity was near 70% and specificity up to 94%, while with straw, the sensitivity value decreased to 41.4%. More generally, the global accuracy was better with data from trial 2 (84.2%) than from trial 3 (69.2%).

Table 2: Binary classification within the two trials (%)

	Trial 2			***Trial 3***		
State	Lying	Standing	Moving	Lying	Standing	Moving
Sensitivity	94.3	66.9	68.4	89.1	67.5	41.4
Specificity	83.2	94.1	93.7	96.2	75.9	78.3
Accuracy		84.2			69.2	

Discussion

Two major hypotheses can explain the fact that better results were observed for sows penned on a fully slatted floor than for sows penned with straw. Firstly, the algorithm was developed using only sows penned on a slatted floor and should be better adjusted to this kind of environment. Secondly, sows penned on a floor with straw exhibited high levels of investigation at ground level and the straw produced a higher number of head movements. Since the accelerometer sensor is fixed on an ear tag, any head movements, even when the sow was not walking, could be analysed as a moving state.

Nevertheless, with regard to the total time spent “lying” in the different trials (66.57% and 22.69%) and because the specificity is very good for evaluation of whether a sows is lying or not, it is likely that the sensitivity will increase over a full day’s analysis. In fact, as the sows can sleep for at least 60% of the daytime, we suggest that trial 3 overestimates the standing time. The next step will be to calculate the accuracy over a 24-hour period.

In a recent study Ramonet and Bertin (2015) reported a sensitivity of 98.8% and a specificity 99.8% (lying or not), which was higher than in our results, with accelerometers fixed to the legs of the animal. Sensor position is a real issue. When sensors are fixed to the leg (Ringgenberg & al., 2010) or around the neck

(Cornou & Lundbye-Christensen, 2008) of a sow, it is easier to determine its state (lying, standing or walking), but it is difficult to transfer this system into commercial breeding. Indeed, the device was manipulated by the other sows in the group so good protection is needed, for instance using repulsive lotion, or it will be necessary to accept the loss of some sensors.
With European implementation of group-housed sows during gestation, sows have more opportunities to move freely in the pen, promoting increased activity levels, linked in particular to social interactions in dynamic groups when new sows are introduced or to competition for access to the automatic feeder (Spoolder et al, 2009). The development of precision feeding according to the energy expended individually by each sow should improve feeding management within the sow herd. In addition, identification of potential health state indicators, based on the onset of changes in physical activity, can be a useful way of managing herd health, which is generally more difficult to assess in a big dynamic group of sows. Therefore, in our study we accept a decrease in accuracy when using ear tag accelerometers in order to develop a version that is suitable for on-farm use.

Conclusion

The accuracy of ear tag accelerometers appears to be good enough to assess the energy expended by a sow according to its physical activity level. The results showed that the sensitivity of the ear tag sensor was higher than 90% on average for sows lying or standing (on a fully slatted floor or on a concrete floor with straw). However it is clearly difficult to determine whether the sow is walking or not due to numerous technical noises (head movements, repeatability and duration of the signal, etc.). These issues are even more evident in housing conditions with the provision of straw, which generates a high level of straw-directed investigation behaviour, which tricks the algorithm. The accelerometer is designed to work more efficiently on sows housed in groups on a slatted floor. Further investigations are needed to evaluate the expected gains in the homogeneity of sow back fat thickness reserves when the individual activity level is taken into account.

Funding and acknowledgement

This project is co-financed by the IFIP-Institut du porc, INRA, Rf-track, the Chambres d’agriculture de Bretagne, and the French government: Ministère de l’agriculture et de la forêt. It is one of the winners of the call for proposals CASDAR Research & Technology.

References

Cornou C., Lundbye-Christensen S., 2008. Classifying sows' activity types from acceleration pattern an application of the multi-process Kalman Filter. Appl. Animal Behav. Sci., 111, 262-273.

Cornou C., Lundbye-Christensen S., Kristensen A. R., 2011. Modelling and monitoring sows' activity types in farrowing house using acceleration data. Comput. Electron. Agric., 76, 316–324.

Noblet J., Shi X.S., Dubois S., 1993. Energy cost of standing activity in sows. Livest. Prod. Sc., 34, 127-136.

Noblet J., Shi X.S., Dubois S., 1994. Composantes de la dépense énergétique au cours du nycthémère chez la truie adulte à l'entretien: rôle de l'activité physique. Inra. Prod. Anim., 7, 135-142.

Quiniou N., 2016. Une activité motrice coûteuse en énergie. Tech Porc, 29, 18-19.

Ramonet Y., Bertin C., 2015. Utilisation d'accéléromètres pour évaluer l'activité physique des truies gestantes logées en groupes. Développement de la méthode et utilisation dans six élevages au DAC. Rapport d'étude. Chambres d'agriculture de Bretagne, 12 p.

Ringgenberg N., Bergeron R., Devillers N., 2010. Validation of accelerometers to automatically record sow postures and stepping behaviour. Appl. Anim. Behav. Sci., 128, 37–44.

Spoolder HAM., Geudeke MJ., Van der Peet-Schwering CMC. , Soede, NM., 2009. Group housing of sows in early pregnancy: A review of success and risk factors. Livestock Science, 125, 1-14.

Studnitz M., Jensen MB., Pedersen LJ., 2007. Why do pigs root and in what will they root? : a review on the exploratory behaviour of pigs in relation to environmental enrichment. Applied Animal Behaviour Science 107, 183–197.

Session 19

PLF and big data

Linking veterinary data for improved biosecurity and animal health: A shared Australian-European system?

E. Newell[1], N. Lyons[2], D. Ryan[3], M. Ward[1], S. Lomax[1], C. Clark[1],
[1]*Dairy Science Group, Faculty of Science, University of Sydney, Australia*
[2]*Intensive Livestock Industries, NSW Department of Primary Industries, Australia*
[3]*Animal Biosecurity and Welfare, NSW Department of Primary Industries, Australia*
cameron.clark@sydney.edu.au

Abstract

There are common reproductive and animal health issues are shared between the predominantly Holstein cattle of both Australia and Europe. Whilst aspects of reduced health are recorded, much data is missed. Here lies an opportunity to use veterinary health data to improve herd health and biosecurity in both Australia and Europe. A survey on Australian veterinarian data collection, use and reporting was compiled, tested and emailed to members of the Australian Cattle Veterinarian's Association. The survey was focused on veterinarians with dairy farmers as clients. Results revealed that 86% of veterinarians created a report from their consultation, primarily on a specific computer programme (71%), with individual animal ID recorded 75% of the time. Reproductive issues, mastitis and lameness were the top 3 animal health issues; however, 89% of veterinarians identified undiagnosed cases of reduced health. 83% of veterinarians held the data within their practice without sharing with state organisations or other veterinary practices. However, 71% of respondents were willing to share data with a centralised database provided a streamlined process was in place. The centralised system would therefore need to be automated to minimise time input. This survey highlights the opportunity to use existing veterinary data to significantly reduce potential biosecurity risks and increase the health of dairy cows by enabling industry extension.

Introduction

The New South Wales (NSW) department of primary industries (DPI) biosecurity strategy aims to prevent the entry of biosecurity threats into NSW, contain and eradicate biosecurity threats before they become established and spread in NSW, effectively manage biosecurity problems to minimise their impacts in NSW, ensure cooperation between NSW DPI and other agencies, industry and the community to manage biosecurity threats and problems and maintain NSW DPI's capacity to manage biosecurity in NSW. However of the

91% of dairy farmers that report unusual health events to their veterinarian, only 6% contact their state DPI (Dairy Australia, 2012).
The collection and collation of veterinary practice data into a centralised NSW DPI database would enable significantly improved health of dairy cows in NSW by enabling targeted extension, the development of a novel method for disease surveillance and improved biosecurity. Such a programme would rely on veterinarians entering data of value into a database. But such collation of data and associated information would need to be perceived as valuable (to the practice, veterinarian and/or Industry) for data entry to occur.
Our objective was to determine Australian veterinarian dairy cattle health data collection, use, reporting and willingness to share these data in a centralised system as a method for disease surveillance and improved biosecurity.

Material and methods

This survey was conducted in November 2015 and focused on Australian veterinarian data collection, use and reporting. The survey was designed by multidisciplinary teams including researchers, farmers and extension personnel, and piloted with a small farmer group to refine methodology and logic flow. The survey covered a broad range of questions including but not limited to farmer and farm demographics, historic data held by veterinarians and how these data were stored, current veterinarian animal health data collection and willingness to share data. As data entry for collation into a centralised database would be voluntary, understanding what would drive veterinarians to enter such data is crucial to the success of such a programme.
The survey was internet-based using Google Forms and included up to 22 questions depending on each respondent's profile. The survey was distributed online to a special interest group (Australian Cattle Veterinarians) of the Australian Veterinary Association.

Results and discussion

Respondent demographics
A total of 49 veterinarians responded to the survey of these 36 had dairy farmers as clients. Of these dairy veterinarians 69% were male and 31% female with the greatest number of participants from the 25-34 year age bracket (Figure 1). The location of practice was representative of dairy cattle distribution in Australia (Figure 2).

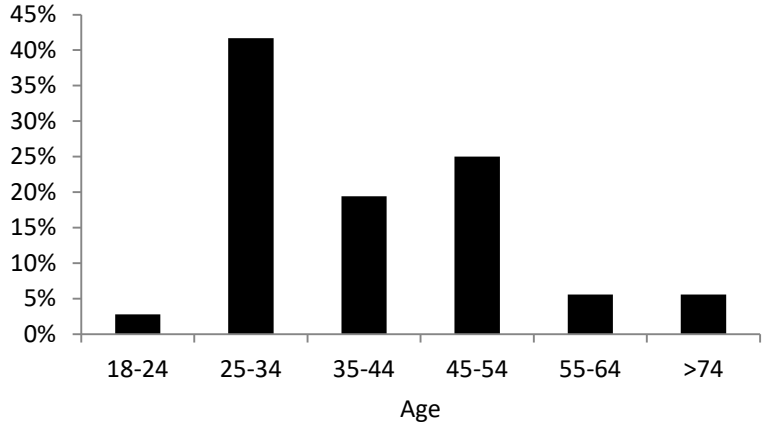


Figure 1: Percentage of responses from veterinarians in each age bracket

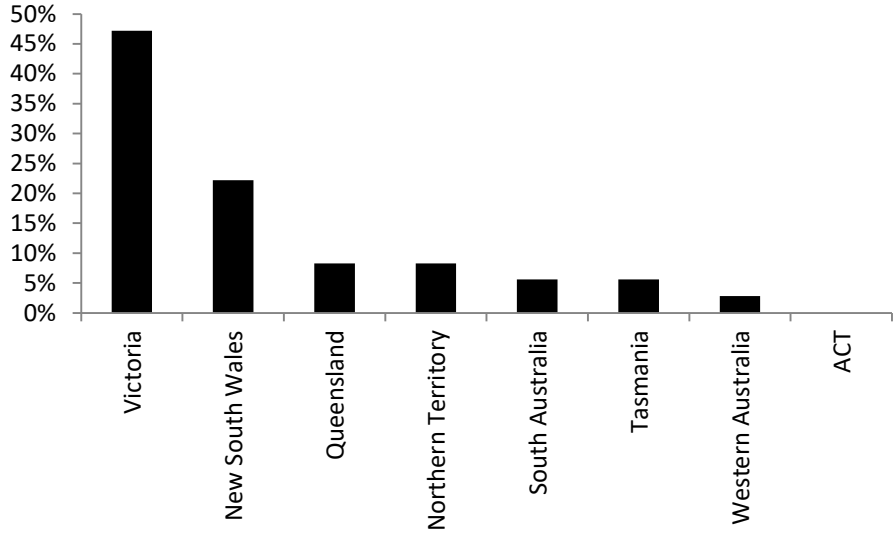


Figure 2: Percentage of responses from veterinarians by location (state or territory of Australia).

Data collected by veterinarians

Dairy veterinarians have access to historic cow data generated by technology on 1/3rd (35%) of farms and access to previous farmer treatment and animal health records on less than half (45%) of farms. These data are kept primarily by farmers on a desktop computer (53%) followed by hard copy (29%). This indicates that veterinarians have access to some historic data, however there is great potential for improving electronic data storage to allow for better access to health records on farms.

There was a high level of reported data storage by veterinarians. In this study 86% of veterinarians created a report from their consultation. Of those that create a report, 42% create the report back at the office, 36% onto paper on farm and 16% directly on a handheld device with only 2 veterinarians using a handheld device with information downloaded directly to the office computer. Importantly, animal ID was recorded 75% of the time when a report is created. High quality data is being stored by veterinarians electronically, highlighting the opportunity to use existing veterinary data to significantly increase the health of dairy cows. Furthermore, 71% of veterinarians use a specific computer programme to collate records. Vision VPM was the primary software used however there was a spread across various programmes (>6 in total). For data to be shared across practices, there would be a need to extract and collate differing presentation of data across systems, which limits the universal availability of important health data. Therefore an integrated online database available to all practices would be of great value.

Data use by veterinarians and reporting

The majority (86%) of veterinarians use some form of farm data for consultations with previous milk yield and animal health records being the primary data used. Data generated from consultations was typically held (83% of respondants) within the practice and not shared with the DPI or other practices. This storage important health information in these digital data silos presents an important biosecurity risk, particularly in the incidence of disease outbreak. Without linkages between practices and government, the ability to clearly and concisely map disease spread is limited. Further, of the data held within practices 61% of those vets did not have the ability to analyse all recorded data within the management database to find statistics about incidence of diseases in either a certain region, a certain period of time or in a particular type/size of farm.

Reproductive issues, mastitis and lameness were the top 3 animal health issues that veterinarians dealt with. However, 89% of veterinarians identified that some cases of reduced health or abnormal appearance would remain undiagnosed. This issue is magnified as a biosecurity risk when combined with the limited sharing of important veterinary data.

A centralised system

Importantly, 71% of veterinarians would be willing to share their data with a centralised database provided anonymity was maintained. However these veterinarians would need this centralised database to add value to the data that they collect and be automated for them to participate. In this regard, the centralised system taking too much of their time was the reason for 78% of

veterinarians to not participate. Currently, the technology is available to develop a centralised system for automated, integrated data storage that is simple and easy to use. Investment in resources toward this should be a government iniative, not only nationally but internationally, and has the potential to greatly improve herd health, disease control and early detection regionally and internationally. It is clear that compliance will rely on a simple and quick input system, and further work is necessary to explore this component of the veterinary attitudes and practices.

Conclusions

This survey highlights a major biosecurity risk for the NSW (Australian) dairy industry. Almost all veterinarians (89%) identified cases of reduced health or abnormal appearance that remained undiagnosed. Almost all of these data/information (83%) were not shared outside of their respective veterinary practice. Whilst highlighting a risk, this survey also highlights the opportunity to use existing veterinary data to significantly increase the health of dairy cows by enabling targeted extension; to develop a novel method for disease surveillance; and to significantly improve biosecurity surveillance. The vast majority of veterinarians create detailed reports and all of these veterinarians store this information at the practice using a veterinary computer programme. Importantly, the majority of veterinarians were prepared to share these data with a centralised database. Veterinarians would require this system to be automated to minimise (or eliminate) their time input and for this system to create value for their practice.

References

Dairy Australia. (2012). *Dairy 2012: Situation and Outlook* (pp. 67). Victoria, Australia.

Barriers and accelerators in the adoption of a data sharing innovation by service providing organisations

G. Paradies[1], C. van der Weerdt[2] & M. Vonder[3]
[1]*Department of Human Behaviour and Organisational Innovation, Earth. Life and Social Sciences, TNO, Kampweg 5, 3769 DE Soesterberg, the Netherlands*
[2]*Department of Human Behaviour and Organisational Innovation, Earth. Life and Social Sciences, TNO, Eemsgolaan 3, 9727 DW Groningen, the Netherlands*
[3]*Department of Monitoring & Control Services, Technical Sciences, TNO, Eemsgolaan 3, 9727 DW Groningen, the Netherlands*
Geerte.Paradies@tno.nl

Abstract

Service organisations active in the dairy farming value chain (for instance, in feed or genetics) are often dependent on farmer data. Innovative business models for these service organisations can be based upon inter-company data exchange. The adoption of data-driven innovations often requires upfront investments. Furthermore, beyond financial means, it also requires change within organisations, for example, because employees need to be trained on the innovation. This can make the adoption of an innovation difficult. The required changes can be regarded as either barriers or accelerators; barriers might form bottlenecks in further adoption of an innovation, whereas accelerators help to stimulate adoption. It is therefore pivotal to gain insight into the barriers and accelerators in the organisational adoption process.

Several workshops with different stakeholders of the dairy farming value chain were held to identify barriers and accelerators for the adoption of a technology that facilitates sharing and combining dairy farming related data (the InfoBroker). Different barriers and accelerators were uncovered. An important accelerator is the expectation to gain a competitive advantage with data-based models. An important barrier is that there are a lot of perceived insecurities in the process to come to data driven services. The factors were plotted on an existing model for innovation adoption. The model was then extended on the basis of the findings in the workshops. The identified barriers and accelerators can be translated into measures to, on the one hand, overcome those barriers and, on the other hand, utilise the accelerators. Examples are: providing decision makers and users of the innovation with the most relevant and persuasive information, and establishing precise requirements for employee training.

Keywords: Innovation adoption; service organizations; data driven services; linked data; infobroker

Introduction

Linked data services

Service organisations active in the dairy farming value chain (for instance, in feed or genetics) are often dependent on farmer data and could be more so in the future when they engage in precision farming and base their services on combined data sources. Precision dairy farming could lead to improvements in productivity and animal wellbeing by enabling the farmer to quickly respond to changes in the cow's situation, and providing cow centered advice (Lokhorst & Wulfse, 2015). More and more it is being acknowledged that innovative business models for these service organisations can be based upon inter-company data exchange for example by combining sensor data coming from milking machines, with sensor data from fertility testing (Mutsaers, 2015).

The (data sharing) innovation: the InfoBroker

Dairy farms and third party service providers that (want to) deal with inter-company data exchange face several challenges. To quickly respond to changes in a cow's situation, the sensor data per cow needs to be available in near real time, and coming from different sources (organisations), which means the data is shared with different parties. This last point raises the problem of how to address the matter of who is owner of the data. In order to overcome these challenge the InfoBroker was developed. This data sharing innovation is a software platform that is able to link and manage different sources of data without storing the data in a central place, and has the farmer in control of the data (Vonder, van der Waaij, Harmsma, & Donker, 2015).

Innovation adoption

The adoption of software such as the InfoBroker, which enables data-driven services based on linked data, often requires upfront investments. Furthermore, beyond financial means, it also requires change within organisations, for example, because employees need to be trained on the innovation, or their businesses model needs to be adapted. This can make the adoption of an innovation difficult. These required changes can be regarded as either barriers or accelerators; barriers might form bottlenecks in further adoption of an innovation, whereas accelerators help to stimulate adoption. It is therefore pivotal to gain insight into the barriers or accelerators in the organisational adoption process.

To explain innovation adoption several models are available (Wisdom et al, 2014). For the purpose of this study the model by Frambach and Schollewaert (2002; see Figure 1) was chosen as a theoretical framework, since it is directed at the organisational level and distinguishes different phases in the adoption process: awareness; consideration; intention; adoption decision; and continued use.

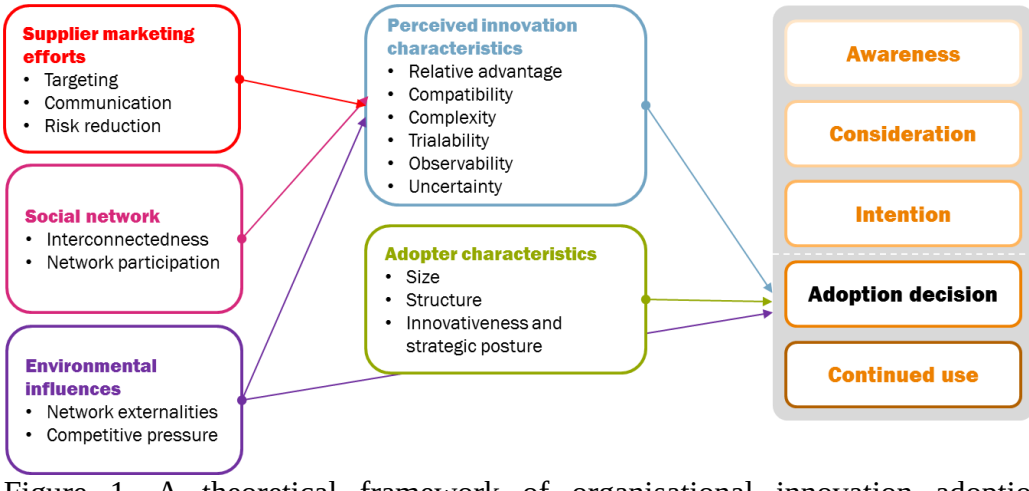


Figure 1. A theoretical framework of organisational innovation adoption (Frambach and Schollewaert, 2002).

Barriers with regard to the adoption of data driven precision farming services that were found in earlier research, by means of a focus group with a wide variety of actors, are that many precision farming applications have not yet been demonstrated ("trialability" in the theoretical framework), the economic benefits of precision farming have not yet been assessed, and new business models for data management are unclear ("uncertainty" in the theoretical model). In addition, it was said that precision farming needs the collaboration of all stakeholders for it to be widely adopted. Lastly, independent advisers do not yet have the appropriate awareness, knowledge, training and experience in precision farming (EIP Agri, 2015).

The current research

Several organisations in the Dutch dairy farming industry expressed the intention to use the InfoBroker by participating in a research consortium. Reasons to become part of the consortium were 1) a changing industry environment because of new environmental regulations, and the emergence of sensor hardware, 2) access to new data sources from other actors and other sensors, 3) gaining experience: new forms of collaborating and using new tools and sharing data, and 4) expected efficiency gains by big data analyses and sensor technologies

(Mutsaers, 2015). However, none of the organisations are actually utilizing the InfoBroker so far.In order to find ways to increase chances of adoption of the InfoBroker, the current research thus focusses on the question: what are at this moment in time the barriers and accelerators for the adoption of the InfoBroker by service providing organisations?

Material and Methods

In order to find out which barriers and accelerators were experienced with regard to adopting the InfoBroker, several workshops were initiated with three organisations who had expressed the intention to adopt the InfoBroker. They are different stakeholders of the dairy farming value chain, and all of them cooperations, in young stock nutrition or genetics. In the course of four months five workshops were facilitated. The workshops evolved around the joint development of a data driven service for dairy farmers. This enabled us to observe how they experienced and talked about the InfoBroker.

Results and Discussion

The transcripts of the workshops were mapped onto the earlier-mentioned theoretical framework of innovation adoption (Frambach and Schollewaert, 2002). Different barriers and accelerators were uncovered. They are listed in Table 1 to 5. Several drivers and barriers could not be mapped onto the theoretical framework. For this reason, the framework was extended with “perception of the maturity of the innovation” which is influenced by the extent to which the innovation (the InfoBroker in this case) is completed, and by the role that the organisation had in the development of the innovation. These factors can be found in Table 6.

N.B. not for every factor a driver and a barrier were uncovered, and for some factors more drivers or barriers were uncovered.

Table 1. Perceived innovation characteristics: drivers and barriers for the adoption of the InfoBroker.

Perceived innovation characteristics	
Factor	Drivers and barriers
Relative advantage *Perceived advantage of adopting the innovation relative to using alternatives.*	Driver: Acquiring data is seen as the most important relative advantage compared to not working with the InfoBroker. Participants expect to get the chance to beat the competition with by sensor data analysis developed models and expertise. Since there is no data available yet, the only experienced advantage at the moment is the strengthening of their strategic position.
Compatibility *Perceived compatibility of the innovation with existing systems and procedures within the organisation.*	Barrier: There are too many insecurities to establish the compatibility with current organisational systems.
Complexity *The extent to which the innovation and its implications are perceived as complex.*	Driver: The perceived complexity of the InfoBroker is low.
	Barrier: The process before the InfoBroker can be used is perceived as complex: placing sensors, collecting data, and defining business models.
Trialability *The extent to which the innovation can be tried before purchase.*	Driver: A demo of the InfoBroker was shown to the organisations.
	Barrier: It is not possible to do trials with the InfoBroker since there is hardly any (relevant) data yet.
Observability *The extent to which the innovation is visible in the world.*	Barrier: To show how the InfoBroker works different applications (parts of the InfoBroker) are required, which have to be operated by an expert from a third party.
	Barrier: It is difficult to picture the InfoBroker. Different metaphors are being used (drawer, phone book, high way). The software is invisible.
Insecurity *Perceived insecurities with regard to adopting the innovation.*	Barrier: There are a lot of insecurities with regard to collaborating on data driven services, who will make certain expenses, and who will take on which activities.

Table 2. Adopter characteristics: drivers and barriers for the adoption of the InfoBroker.

Adopter characteristics	
Factor	Drivers and barriers
Size *Size of the organisation..*	Driver: The organisations feel that since they are the biggest players in the value chain, they have the responsibility to serve the entire Dutch dairy market.
Structure *Centralized organisations are less prone to initiate innovations, but are better prepared for implementation.*	Driver: For all organisations there is commitment at CEO-level to adopt the InfoBroker.
	Barrier: Unclear what form the commitment from higher management has to implement the InfoBroker is delaying the process of adoption.
	Barrier: There are no inhouse programmers within the organisationsm preventing feelings of ownership.
	Barrier: To get things to change within the (large) organisations different people need to agree (culture of lobbying).
Innovativeness *The extent to which an oranisation is inclined to change.*	Driver: Every organisation has an innovation team and is directed at innovation in the sector.
Strategic position *The extent to which an organisation uses innovativeness as a (marketing) strategy.*	Driver: The organisations feel they have a pioneering role in the dairy sector. The InfoBroker could strengthen this position.

Table 3. Supplier marketing efforts: drivers and barriers for the adoption of the InfoBroker.

Supplier marketing efforts	
Factors	Drivers and barriers
Targeting *The extent to which the most promising target groups are selected for marketing.*	Barrier: The consortium decided to make the InfoBroker only available to the consortium partners for the next two year. This means other organisations are not targeted.
	Driver: The consortium decided to make the InfoBroker only available to the consortium to be able to further develop the InfoBroker for other target groups.
Communication *The extent to which is communicated, and the quality of*	Barrier: Communication directed at other organisations has not been discussed, since it was decided not to

the communication, regarding the innovation.	communicate at this moment in time.
Risk reduction *The extent to which perceived risks are being reduced, for example by a trial period, or a discount.*	Driver: the consortium was co-financed by government funding. This reduced the financial risks of the innovation.
	Barrier: It is unclear what the concrete risks are for the different organisations.

Table 4. Social network: drivers and barriers for the adoption of the InfoBroker.

Social network	
Factors	Drivers and barriers
Interconnectedness *The extent to which an organisation is connected with other stakeholeders amd exchanges information.*	Driver: the organisations work with each other on different levels which creates a strong bond.
	Barrier: It is unclear what the interconnectedness is with other organisations.
Network participation *The extent to which an organisation participates in networking events.*	Driver: the organisations visit conferences.
	Barrier: The consortium decided not to expand the consortium with other organisations for the next two years.

Table 5. Environmental influences: drivers and barriers for the adoption of the InfoBroker.

Environmental influences	
Factors	Drivers and barriers
Network externalities Influences from the environment or ecosystem of the organisation.	Driver: New regulations for farmers provide more urgency for data driven services, and hereby for the InfoBroker.
Competitive pressure *The extent to which an organisations experiences competitive pressure to adopt the innovation.*	Driver and barrier: The organisations experience competition by a few big suppliers who manage large part of the data.

Table 6. The theoretical framework was extended by: the perception of the maturity of the innovation: drivers and barriers for the adoption of the InfoBroker.

Perception of the maturity of the innovation	
Factors	Drivers and barriers
Phase of the innovation *The extent to which the innovation is fully developed or a prototype.*	Barrier: the InfoBroker is in an early stage of readiness, and not yet fully supported by a helpdesk for instance.
Role of the organisation in the development of the innovation *The extemt tp which an organisation was or is involved in the development of the innovation.*	Driver: the organisations were included in the development of the InfoBroker which helps to make them feel owner of the innovation.

Conclusion

We investigated what at this moment in time (2016) the barriers and accelerators are for the adoption of the InfoBroker by service providing organisations. We found that the major drivers for the adoption of the InfoBroker are that the organisations expect to acquire more data, which enables them to provide data driven services. In addition, the organisations feel they are capable of leading the sector in the trend towards data driven precision farming, and that this will strengthen their strategic position. The government co-financing of consortium activities towards developing the InfoBroker reduced the risk that is often associated with innovating. Since the organisations were involved in the consortium in which the InfoBroker was developed, they feel ownership for the innovation. Another driver is that there is commitment at CEO-level to adopt the InfoBroker.

Next to drivers there are several barriers that prevent adoption at this moment. There are several insecurities regarding the adoption of de InfoBroker and the process of developing data driven services. The InfoBroker is not perceived as being complicated software, but the process of developing and exploiting sensor data driven services in collaboration with each other and other organisations ís perceived as complex. Since there is not a lot of relevant sensor data yet, the trailability of the InfoBroker is perceived as low, which creates uncertainty whether the InfoBroker will serve their needs, and causes the InfoBroker not to

be part of the conversation during most of the development phase of the services. It is difficult for the organisation representatives to picture what the InfoBroker is, does, and what the advantages are over other option for data sharing.

The identified barriers and accelerators can be translated into measures to, one the one hand, overcome those barriers and, on the other hand, utilise the accelerators. They can for example be used to develop methods to aid innovation development and adoption in consortiums. Other examples of measures are providing decision makers and users of the innovation with the most relevant and persuasive information, and establishing precise requirements for employee training. The measures to respectively overcome and utilize barriers and drivers are central in the finalisation of the research in 2017 and 2018.

Acknowledgements

This research was supported and financed by the Dutch Top Sector High Tech Systems and Materials. We thank our colleagues from the organisations in the dairy farming value chain who provided insight and expertise that greatly assisted the research. We also thank our colleagues Jenny de Boer and Frank Berkers for organising the workshops.

References

The European Innovation Partnership 'Agricultural Productivity and Sustainability' (EIP-AGRI). Focus Group Precision Farming – Final Report. (2015).

Frambach R.T. & N. Schollewaert (2002). Organizational innovation adoption A multi-level framework of determinants and opportunities for future research. Journal of Business Research 55: pp 163-176

Lokhorst, C. & Wulfse, B. J. (2015). Chain cooperation as a critical success factor in Smart Dairy Farming. In Guarino, M. Berckmans, D., 7th European Conference on Precision Livestock Farming, EC-PLF 2015, 15-18 September 2015: pp 643-650. European Conference on Precision Livestock Farming.

Mutsaers, T. (2015). The Role of Innovation Ecosystems for Orchestrating Technological Change (Master’s thesis, Eindhoven University of Technology, the Netherlands)

Vonder, M., van der Waaij, B., Harmsma, E. & Donker, G. (2015). Near real-time large scale (sensor) data provisioning for PLF. In Guarino, M. Berckmans, D., 7th European Conference on Precision Livestock Farming, EC-PLF 2015, 15 September 2015 through 18 September 2015: pp 290-297. European Conference on Precision Livestock Farming

Wisdom, J.P., Chor, K.H.B., Hoagwood, K.E. & Horwitz, S.M. (2014). Innovation Adoption: A Review of Theories and Constructs. Administration and Policy in Mental Health and Mental Health Services Research, 41(4): pp 480-502.

An innovative mathematical approach for a highly informative treatment of automatic milking system datasets: development and testing of enhanced clustering models

F. Bonora, P. Tassinari, D. Torreggiani and S. Benni
Agricultural Engineering, Department of Agricultural Sciences, Alma Mater Studiorum (UniBo) Viale Fanin, 48, 40127 – Bologna (Italy)
stefano.benni@unibo.it

Abstract

New devices and studies have exponentially increased the amount of data available on modern farms. Farmers need to convert this data into useful, immediate and practical information for farm management and animal welfare. Therefore, in recent years many mathematical models already used in other fields, such as neural networks, image processing, regressions and clustering, have been applied to precision livestock farming.
The goal of this study was to develop a clustering method for herd characterisation on dairy farms. Specifically, a cluster-graph approach was applied to a dataset collected through the automatic milking system (AMS) of an Italian dairy farm and containing real-time information for each cow: daily milking frequency, activity, parity, weight, milking frequency, and days of lactation. The clusters were updated every month within the study time span to reflect changes in animal conditions.
The results represent a scientific method of transforming the amount of data available on the farm into user-friendly and highly informative data representations, such as graphs and plots, which can provide farmers with valid herd management support, particularly in terms of time and cost optimisation. By comparing subgroups for every single month, clustering can help farmers to take the most appropriate action promptly in order to increase animal welfare and productivity. Integration of the dataset into other farms through new devices and insights is planned in order to further refine the model.

Keywords: precision livestock farming, graph theory, cluster analysis, herd characterization.

Introduction

Information and communications technologies (ICT) have been becoming ever more popular in agriculture and their application in precision livestock farming (PLF) has increased very quickly in recent decades, especially in dairy cattle barns. It is broadly acknowledged that the main expected benefits from PLF are real-time

monitoring of animal welfare and health, early disease alerts, an increase in milk yield, a reduction in production costs, and improvements to farmers' working conditions and quality of life. As is well known, the introduction of automatic milking systems (AMS) in the late 1990s has fundamentally changed the barn layout and herd management on dairy farms.

Many studies in recent years have focused on data from AMS-equipped livestock farms (Westin et al., 2016). In particular, some authors have described the effects of the introduction of AMS on milking performance (Gygax et al., 2007), while other researchers have identified the introduction of the new milking system as a driver for increased milk production (Sitkowska et al., 2015). On the one hand, AMSs measure and record specific data about milk production and cow behaviour, providing farmers with useful real-time information about each cow; on the other hand, the remarkable amount of information stored in an AMS database has great potential for herd characterisation and management optimisation which is still underexploited.

The goal of this study was to develop a clustering method for herd characterisation in dairy farms. Specifically, a cluster-graph approach is applied to a dataset collected through the AMS of an Italian dairy farm and containing real-time information for each cow: daily milking frequency, activity, parity, weight, milking frequency, and days of lactation. The clusters were updated every month within the study time span to reflect changes in animal conditions.

Material and methods

The methodology was calibrated and tested on a dairy farm located in the municipality of Budrio, about 20 km north-east of Bologna (Emilia Romagna Region, Italy). The barn is a rectangular building 51 m long and 23 m wide, with SW-NE orientation of the longitudinal axis. It consists of a storage area for straw and hay along the SE side, a resting area in the central part of the building, and a feeding area with an external feed delivery lane on the NW side. The areas accessible to cattle have a precast concrete slatted floor. The resting area hosts 78 cubicles with straw bedding, where about 65 lactating and 13 dry Friesian cows are housed: two blocks of head-to-head rows are located in the central area, and another row runs along the entire length of the resting area near the storage lane. Dry cows are housed in the NE part of the two central rows of cubicles. The milking parlour is located on the SW side of the building, where there is also an office and a technical plant room. Ventilation is controlled by three high-volume and low-speed (HVLS) fans with five horizontal blades, which are activated by a temperature-humidity sensor situated in the middle of the barn. Cows are milked with a Lely "Astronaut A3 Next" robotic milking system, which is located on the SW side of the barn.

Data acquisition

Cow-related and milk yield data were recorded by the AMS each time a cow passed through the milking unit. The following parameters were collected in a matrix called "visit":

- Cow identification number;
- Date and time of cow passage;
- Milk yield;
- Days of lactation;
- Feed intake (supplementation with additional concentrates). Total daily amount was calculated and provided by the AMS based on milk yield and day of lactation;
- Cow weight;
- Parity;
- Mastitis: in every single milking event, it is equal to 1 if the AMS identifies mastitis, otherwise it is equal to 0. The final output is the average of the variable.

Cow behaviour data were acquired by means of a cow identification and activity sensor mounted on a collar, which monitors the activity levels (A) by means of acceleration sensors measuring the duration and intensity of every movement of the animal. Cow activity was recorded in 2-hour blocks and downloaded each time a cow passed through the milking unit. Based on the activity data downloaded by the AMS management software, we created an "activity" matrix, where each row corresponded to a two-hour acquisition period, and the two columns contained the cow identification number and the mean activity of each cow. The "visit" and "activity" matrices were processed jointly to obtain synchronous data, as described in a previous paper (Bonora et al., 2016).

Clustering

The cow clustering based on production and behavioural features focused on data collected over more than one year (from June 2015 to August 2016) and applied to the overall number of lactating cows which were reared in the barn during the study period considered for every single month.

A k-means algorithm (MacQueen, 1967) was used to study the following parameters for each cow:

- Number of milking events per day;
- Parity;
- Average daily activity;
- Milking regularity, in terms of standard deviation of the time intervals between milking events in the study period;
- Days in milk.

For each variable, different k values were selected a posteriori to highlight particular trends. For the number of milking events per day, milking regularity and activity, the k values were selected as described by Bonora et al. (2016). For parity, $k = 3$ was selected on the basis of the results of that study, which indicated that three main groups can clearly be recognized. For the lactation curve, it is known that three fundamental phases can be identified, with transitions corresponding to about 90 and 210 days, therefore k was selected as equal to 3 for the variable days in milk.
The clusters obtained through the k-means algorithm were combined in a network graph using the Gephi software (0.9.1 version), an open source and cross-platform exploration tool for networks and complex systems (Bastian et al., 2009). The network designed assigned a node to each cow and linked two nodes if the cows belonged to at least one common "k-means cluster". The weighting of the link between two nodes A and B was defined by means of an overall "similarity index" (S), calculated for each parameter i according to Equation 1:

$$S_i = 1 - \frac{variable(A)_{\mathrm{i}} - variable(B)_{\mathrm{i}}}{centroid_{\mathrm{i}}} \quad (1)$$

The graph was then analysed by means of proper routines to identify subnetworks, i.e. graphs composed of subsets of nodes and edges from the starting network. This research was based on modularity, a procedure which minimises the number of edges from two different clusters (Newman, 2006).

Results and discussion

The clustering model organises the herd in three different clusters related to each 30-day period of the study time span, having as the "main variable" one of the above-mentioned parameters. The main variable used in the diagrams shown in Figure 1 is the cow identification number, i.e. each month the number of cows remaining in the same cluster as the previous month was maximised.
Figure 1 was drawn using the "Force Atlas" layout of Gephi (Repulsion strength = 10.000, Gravity = 400, adjustment by sizes). Each node was characterised by a number, the CID of the cow, and a colour that identified the cluster. This network represents the first immediate result that could be extrapolated from the AMS dataset.

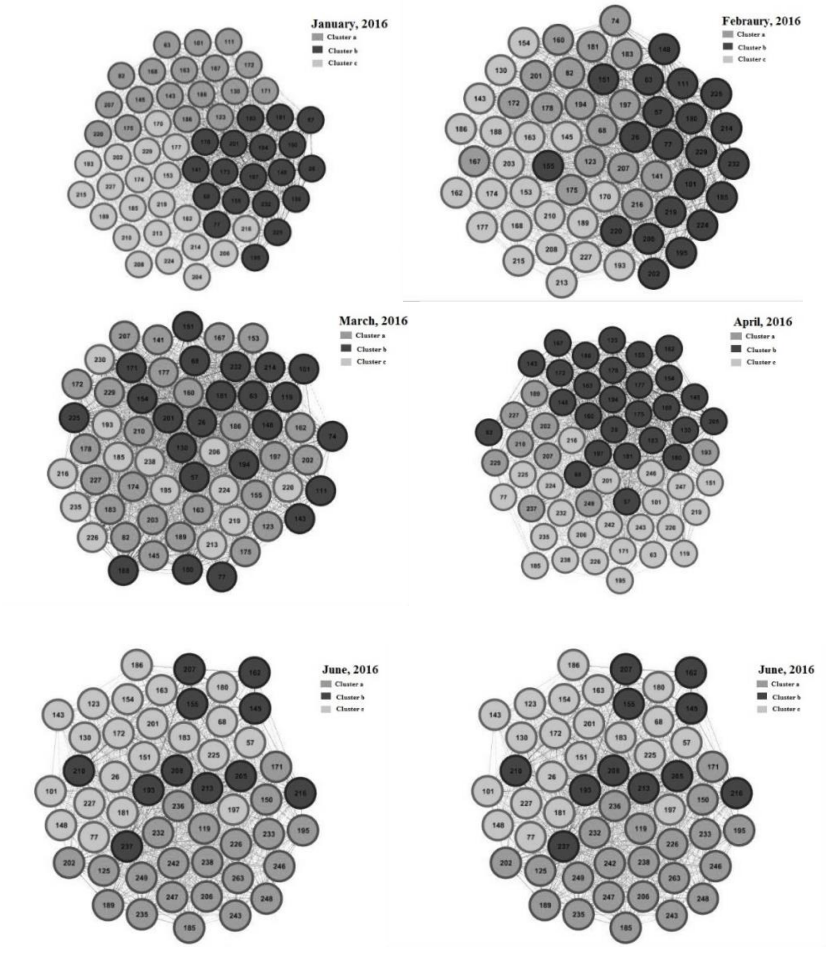


Figure 1: Monthly Gephi plots from January 2016 to June 2016. Every cow is a node and the colour of the node represents a specific cluster. The light-coloured lines are the edges that link different nodes

Table 1. Cardinality of the three clusters in the first six months of 2016.

Month / Cluster	a	b	c
January	18	19	21
February	17	21	21
March	25	23	13
April	9	27	23
May	23	20	6
June	22	11	21

Figure 2 represents the monthly values of the AMS-recorded parameters.

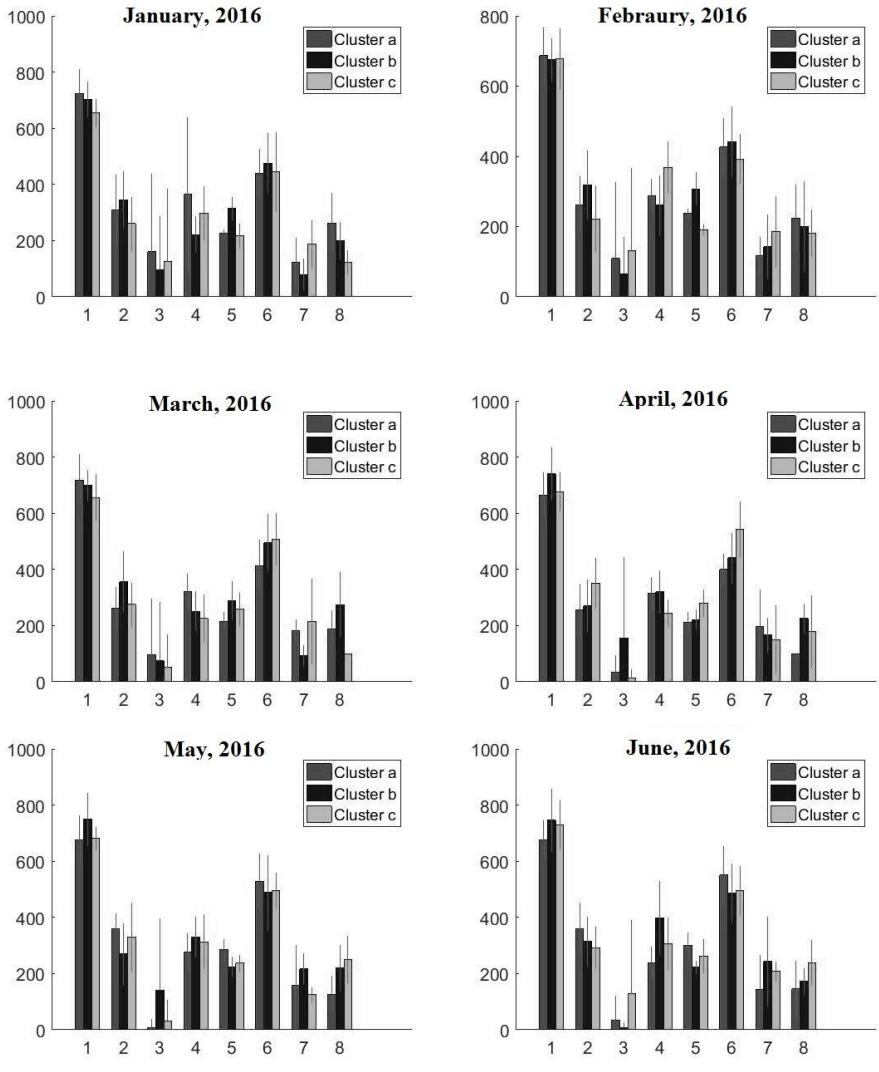


Figure 2: Monthly histograms of averages and standard deviations of herd variables:
1 = weight (kg); 2 = mean daily milk yield (dl); 3 = mastitis (‰); 4 = milking regularity x 10^2 (hour); 5 = daily milking x 10^2; 6 = activity x 10; 7 = lactation (days); 8 = parity x 10^2

Finally, Figure 3 illustrates the summary for one year for each parameter, in terms of monthly averaged values, thus representing the herd trend (Figure 3).

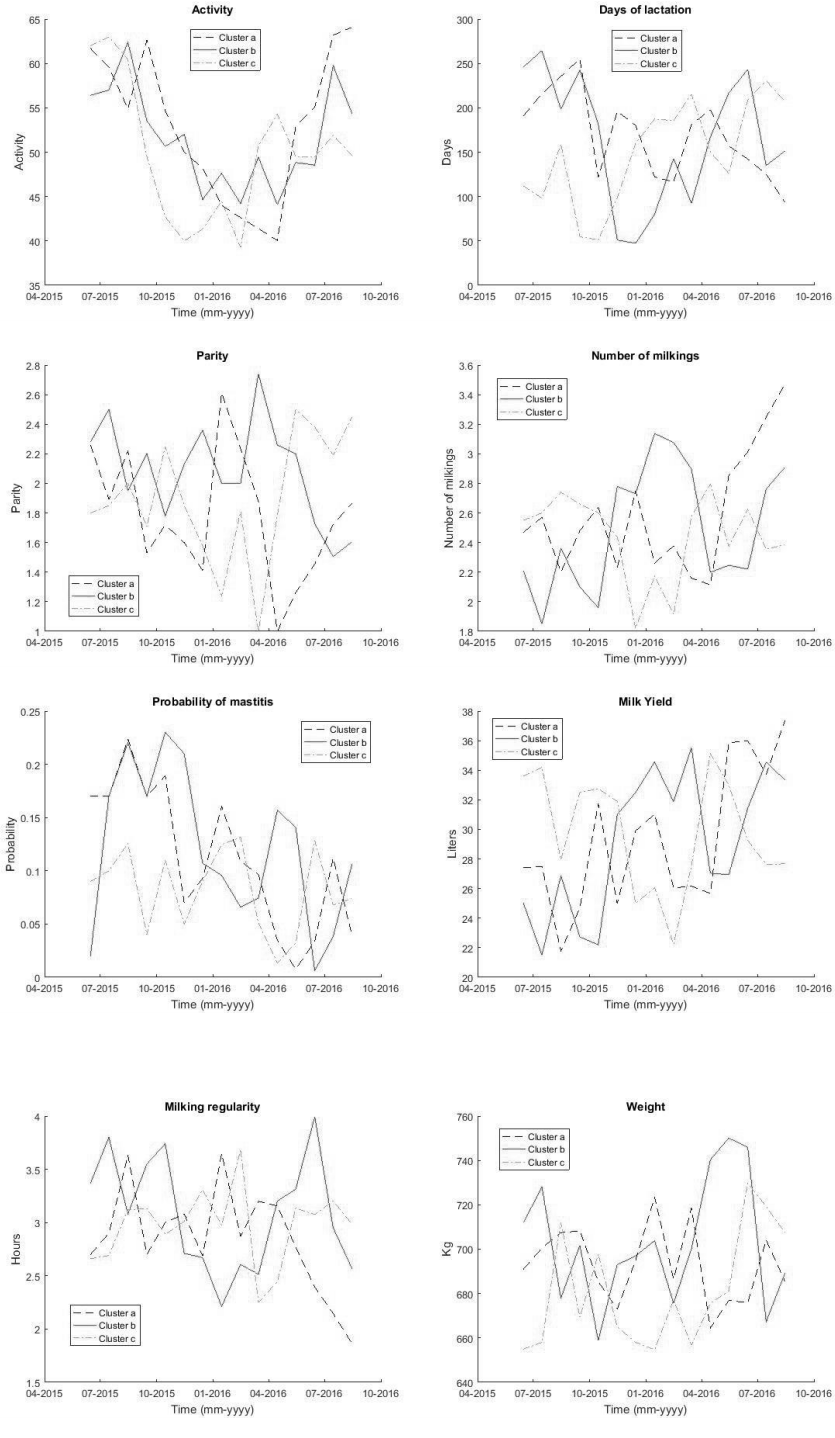


Figure 3: Yearly trend of the main variables. Every line represents a single cluster

Combined analysis of the automatically generated diagrams illustrated in Figures 1, 2 and 3 makes it possible to analyse the animals in specific time intervals and to compare their conditions with those of previous months, thus achieving detailed monitoring of the herd. Moreover the trends of the parameters characterising the cluster provide a dynamic characterisation of the herd.

Conclusions

The study developed a scientific methodology for processing the data available on the farm by converting it into user-friendly and highly informative numerical and graphical representations of cow conditions, which can provide farmers with useful and valid support in herd management, particularly in terms of time and cost optimisation. Thanks to the comparison of subgroups for every single month, clustering can help farmers to identify the most significant parameters characterising the animals in terms of productivity and welfare, and thus take the most appropriate action without delay.
Integration of the dataset into other farms through new monitoring devices and insights is planned to allow further refinement of the model and consequently enhance the analytical procedure.

Acknowledgments

The study was conducted as part of a research agreement between the Department of Agricultural Sciences of the University of Bologna and the dairy farm Piazzi (Budrio, BO, Italy)

References

Bastian, M., Heymann, S., and Jacomy, M. 2009. Gephi: An Open Source Software for Exploring and Manipulating Networks. *Third International AAAI Conference on Weblogs and Social Media*, 361–362.

Bonora, F., Benni, S., Barbaresi, A., Tassinari, P., and Torreggiani, D. 2016. Comprehensive analysis of AMS data: a cluster-graph approach tested on a dairy farm, in: Kamphuis C., Steeneveld W. (eds) *Precision Dairy Farming 2016*, Wageningen Academic Publisher, 251 – 256.

Gygax, L., Neuffer, I., Kaufmann, C., Hauser, R., and Wechsler, B. 2007. Comparison of functional aspects in two automatic milking systems and auto-tandem milking parlors. *Journal of Dairy Science*, **90**(9) 4265–4274.

MacQueen, J. B., 1967. K means. Some Methods for classification and Analysis of Multivariate Observations. *5th Berkeley Symposium on Mathematical Statistics and Probability*, **1**(233) 281–297.

Newman, M., 2006. Modularity and community structure in networks. *Proceedings of the National Academic of Science*, **103**(23) 8577–8582.

Sitkowska, B. Piwczyński, D., Aerts, J., and Waśkowicz, M. 2015. Changes in milking parameters with robotic milking. *Archives of Animal Breeding*, **58**(1) 137–143.

Westin, R., Vaughan, A., de Passillé, A. M., DeVries, T.J., Pajor, E.A., Pellerin, D., Siegford, J.M. , Vasseur, E., and Rushen, J. 2016. Lying times of lactating cows on dairy farms with automatic milking systems and the relation to lameness, leg lesions, and body condition score. *Journal of Dairy Science*, **99**(1) 551–561.

Precision livestock farming and big data: a new challenge for the poultry sector and prospects

P. Créach[1], E. Doutart[2], I. Bouvarel[3]
[1]*ITAVI - 41, rue de Beaucemaine, 22440 Ploufragan, France*
[2]*Institut de l'Elevage – 149 rue de Bercy – 75012 PARIS*
[3]*ITAVI - Centre INRA Val de Loire – 37380 Nouzilly, France*
creach@itavi.asso.fr

Abstract

Precision Livestock Farming (PLF) is defined as the coordinated use of technologies to measure different indicators on animals and their environment, in order to improve livestock monitoring and management. PLF allows real-time management of different types of data (data from the animals, their feed consumption, the atmosphere in the barn, etc.). These data support decision-making by the farmer (e.g. management of ventilation and heating). PLF uses modern information and communication technologies to exchange, transform and provide feedback to the farmer. PLF can also involve the use of automatic systems and robots which relieve the farmer of certain tedious tasks.
Soon, the farmer will be able to manage production, health, behaviour and welfare parameters of the flock in real time. A major issue is to learn from the multiple data generated and utilise it to create and develop appropriate livestock management tools for the farmer. Smartphone applications used outside the agricultural sector will be presented as examples of technology which can be transferred to the poultry sector. This prospect will make it possible to identify new approaches for the future of the poultry sector.
The digital revolution provides an opportunity to rethink production systems. This revolution will encourage and facilitate communication between parties (product traceability and transparency among stakeholders). PLF technologies generate a huge amount of data, with various formats and sources. The challenges are to share these data between stakeholders and improve the statistical processing of big data to design and develop new management tools for the farmers.

Keywords: Precision Livestock Farming (PLF), poultry sector, equipments, technologies, innovations, big data

Introduction

The availability of new technologies nowadays allows us to manage livestock farming differently. Increasingly demanding breeds need precise management to allow full expression of their genetic potential. Technologies such as image analysis of animal movement can also be used to manage outdoor rearing more efficiently.

As well as ensuring animal productivity, farmers must guarantee the welfare and health of the flock, while limiting the environmental impact of the farm. The increasing number of sensors in the building (thermometer, hygrometer, carbon dioxide sensor, vacuum gauge) generates a large amount of data. As a result, a wealth of information is generated every day, in different formats. Moreover, new formats such as images or soundtracks will be used. One of the major issues is to learn from this multiplicity of data and to utilise it by designing and developing farm management tools. These new technologies present themselves as the solution to guide the farmer's decision-making and facilitate his work by freeing him from tedious tasks.

Some tasks are now automated, such as regulation of the internal atmosphere of the barn, feed distribution or triggering of nebulisation. For some time now, these automatic systems have relieved the farmer of the task of opening and closing the shutters manually several times a day. This gain of time allows farmers to concentrate more on animal observation or on their hobbies. PLF tools do not replace the farmer but complement his observations in a more precise and objective way.

PLF can thus contribute to the evolution of production systems by making them more efficient. Moreover, the arrival of digital technology will facilitate exchanges and communication between every link in the poultry sector. These different elements are presented below.

1. Precision livestock farming : background and operational scope

1.1. Operational scope and challenges of PLF

To meet the challenges of multi-performance livestock farming, farmers are equipping themselves with new digital and communication technologies as well as sensors. These tools allow the breeder to measure and record environmental parameters and production, health and animal welfare indicators. The data obtained are used as the basis for decision-making in livestock farming in order to adjust management systems on the basis of animal needs and targeted objectives.

The principle underlying PLF is to use these technologies to monitor and manage breeding through real-time and continuous use of large quantities of data

obtained from animals, buildings, equipments, sensors or data entered by the farmer according to his observations. The use of this data allows immediate and appropriate action to be taken to improve animal status and/or living conditions (Berckmans, 2013).

More and more barns are "connected" and use wireless networks and the Internet of Things. The farmer is surrounded by connected tools which change his job and his way of working (method, organisation). Information and communication technologies (ICT) such as smartphones and tablets are part of the farmer's daily life. They are real tools for the farmer these days. ICT allow users to communicate, access sources of information, and store, handle, produce and transfer information in all its forms (text, images, sound, etc.). The connected tools have the advantage of being mobile and therefore allow the farmer to consult and enter data from the livestock building or his own house. Moreover, these tools safeguard the information with backup systems and online data recovery of the parameter history relating to the flock and its housing conditions (animal weight, indoor atmosphere, etc.). Remote, automatic updates make these technologies increasingly efficient.

However, difficulties with internet access in rural areas can be a significant barrier to the deployment and effective functioning of these connected objects.

1.2. Mega data and adaptive real time algorithm

The PLF principle is based on continuous, real-time data collection. This data gathering is made possible thanks to technological advancement and web evolution since the 90s. The word "web" is a contraction of "World Wide Web" (hence the acronym). One of the possibilities offered by the internet network is navigation between hyperlinked documents. For more than sixty years, storage has been evolving in terms of cost and capacity. The cost has decreased from € 26 000 000 per GB in 1956 (the first hard drive had a 5 MB capacity) to less than 5 cents per GB in 2017 (today's hard drives exceed 10 TB). In a few decades, the price has been divided by 520 million. The 1990s were characterized by the 1.0 or traditional web, a static web which focused on information distribution. The first e-trade websites date from this era. Program and software ownership costs were enormous. The perspective of the web changed completely with the appearance of the 2.0 or social web in 2000. It encouraged the exchange and sharing of information and content (texts, videos, images or other documents) and saw the emergence of social networks, smartphones and blogs. The web was boosted and democratised. The semantic or 3.0 web appeared in 2010 with the aim of organising the vast amount of data available according to the context and needs of users by taking into account, for instance, their locality or preferences. This more portable web attempts to give a meaning to the data and improves the connection between the real and virtual

worlds. It answers the mobile user's needs by always being connected to a multitude of fun and clever support systems.
As a result, a wealth of information can immediately be obtained in order to develop useful and reactive tools for farmers. Prediction is the tool of choice of this new field. The goal is to gather the maximum amount of information and to run it with one or more algorithms in order to obtain the best prediction possible of the studied phenomenon, without trying to explain the parameters of the model. With this continuous acquisition of data, the algorithm "learns" with every new entry to adapt itself to the user and send the most relevant and earliest alert possible. Sometimes, the alert can be a source of tension for the farmer. Indeed, alerts can be triggered at any time during the day or night, which can cause some stress and a feeling of work enslavement (Hostiou et al., 2014). It is thus important to build an efficient algorithm which allows continuous follow-up and which only triggers alerts in the event of a problem that cannot be anticipated.
To date, very few prediction tools are used in the poultry sector and as a result, technicians and farmers only take remedial action. The challenge for prediction technology is to develop guidance tools (for example in the fields of breeding, feeding or genetics) for the poultry industry. To do this, it is necessary to bring together poultry-related, software and statistical skills.

1.3. Examples of PLF for poultry: guidance and follow-up tools for flocks now and in the future

1.3.1 Which tools for today's farmer?

Sensors are available to all farmers and are now ubiquitous in poultry housing.

Sensors are used primarily for management of indoor parameters for ventilation or heating regulation (continuous measurement of temperature, moisture levels, carbon dioxide concentration, ventilation, etc.). It is also possible to **record water and feed consumption accurately and in real time** (using strain gauges [pictures 1 and 2] or innovative telemetry systems).

Pictures 1 (photo credit: Tuffigo-Rapidex) and 2 (photo credit: Sodalec): Strain gauges

Automatic weighing devices enable farmers to record the precise animal weight (picture 3) easily and in real time. This data enables the farmer to control the most important breeding parameters in real time: average weight, growth, animal homogeneity. The most common **automatic weighing systems** use a suspended tray system (with a suspended strain gauge) and record the weight of each animal as it steps on the tray. Compared to manual weighing, these automatic weighing devices do not require human intervention and do not disturb the animals.

Picture 3: Automatic weighing device with suspended tray PESbox (Tuffigo-Rapidex) (photo credit: ITAVI)

The lighting can be controlled with **photoelectric cells**. These cells can maintain a chosen lighting level depending on natural light input. Electric, precise and connected dosing pump systems capture and record all treatments applied to the animals via the drinking water. Most of the data are synthesised by an **electronic controller**, which handles, for example, ventilation regulation, heating within the house or the triggering of automatic nebulisation. By using the internet, the farmer can gain remote access to the computer from a smartphone or tablet (pictures 4 and 5).

Pictures 4 (photo credit: Tuffigo-Rapidex) and 5 (photo credit: ELEVAGEélec): Electronic touchscreen controller AVITOUCH (Tuffigo Rapidex) for centralisation of breeding parameters and remote access from a smartphone.

1.3.2 Which tools for tomorrow's farmer?

Farmers will soon be able to measure ammonia concentrations and dust levels in the barn continuously. In the future, control of heating and ventilation will include all the parameters measured continuously in the animal's environment.

Recently, **tools based on image analysis of poultry behaviour** have been developed. Video images associated with image analysis algorithms examine animal movement (Dawkins et al., 2009) and distribution (Kashiha et al., 2013) in order to alert the breeder in case of abnormality (picture 6). These behavioural anomalies can be precursors of latent health issues or simply water or feed access problems. The farmer will be able to take action earlier to prevent complications or production loss due to delayed care, which generates additional costs such as veterinary treatment.

Picture 6:Video image of a broiler flock in the barn (photo credit: ITAVI).

Recording **sounds** in the barn is also a promising technology for detecting health, stress or growth issues. For example, the University of Leuven studied the food intake of broilers using automated and continuous monitoring with audio technology. Under experimental conditions, a correlation was found between ingested feed and broiler feed pecking sounds (Berckmans et al., 2015).
Recently, **mobile robots** have been developed for laying hen breeding (eggs for consumption and hatching eggs) to reduce the hassle of the breeder's work, especially by collecting eggs or dead animals from the ground. For example, the Ti-One robot, which is under development, was designed by a farmer to encourage laying hens to lay eggs in their nests. The motion of the robot in the building, with the help of adequate stimuli, activates the animals and offers lots of possibilities.

1.3.3 Interoperability of data, cloud and data sharing

Today, cloud solutions are being developed to allow farmers to save data elsewhere than on the breeding site. These include Cloud MyTuffigoRapidex developed by Tuffigo-Rapidex (http://mytuffigorapidex.com/). The cloud has several advantages: for example, breeders can recover data in the event of a power failure. This solution also allows data sharing, depending on what the breeder decides.
Breeders transmit various types of information about the flock to their partners (production organisations, feed suppliers, slaughterhouse, etc.). For example, at the end of the flock the production organisation can be supplied with data on growth, mortality, antibiotic use, etc. Real-time data collection allows the production organisation to intervene earlier in case of a problem, and thus to better schedule its visits to the farm. Planning of day-old chick deliveries should

also be improved. Pooling of the data enables the farmer to compare his performance with other farmers from his production organisation or to compare current performance with previous flocks.
Computerised data retrieval, from farm to breeding company, would make it possible to adapt selection programmes more accurately and to rear animals that are better adapted to their environment. Commercial poultry are hybrids which require phenotypic data (growth, disease resistance, etc.) to assess the effects of breeding programmes. On the other hand, information transmission to food formulators would provide them with real-time feedback on the performance observed with monthly food formulations. Computerised transmission of livestock data would allow better formulation decisions based on robust data. The farmer may also allow his building installer to access the cloud for maintenance purposes. Other players in the poultry sector can potentially have remote access to the cloud (equipment installers, veterinarians or slaughterhouses, for example). This type of innovation is a real tool which will simplify procedures, encourage collaboration and save the farmer's time.
In addition, a collaborative traceability platform GS1 is being deployed to enable all players in the food chain (upstream agriculture, food industry, wholesalers, logisticians, distributors, solution providers) to share data between themselves and with end consumers. This tool therefore makes it possible to trace the life cycle of a product, from the producer to the consumer.

2. Outlook for PLF data: development of big data

2.1. Big data issues in animal husbandry

The world of animal husbandry is no exception: it is evolving, modernising, and has entered the digital age. Barns are increasingly equipped with sensors. Domotics or smart buildings (a set of technologies which integrate all the automation systems in terms of security, energy management, communication, etc.) is becoming more and more popular and large amounts of information are collected every day.

<u>Everyone is talking about big data but what about poultry production?</u>
Originally and theoretically, big data is defined by the 3Vs: Volume, Velocity and Variety. Now, other Vs are also associated with it, such as Value and Veracity. The real novelty of these data is not in the volume V, but rather in the other two original Vs: variety and velocity. Indeed, big data is not associated with bigger data centres which store more and more data. The novelty lies in the ability to retrieve data from all sides: experiments, field surveys, daily data from sensors, weather, open data, geolocation, internet tweets, etc. These data take up space but are mainly heterogeneous (different formats and origins) and arrive in

more or less continuous flows. This is new for the animal husbandry sector which has to face these challenges and arm itself to take advantage of the new multiplicity of technologies.

Three key factors explain the development of big data:

(i) The cost of storage (already mentioned above in this article), which is constantly decreasing and which is becoming less of a relevant criterion for companies. In addition, cloud computing solutions allow flexible data management and real business needs.

(ii) Distributed storage platforms and very high-speed networks. With these technologies, the data storage location does not really matter. It is now stored in distinct, and sometimes unidentified, physical locations.

(iii) New technologies for data management and analysis. Among these technological solutions linked to big data, one of the references is the Hadoop platform (Apache Foundation) which allows the development and management of distributed applications involving huge amounts of evolving data.

Today, data ownership is one of the biggest problems encountered in the animal husbandry world, ahead of storage and data. In France, as in many countries, the notion of data ownership has no status. Ownership can only relate to intellectual creations based on these data (intellectual property such as copyright, trademark law, patents). A single piece of data has no value, but analysis of that data adds value. The digital era is also the era of data sharing, and data collection becomes useful through combining the acquisition and exploitation of information. Today, many companies are seeking to improve their knowledge of big data in order to complement and adapt their products or services in order to meet the expectations of their customers, but the first step is to share these data.

2.2. Big data analysis: upheaval in statistical processing?

The arrival of these new data also raises the question of statistical processing and the new skills that need to be acquired. The principles underlying classical statistics and statistical testing no longer have a place in large data volumes, and even a very small deviation is likely to be significant. Nevertheless data mining methods remain relevant, but existing models need to be adapted. The analytical philosophy is changing, but the techniques are not revolutionary. The disruption is mainly in data storage, with the need for new databases such as NoSql (Not Only SQL) to store unstructured data. Another change is processing with data parallelisation (sharing a large dataset into fractions that can be processed in parallel) and thus distributing the calculations over different clusters (computers). Analysis can then be carried out on the entire dataset even if it cannot be physically stored on a single machine.

With the arrival of big data, a new profession of data scientist has emerged. It combines computer skills in storing and managing complex data with increased programming needs and statistical knowledge in the use of more or less advanced techniques of data mining and algorithm forecasting. The data scientist must have business skills as well as computer and statistical skills. However, business skills require a variety of expertise in the animal husbandry sector. Thus, an interesting solution would be to combine the skills of a team (computer scientists, statisticians, engineers or agronomists and farmers) in order to combine knowledge and lead projects of this scale. More recently, the DataLab concept has appeared, which brings together different specialisms (statisticians, IT specialists, communication specialist, business expert, visualisation expert), and now also includes the skills of a data scientist.
Thanks to Data Scientist and Data lab, data can be analysed in a different and more reactive way.
At present, in livestock farming, data are gathered from everywhere but are not actually collected together and shared. The databases are analysed more or less separately over a long period and with different levels of extraction. Data are then analysed using models and made available in the field. With new technologies and sharing of data, the treatment will be different. The data will arrive in a more or less continuous flow, models will be developed using machine learning algorithms (Figure 1) which learn continuously thanks to the new data arriving in a continuous flow. The farmer or technician can visualise results on a day-to-day basis and adapt practices faster than in a conventional case where the results arrive months later.

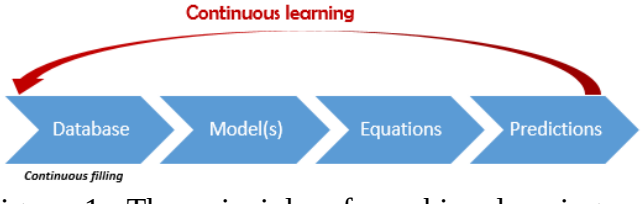


Figure 1: The principle of machine learning: continuous adaptation by the algorithm created by the statistician, possible thanks to large datasets (photo credit: ITAVI).

Big data has only just begun in livestock farming and discussions around the sharing of data are ongoing. Different storage systems are being used to capture the data, data scientist training is emerging, and statisticians are applying big data algorithms to detailed data. Everything is in place to allow great advances in this field.

2.3. Big Data: examples that could be transferred to the poultry sector

To broaden the scope of possibilities and to consider new applications in poultry production, various examples of innovations or smartphone applications, developed outside the framework of poultry production, are presented below.

Embedded sensors to improve traceability: **Tranxens** has developed a system for tracking freight containers via numerous on-board sensors, making it possible to identify the position of the container and whether it has undergone shocks or variations in temperature, for example. Tools like this could bring greater transparency between the stakeholders in the sector, e.g. **precise knowledge of the conditions during transport of the chicks** from the hatchery to the barn or from the barn to the slaughterhouse.

Connected clothing: the **Medata.lab** project improves the diagnosis of epilepsy by connected clothing to capture health data (electro-encephalogram, electrocardiogram, etc.). These textiles could be adapted for broilers to measure health data. Unlike flock management, this connected garment will make it possible to follow individual animals which are representative of the flock. These sentinel animals could be equipped with this type of micro-sensor (thermometer, pedometer, accelerometer, RFID chips, etc.) and would provide information at the individual scale. On a short term basis, this type of development could be applied in research and on a medium term basis in commercial farming. This connected technology could also be adapted to measure the warning signs of carbon **monoxide poisoning in farmers, to prevent the risk of poisoning.**

Better forecasting: In San Francisco, criminological data are analysed to predict future offences that will occur at a given time and place. This prediction tool uses machine learning algorithms. In poultry farms, farmers must communicate the estimated weight of their animals to the slaughterhouse at least 48 hours before slaughter (sometimes earlier for some production organisations). This data is important in enabling the slaughterhouse to meet the requirements of their downstream customers, particularly in terms of size. The farmer uses the typical growth curve and the estimated weight of his animals. The slaughterhouse sets up bonus-malus systems to encourage **farmers to be precise in predicting the weight of broilers**. These machine learning algorithms could be used to predict the growth and final weight of animals before slaughter earlier and more precisely. Moreover, this data could be automatically transmitted to the slaughterhouse.

Networking: For a company that is launching internationally, the ability to find the right foreign partners is important. The Powerlinx platform identifies companies with common interests (in strategic terms, products / services, customers, etc.). Social networks can also help to promote exchanges between farmers beyond the production organisation. Farmers could exchange information, for example about equipment or an animal breed, on dedicated forums. These exchanges would allow farmers to share their point of view and / or help guide their technical or strategic choices. The surrounding companies, with access to this kind of information, could also guide their development according to producer feedback. This would improve responsiveness.

These various examples highlight the importance of interchange and transparency between poultry sector stakeholders. Economic sociology has highlighted the influence of social networks in coordination between economic players and the circulation of goods (Ferrarry, 2001).

Conclusion

This article highlights the various factors influencing developments in order to advance production systems and promote communication between actors. Future developments must emerge from the needs of the stakeholders in the poultry sector, especially from farmers. Considering the tools presented from outside the agricultural sector, the precision tools of tomorrow will have to favour exchanges between the different players in the sector. These exchanges will promote data sharing in order to add value to data processing. Given the constraints on production (administrative, environmental, animal welfare), precision tools will make the farmer's job easier. These technologies and the arrival of digital breeding will certainly attract the younger generation of farmers, by combining the digital with the technical.

In poultry farming, it is notable that the data provided by the available technology are only partially exploited. A key step in taking full advantage of PLF is to analyse data differently and develop algorithms that process real-time data in order to be more reactive. These analyses provide added value for farmers and stakeholders. Thus, the sector will have to propose a global solution which combines the existing technologies.

References

Berckmans D., 2013. Basic principles of PLF: Gold standard, labelling and field data. In Proceedings of the 6th European Conference on Precision Livestock Farming, ECPLF2013, Leuven, 21-29.

Berckmans et al., 2015, Elevage de précision : l'intérêt pour l'éleveur du futur ; communication orale 15ème journée d'étude des productions porcines et avicoles à Beez.

Dawkins M., Lee H., Waitt C., Roberts S., 2009. Optical flow patterns in broiler chicken flocks as automated measures od behavior and gait; Applied animal behavior science 119, pp 203-209.

Ferrarry M, 2001. Pour la théorie de l'échange dans les réseaux sociaux. Un essai sur le don dans les réseaux industriels de la Silicon Valley. n°111,182p.

Hostiou N., Allain C., Chauvat S., Turlot A., Fagon J., 2014. Conséquences de l'élevage de précision sur le travail des éleveurs. Renc. Rech. Ruminants, 21, 11-14.

Kashiha M., Pluk A., Bahr C., Vranken E. et Berckmans D., 2013. Development of an early warning system for a broiler house using computer vision; Biosystems engineering 116, pp 36-45.

IoF2020 - the Internet Of Meat: towards applications of Internet of Things in the meat supply chain

J. Maselyne[1*], K. Mertens[2], A. Van Nuffel[1], H. Scholten[3], I. N. Athanasiadis[3], M. Larrañaga[4], I. Fernández[4]
[1]*ILVO (Flanders research institute for agriculture, fisheries and food), Technology and food Science Unit, Burgemeester Van Gansberghelaan 92 bus 1, 9820 Merelbeke Belgium*
[2]*Porphyrio NV, Warotstraat 50, 3020 Leuven-Herent, Belgium*
[3]*Wageningen University, Department of Social Sciences, P.O. Box 8130, 6700 EW Wageningen, the Netherlands*
[4]*IK4 – Tekniker, Electronics and communications unit, PARKE TEKNOLOGIKOA, C/ Iñaki Goenaga,5,20600 Eibar, Gipuzkoa (Spain)*
jarissa.maselyne@ilvo.vlaanderen.be

Abstract

To enable all actors in the meat supply chain to monitor, manage and optimise their production process, Internet of Things applications create multiple opportunities. In the IoF2020 project (Internet of Food and Farm 2020), starting early 2017, 11 partners from five countries focus on large-scale implementations of IoT via three use cases in the meat supply chain: pig farm management, poultry chain monitoring and meat transparency and traceability. Farmer's lack of accessibility to information to monitor their production on a continuous basis will be addressed by installing and integrating IoT sensors for environmental and animal monitoring. In addition, early warning systems will be developed, linking different data-streams to provide valuable feedback to the farmer, as well as information transfer to other stakeholders. Doing so, preventive or corrective actions for diseases, boar taint, bird mortality, feed waste, environment, etc. can be taken. Further, also EPCIS-based tracebility from farm to fork will be enabled, so that consumers receive reliable information on meat origin and quality. The current progress of these three use cases, as well as the planned developments will be presented. By addressing several technological and business challenges, as well as EU-wide dissemination, IoF2020 aims to contribute to the digital revolution in Smart Farming.

Keywords: Internet of Things, meat, pigs, poultry, traceability, IoF2020

Introduction

The meat production sector is undoubtably an important part of the European agricultural sector. Looking at EU statistics, there are almost 7 million livestock farms in the EU which is more than half of the total number of farms (Marquer & Forti, 2015). The economic relevance of animal production is 43.1% of the EU agricultural output, of which 57.5% is animal output (slaughter, herd renewal or further growing and fattening) and the rest is animal products (milk, eggs, wool etc.). The different meat categories are (Marquer & Forti, 2015):

- Pig meat – 23.5% of EU farms – 9% of EU agricultural output
- Bovine (cattle, buffalo, veal, etc.) – 21.4% of EU farms – 8.1% of EU agricultural output
- Broilers – 18.7% of EU farms – 5.5% of EU agricultural output
- Sheep & goats – 12.1% of farms – 1.4% of agricultural output

With an increase in world consumption and production, it is essential that aspects as sustainability, welfare, environment, quality and traceability receive the maximum of attention. To solve challenges like resource efficiency, disease and risk management, it is important for the meat production sector to stay on top of their production process, monitoring and if needed controlling every part of it. One of the innovations that can help achieve this is a technological innovation to bring Internet of Things (IoT) to the agricultural domain. This is what the newly started project IoF2020 (Internet of Food and Farm, *iof2020.eu*, 1/1/2017-31/12/2020) is about. With over 70 partners in total, IoF2020 aims to accelerate the uptake of IoT technologies in the European farming and food chains, with a primary focus on 5 trials (arable, dairy, fruit, vegetables and meat).

The Meat trial consists of three use cases, two vertical use cases aim to support the meat value chain through knowledge-based livestock production systems with smart sensors and data integration, in pig and poultry. The third horizontal use case concentrates on meat tracebility and transparency.

Use case 1: Pig production management

This use case will work on combining data across the value chain in order to provide the pig farmers with crucial information to effectively steer their management to reduce boar taint, health problems, productivity problems, etc. This information is currently lacking, fragmented or collected only post-hoc. In a

next step, this data could enable valuable information transfer to other relevant stakeholders as well (breeders, food processors, feed suppliers, veterinarians, consumers, etc.).

Short description

The main goal of this use case is to enable a revolution in the management of pig farms via optimal use of data throughout the chain. This use case will work on collecting crucial information automatically and linking data to provide feedback to the farmer via an easy to use interface (data dashboard). In addition, a cooperation will be set up with the horizontal use case related to meat traceability and transparency. By providing management information to the pig farmer focussing on opportunities to improve his management, several goals are combined:

- Sustainable production (e.g. animal welfare and use of feed ingredients)
- Optimisation on supply chain level (instead of optimisation on farm level)
- Creating maximum added value, regarding intrinsic product quality (e.g. reduce boar taint in meat) as well as extrinsic product characteristics (e.g. animal welfare, carbon footprint)

Partners involved in the use case are ILVO (Belgium), Porphyrio NV (Belgium), VION (the Netherlands), ZLTO (the Netherlands) and ISMB (Italy). The use case will be deployed on five fattening pig farms, covering both conventional and organic farms.

Use case specific challenges

In the use case the automated gathering of production data and problem detection during growing-finishing phase will be deployed and improved, using direct feedback of the farmers. This will be done using group level data (based on Porphyrio NV Business Intelligence Dashboard), but also using individual level data (based on the PigWise project (Maselyne, 2016; Scalera, 2013a, b)). There is a large variation in productivity between farms and the last decades the main improvements were made at the level of the breeding (sow productivity), whereas fattening pig productivity has stagnated recently (van der Peet-Schwering et al., 2009). One of the reasons could be that information is most often only collected post-hoc (at the slaughterhouse) and only on batch level (Maselyne, 2016). Data streams are also not sufficiently linked for the farmer to be able to take the correct actions. The economic impact of health problems can therefore accumulate quickly, for example the cost of clinical ileitis is €8.7 per present pig and the cost of clinical circovirus is €6.6 per present pig (Boehringer

Ingelheim, 2010; Holyoake et al., 2010). If this can be reduced by 10%, this is already a gain of €1.5 per present pig, or €369 million in the EU.
By linking data across the supply chain, the challenges of optimization of pig production on supply chain level and boar taint reduction (Aluwé, 2012; Van der Peet-Schwering, 2013) are also being targeted. At the moment 3-4% of the boar carcasses (25-30% of the slaughtered pigs) are devalued by about €25. With over 246 million slaughtered pigs at EU level, this corresponds to a loss of about €54 million yearly. A reduction of boar taint by 20% by preventive measures on the farm and in the genetics could thus lead to a reduction of losses of €10.8 million and improve general market acceptation of boar production. Finally, through a consumer survey, there will be investigated how consumers differentiate and evaluate their meat, and especially how they look towards the use of technology in pig farming.

Use case specific outcomes

Recent technological developments have led to large possibilities that are not fully exploited on the pig farms at the moment. This use case aims to change that. The first step is to collect and link data of individual animals or animal groups on the farm (a.o. via sensors) and at other places in the value chain (slaughterhouse, breeders). Then, this data is processed to get:

- Management info for the farmer for the purpose of better and more market-aimed production, via a Business intelligence dashboard including:
    - Boar taint prevalence & related analysis (linked to genetics, feed type, etc.)
    - Slaughterhouse performance & related analysis (linked to genetics, feed type, etc.)
    - Sensor data analytics & early warning systems (feed, water, growth, etc.)
- (New) knowledge on relations between:
    - Animal data (genetics, feed, growth, age, weight, etc.)
    - Farm management (a.o. housing, hygiene, health level)
    - Meat quality (a.o. boar taint)
    - Added value for the customer/consumer

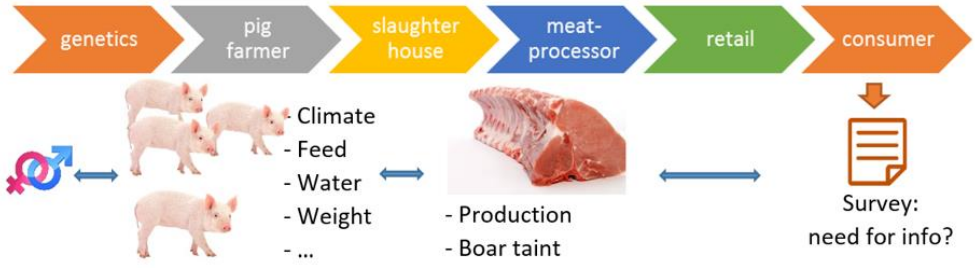


Figure 1: Diagram of the use case Pig farm management

Use case 2: Poultry chain management

The end goal of the use case Poultry chain management is to have efficient growth of poultry, with respect to animal welfare, to a desired and accurate end weight required by the processing plant. This will be enabled via sensor networks and improved sensor technologies so that online information of critical parameters in the poultry growing process, during logistics and at the slaughtering plant can be collected.

Short description

This use case will work on improvement of the poultry production, logistics and processing processes, necessary to arm the European poultry meat sector on the competitive world market. Technology will play an important role to achieve this. This use case pretends to improve the performance of the poultry production chain processes through IoT driven technologies, focusing mainly on controlling the growing process of the poultry, reducing birds' mortality, and improving their physical condition as well as welfare. Partners in the use case are IK4-Tekniker (Spain), Porphyrio NV (Belgium), SADA p.a SA (Spain) and Exafan (Spain). The use case will be deployed on four broiler farms in Spain.

Use case specific challenges

Three critical points define the efficiency and product quality of the poultry meat, starting from the broiler farm to the processing plant. In each step, IoT technology brings value, and moreover, linkage between these steps adds the second level of value:

- Farm level: Monitor and combine different aspects in the farm such as environmental conditions (such as temperature, humidity, etc.) and/or birds intake behaviours (feed and water consumption) for an efficient growth of

poultry, regarding welfare, for the final aim of getting a uniformed end weight of birds, crucial for the processing in the slaughterhouse.

- Logistics: Monitor and optimize broiler handling and transport environmental conditions to reduce negative impacts (such as broken wings or hematomas due to sudden bird load to transport cells) on the poultry and increase comfort levels.
- Processing plant: Optimize slaughtering and improve rendability and product-market fit, with traceability from all stages.

In numbers, the impact on the European market is potentially very large. When birds for roast are below a threshold of weight, these are dismissed. In Europe the production of broilers for roast is around 1560 million, thus improving the uniformity of the flock by 10% (which is a key performance indicator of the use case) will allow to reduce the number of dismissed birds with 78 million (125.97 million €). Broiler deaths during the production phase and transport is currently on average 6% and 0.2% (personal communication, SADA p.a SA). With the system of the pilot, including better monitoring of the ambient parameters and early warning systems, there is expected to lower the birds mortality by a 15% in transport and 10% in farms, leading to a reduction of 33.85 million at EU level, with a total save of 160.797 million €. Also the impact of improving the bird's physical condition and the indirect economic impact quickly lead to high gains, so the total revenue for the European market would be near 400 million € with a reduction of 137.85 million birds dismissed.

Use case specific outcomes

Collect and link interoperable and traceable IoT devices data in critical meat chain points through smart data analytics, within a big data platform, to give valuable business analytics back to the farmer and other partners in the chain through:

- Poultry Growing Early Warning system aimed to support an optimal birds breeding process
- Bird Manipulation Monitoring system aimed to assess the manipulation process and its impact in animal physical condition and welfare
- Environmental Monitoring system to measure the impact of the transport in animal physical and welfare conditions
- Meat Quality Assessment and Production Management chain-assistants, based on the whole data gathered through IoT devices in the main critical chain points

New knowledge will be also generated in terms of:

- Animal breeding related data
- Farm management (a.o. housing, hygiene, health level)
- Meat quality (a.o. hematomas, broken wings)
- Added value for the customer/consumer

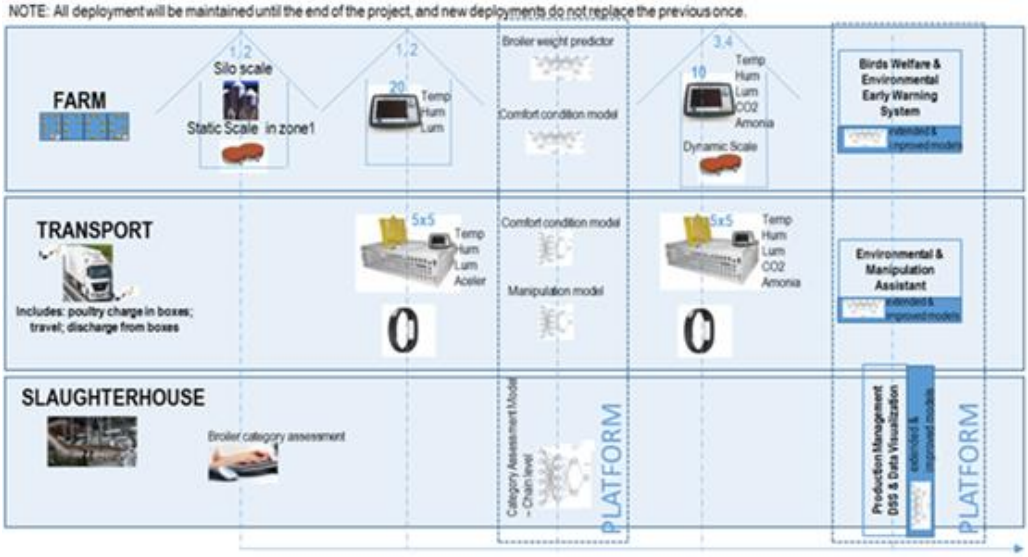


Figure 2: Diagram of the technical solution of the use case Poultry chain management.

Use case 3: Meat transparency and traceability

This use case aims to improve transparency and traceability in the pig supply chain, by developing an ICT solution for collect and share meat-related quality data and traceability data. The use case builds on top of the EPCIS standard, and will further develop the IoT and meat quality dimensions. By employing a widely adopted standard as EPCIS, meat transparency and traceability solutions can be further integrated with existing systems down in the supply chain, including logistics, retailers and eventually consumers.

<u>Short description</u>

The use case will implement a EPCIS infrastructure for capturing and storing all relevant event data in pork supply chains. These will include information on quality aspects of the supply chain partners or their business processes and give access to those data down the pork supply chain. This enables sharing

information and optimising business process, while the consumer at the end of the supply chain is informed on all pork related aspects that they consider as important for their health and ethical well-being. Objects passing the pork supply chain undergo all kind of events of which the *what*, *when*, *where* and *why* are captured and stored conform the EPCIS standard, which will be further extended to incorporate sensor information from pig farms. Partners in the use case are Wageningen University (the Netherlands), GS1 Germany GmbH (Germany) and the European EPC Competence Center (Germany). Relevant data collected on the farm or at the slaughterhouse by the use case 1 will be transformed to EPCIS events and stored in an EPCIS repository.

Use case specific challenges

This use case will demonstrate IoT-enabled transparency and traceability in meat supply chains, where farmers to communicate their practices to retailers and consumers. This could include sharing information about animal friendliness, sensory information collected at the farm level, or the use of certain medication. While improved transparency can contribute to higher margins, it may also allow the detection of problems across the chain, potentially leading to higher product quality and reduced overall waste.

Use case specific outcomes

The use case infrastructure consists of several parts, see Figure 3. First one or more EPCIS repositories will be realized. On top of the EPCIS repositories, several apps, developed in FIspace's MIP trial, add functionality to the infrastructure. A *connector* will be developed to transform farm events into EPCIS. The other events will be captured directly from a farm management system, or ERP. Key aspects of the architecture for the infrastructure are (1) the use of the global standard for event information exchange, i.e. EPCIS (EPC Information Services), (2) the use of global identification standards such as GTIN, SGTIN and GLN and (3) the use of the Core Business Vocabulary.

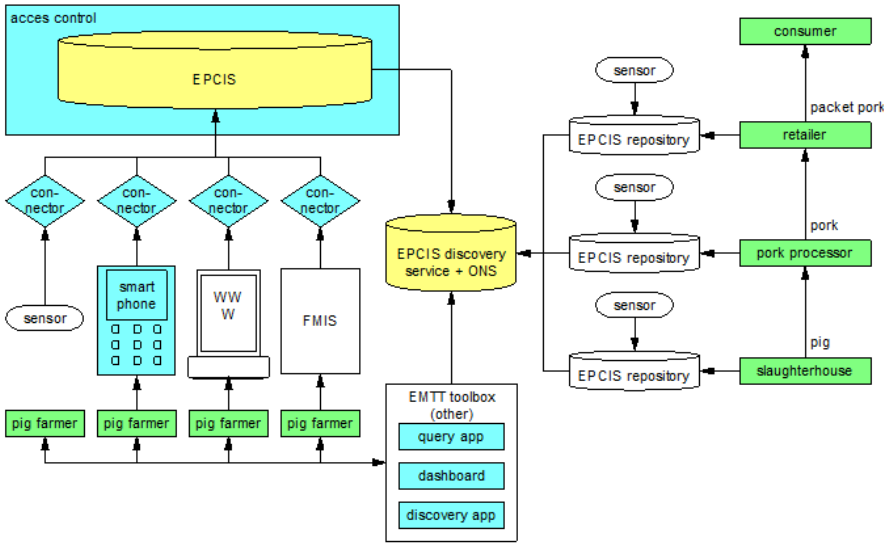


Figure 3: Diagram of the technical solution of the use case Meat transparency and traceability

Conclusions

The project IoF2020 consists of three use cases focussing on meat production: pig and poultry management and meat transparency and traceability. These use cases support our vision of *The Internet of Meat in 2020*, or how IoT technologies can contribute to the meat sector. Technology providers, end-users and research institutes are involved in each use case, aiming at practical implementations to ensure the best uptake of IoT in farming. In the meat trial the main focus will be on using sensor data, in the meantime enhancing the impact of sensor data and combining data of several sensors on the farm, during transport and at the slaughterhouse to give valuable business analytics back to the farmer and other partners in the chain. Besides that, standardization work will enhance the meat transparency and traceability in the meat chain using the EPCIS standard. Work will focus on installation of components during the first year of the project, after which a lean multi-actor approach will lead to further improvements of the systems.

Acknowledgements

IoF2020 has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement no. 731884.

References

Aluwé, M. 2012. *Influence of feed and management strategies on boar taint prevalence*. PhD dissertation, Ghent University.

Boehringer Ingelheim Vetmedica b.v. 2010. *Zakboek varkens*. (Notebook pigs.) http://www.depre.be/archief/17_nl_1297073347.pdf

Holyoake, P.K., Collins, A., and Mullan, B. 2010. *Simulation of the Economic Impact of Lawsonia intracellularis Infection.* IPVS congress, p. 233.

Marquer, T.P. R., Forti, R. 2015. Meat production statistics. *Eurostat*.

Maselyne, J. 2016. *Automated monitoring of feeding and drinking patterns in growing-finishing pigs: towards a warning system for performance, health and welfare problems in individual pigs*. PhD dissertation, KU Leuven.

Scalera, A., Brizzi, P., Tomasi, R., Gregersen, T., Mertens, K., Maselyne, J., Van Nuffel, A., Hessel, E., Van den Weghe, H. 2013a. The PigWise project: a novel approach in livestock farming through synergistic performances monitoring at individual level. In: *Conference on Sustainable Agriculture through ICT innovation - EFITA 2013*, Turin, Italy.

Scalera, A., Conzon, D., Brizzi, P., Tomasi, R., Spirito, M.A., Mertens, K. 2013b. From animal monitoring to early warning systems through the Internet of Things. In: *European Conference on Precision Livestock Farming - EC-PLF 2013*, Leuven, Belgium.

van der Peet-Schwering, C.M.C., Hoofs, A.I.J., van der Wielen, J.H.A., and Binnendijk, G.P. 2009. *Op weg naar 1.000 gram groei. Inventarisatie op een aantal vleesvarkensbedrijven*. (Towards a 1000 g growth. Inventarisation on a number of fattening pig farms). 272

Van der Peet-Schwering, C. M. C., Binnendijk, G.P., Vermeer H.M., Vereijken, P.F.G., Classens, P.J.A.M., Verheijen, R.G.J.A. 2013. *Op weg naar succesvol beren houden* (Towards succesfully keepting entire males). Wageningen UR, Livestock Research.

Session 20

PLF questioned

The effects of PLF on human-animal relationships on farms

F. Kling-Eveillard[1], N. Hostiou[2], E. Ganis[1], A. Philibert[1]
[1] *Institut de l'Elevage, 149 rue de Bercy, 75595 Paris cx 12, France*
[2] *INRA, UMR 1273 Territoires, 63122 Saint-Genès Champanelle, France*
florence.kling@idele.fr

Abstract

Precision livestock farming induces not only technical and economic changes, but also modifies farmers' work. It affects the nature and frequency of their daily tasks, specifically in relation to animals, and the data available about the animals. Consequently, it may affect the quality of the human-animal relationship and how farmers perceive their profession.
To better understand these effects, a survey was carried out on 25 French farms raising three different species and equipped with different tools: milking robots and heat detectors for dairy cows, automatic feeders for sows, and electronic controllers and automatic weighing devices for poultry. Semi-structured interviews were conducted with the farmers.
The main results showed that there were diverse motivations behind the farmers' decision to install new equipment: some sought better working conditions, others to improve their technical management, yet others were induced by value chain incentives. Most mentioned that their job had become more technical, and the majority were satisfied. Farmers' interactions with their animals had changed and sometimes decreased, with less time spent in their presence or in direct contact. Digital data enabled a different view of animals, focusing on problematic individuals. Some farmers continued to observe their animals and used specific practices to facilitate work and reduce animal stress, while others delegated decisions and tasks entirely to their equipment. Nevertheless, some farmers noted limits regarding the place of new technologies on a farm, such as the risk of losing their own autonomy or their ability to observe animals and detect problems.

Keywords: human-animal relationship, precision livestock farming, work, sensor, robot, livestock farmer profession

Introduction

The human-animal relationship is a major issue in livestock farming, both for the farmer and the animal, and reflects how farmers consider the place of animals within their work (Dockès & Kling, 2006). Defined as the degree of closeness or

distance between an animal and a person (Waiblinger et al, 2006), the human-animal relationship develops over the course of daily interactions on the farm. Consequently, it is directly impacted by any change in livestock farming conditions, particularly the arrival of sensors, automated machines and new technology, referred to as precision livestock farming (Hostiou et al, 2017).
With precision livestock farming, automated machines take over certain tasks that were previously carried out by farmers, directly influencing the human-animal relationship (Schewe & Stuart, 2015). Moreover, the production of new, instant and readily accessible data on biological parameters and animal behaviour can influence how farmers perceive their animals and modify their direct observations of their animals (Hostiou et al, 2017). Lastly, the development of tasks linked on the one hand to computers and new technology and, on the other, to equipment and automated machines, can impact how farmers experience and imagine their professions, and their job satisfaction or dissatisfaction (Cornou, 2009). However, the new technology does not necessarily create a greater distance between humans and animals; it can enable new relationships to develop (Lagneaux and Servais, 2014). Farmer profiles were defined by Dockès and Kling (2007) based on their closeness with their animals. Furthermore, several authors (Butler et al, 2012; Schewe and Stuart, 2015; Désire and Hostiou, 2015) have shown a diversity between farmers with regard to the consequences of precision livestock farming on work organisation. This article suggests that diversity also exists between farmers with regard to the consequences of precision livestock farming in terms of how farmers perceive their profession, their animals and the human-animal relationship.

Materials and methods

Survey method

We were interested in farmers' social representations, defined by Jodelet (1989) as "a form of socially formulated and shared knowledge intended for a practical purpose". The study of farmers' representations drew on in-depth, face-to-face, semi-structured interviews. The following topics were addressed: the profession of a livestock farmer (farmer's motivations, place of animals, definition of a "good farmer"); the introduction of precision livestock farming tools (reasons the farmer acquired the equipment, how the transition is carried out); the management of precision livestock farming (use of data, observation tasks, changes in practices related to animals); the human-animal relationship (definition of a good human-animal relationship, challenges and factors behind a good human-animal relationship in livestock farming, relational practices implemented); precision livestock farming and the evolution of the profession (farmer's representations of changes).

Following the qualitative interview, a closed questionnaire was given to the farmers in which they could note the extent to which they agreed (6 levels possible, from “strongly disagree” to “strongly agree”) with statements relating to their representations of animals, their profession, precision livestock farming, and what they appreciate about their work. They also were asked to describe their current and past (prior to the introduction of precision livestock farming) relationships with their animals using a non-graduated scale from “very poor relationship” to “very good relationship”.

Choice of species and equipment to study

The aim of the sample was to encompass diverse changes in the relationship between farmers and their animals resulting from the use of precision livestock farming tools. For this, three species were studied (Prim’Holstein dairy cows (DC), gestating sows (GS), and broiler chickens (BC)), all in conventional livestock farming systems.

We used the following criteria to choose the precision farming tools to study: i) tools widely used on farms, and ii) tools differing in terms of the impact they have on animals’ living conditions and farmers’ working conditions. We selected equipment that was either composed exclusively of sensors or was associated with automated machines (Table 1). Heat detectors for dairy cows (DC) thus function only as sensors. Other equipment combines one or more sensors with one or more automated machines: milking robots (DC), individual sow feeding (ESF or Selfi-feeder) for gestating sows (GS), barn electronic controllers and automatic weighing devices for broiler chickens (BC). The introduction of a milking robot (DC) and automated feeding (GS) led to, or wound up associated with, a new way of managing animals. For dairy cows, this involved a transition from two milkings per day in a milking parlour to cows having direct access to a robot to be milked whenever the cows wish. For gestating sows, group housing replaced individual pens. For broiler chickens, electronic controllers have existed for some time. The new feature is being able to control barn atmosphere parameters from a distance (remote control using, for example, a smartphone) without having to go to the building (to open ventilation hatches, for example).

Table 1: Characteristics of the equipment studied

Species	Gestating sows GS	Dairy cows DC		Broiler chickens BC	
Equipment	Individual feeding (ESF, Selfi-feeder)	Milking robot	Heat detectors	Barn electronic controllers	Automatic weighing device
Main functions of the equipment	Sensor: provides data on consumption Automaton: feed distribution	Sensor: provides data on the quantity and quality of milk produced, frequency of milking, etc. Automatic system: milking	Sensor: provides data on the animals' activity: suspicion of heat	Sensor: provides data on atmosphere parameters of the barn and on animals' water and feed consumption Automatic system: regulates building equipment (ventilation hatches, etc.)	Sensor: provides data on daily growth of chickens Automatic system: automatically weighs a sample of chickens
Changes in terms of farmer-animal interactions	The farmer's presence is no longer associated with meals The farmer moves among the animals for interventions (vaccinations, ultrasounds, etc.)	The farmer no long sees his/her animals and no longer touches them twice a day The farmer may need to move among the herd up to the robot, push certain animals, put down straw, observe, etc.	The farmer can decide to either no longer observe his or her cows, and directly call the inseminator as soon as the sensor sends an alert, or to visually verify before making the call	The farmer no longer moves among his or her animals to operate heating equipment The farmer moves among his or her animals to remove dead birds, and to make occasional repairs.	The farmer can decide either to transmit the data to the producer organisation (and in this case, no longer touches the animals) or to verify by manually weighing a few animals.

Sample and identification of farms to survey

The surveys were conducted in Brittany, the leading livestock farming region in France in terms of number of farms. The sample was composed of 25 farms broken down by the three species and equipment presented above.

The size of the livestock unit was a criterion used to select farms because precision livestock farming accompanies increased herd sizes, which can lead to farmers becoming more detached from their animals. Surveys were therefore conducted for each species in two farm size classes, one above the French average and the other below, without including extremes in either class.

The farmers' contact information was provided by field experts. For dairy cows, the person conducting the survey contacted farmers on a list of 200 livestock farmers identified by their heat detection or milking robot equipment. For

gestating sows, only a few names were provided and the farmers surveyed themselves provided the names of other farmers. For broiler chickens, an expert provided some twenty names. Few farmers refused to participate in the survey.

Analysis method

The interviews with the farmers were recorded. First, a monograph was prepared for each interview summarising the main topics addressed in the survey. The contents of the interviews and the closed questionnaires were then broken down in a grid which served as a support for analysis of the thematic content. The principal findings are shown below.

This analysis then enabled the construction of a concise grid containing the most discriminating variables. Lastly, a statistical analysis combining a multiple correspondence analysis (MCA) and an ascending hierarchical classification (ACH) was carried out. The active variables selected concerned the representations of the profession, the animal and the human-animal relationship. Three profiles were therefore identified. The explanatory variables concerning representations and practices involved in precision livestock farming were then compared with the three profiles selected.

Results

The characteristics of the livestock farms and farmers in the sample

Table 2 presents a breakdown of the farms surveyed according to the diversity criteria selected.

Table2: Breakdown of surveys carried out by species and equipment type

Gestating sows GS				Dairy cows DC					Broiler chickens BC		
< 245		> 300		> 85		> 105			< 25000		> 40000
ESF	Selfi-feeder	ESF	Selfi-feeder	Milking robot	Heat detector	Milking robot	Heat detector	Milking robot + heat detector	Elec. controller.	Autom. weighing + elec. controller	Autom. weighing + elec. controller.
3	2	2	1	2	2	4	1	1	2	1	4
8 farms				10 farms					7 farms		

The farms in the sample were slightly larger than the average French or Breton farm, and the farmers were slightly younger than the average French or Breton farmer. Of the 25 people surveyed, 7 were women and 18 men.

Representations of the profession, the animal and the human-animal relationship

The satisfaction farmers say they find in their work and their definition of what makes a good farmer reflect how they view the place of the animal.

What the farmers appreciate in livestock farming activities can be grouped around three features. Some emphasise the animal, the contact, and the work

with animals. Others mention instead technical features, whether these be technical aspects of animal management, animal genetics, technical monitoring of production or technology at the service of farmers. Lastly, some note the characteristics of their profession, such as being independent, being their own boss, having a real profession, and pleasant working conditions. Diversity with regard to the place of the animal is also found in the farmers' definition of what makes a good farmer. Some farmers define a good farmer as one who takes good care of his or her animals. However, this can mean two different things depending on the individual: taking good care can mean being attentive to the animals' needs so that they are well, or it can mean ensuring that the animals are productive. Other notions are mentioned: a good farmer has strong technical skills, achieves good technical or economic results, or combines animal, technical and economic expertise.

With regard to the representation of the profession, some of the farmers interviewed demonstrated satisfaction with -- or were even passionate about -- their work, while others dwelled on the difficulties involved, and reflected a loss of motivation.

The farmers were questioned about what they thought the human-animal relationship encompassed. It was difficult for most of them to answer this question for two main reasons. One is that they were unfamiliar with the term, the other is that the subject involved a very personal dimension that is not usually discussed in livestock farming. Four farmers thus considered that they did not have a relationship with their animals on the farm (3 BC and 1 GS). It was easier for the farmers to speak about their view of a good human-animal relationship. Most frequently, they mentioned the animal's welfare, and some spoke of the animal's absence of fear in relation to people, or even a mutual sense of trust between the farmer and the animals. For some farmers, good production levels reflected a satisfying human-animal relationship. For the majority, a good human-animal relationship renders it possible to work more easily with the animals, regardless of the species. At the same time, they also mention farmers' well-being, and good livestock farming conditions with equipment.

Three profiles emerge from the statistical analysis of variables involving the representation of the profession, the animal and the human-animal relationship.

Profile A is characterised by a negative image of the profession, experienced as not very rewarding. Farmers with this profile consider that one cannot talk about the human-animal relationship on their farm, and do not enjoy either touching or talking to their animals. These five farmers are all men, working with all three species (2 GS, 2 DC, 1 BC).

Profile B is characterised by a rather positive image of the profession, which the farmers consider rewarding. Independence, a diversity of tasks and technical

features are the characteristics which they find most satisfying. They associate a good human-animal relationship with animal welfare. Thirteen farmers correspond to this profile, 10 men and 3 women, split between the 3 species (3 GS, 4 DC, 6 BC), notably including nearly all of the broiler chicken farmers in the sample (6 out of 7).

Profile C is characterised by the central place occupied by animals. The animals are the main source of job satisfaction for these farmers. They associate a good human-animal relationship with the animals' absence of fear, revealing through this response their feelings for the animal itself. They enjoy touching and observing the animals and say that animals have a memory more often than farmers from the other two profiles. Among these 7 farmers, there are 3 men and 4 women, covering gestating sow and dairy cow farmers (3 GS, 4 DC).

Satisfaction and new practices under precision livestock farming

For many farmers, setting up precision farming tools on their farms was an expression of their desire to work differently: to improve working conditions with robots (work comfort, reduced drudgery, free themselves from the constraint of milking, etc.) or to improve their techniques and performance by using sensors (better identify cows in heat, better adapt feed rations to animals' needs, etc.). In addition to these motives, some farmers were encouraged to invest in new technologies by economic and regulatory incentives. We mentioned in the preceding section a shift to group housing for sows, which is both a consequence of automated feed distribution and required by European regulations. On broiler chicken farms, farmers receive a bonus if they provide an accurate estimation of the weight of the birds in a batch. This has encouraged the installation of automatic weighing devices, as they can provide data on a greater number of chickens than if the birds are weighed manually.

Nearly all of the farmers surveyed (save for one) expressed satisfaction about working with the new technology. They highlight that work is easier and the equipment allows them more control over animal management, particularly with the provision of data. They furthermore consider that precision livestock farming will prove to be indispensable for farms in the future. Mastering new technologies appears to be a new job skill in a profession which has become more technical. The modern image of the profession greatly pleased many of the farmers surveyed, who felt less left behind in relation to other professions. A few farmers (4 sow or dairy with milking robot) describe a profession which is in closer contact with animals and state that they feel "more like a farmer" in livestock farming conditions where they themselves and their animals are less restricted in their activities. According to the farmers interviewed, the improved working conditions and connectivity of the farming profession renders it more attractive to younger generations. A few, however, expressed some reservations

about the tools, which cannot do everything, and noted the importance of also trusting a farmer's eye and gut feelings.

The farmers describe a profession which has not fundamentally changed but which involves new tasks and new daily schedules. They spend more time in front of the computer. They also think that they spend either more time or less time with their animals compared to before the installation of the equipment. For many, "observing" animals includes both direct observations, for example by moving among a herd of cows in a shed, and looking at digital data about the animals on their computer. Furthermore, when questioned about what they thought of as a "good animal", some spoke of the "invisible animal" which does not trigger alerts because it poses no problems.

The morning routine illustrates the diversity of practices between farmers. Only 5 farmers (4 of whom were women) say they start their day by first looking at the animals, while all of the others begin by looking at the computer and the daily alerts before going to see the animals. A range of practices was also identified with regard to delegating a task or a decision to a tool. Some farmers verify the data provided by a sensor. For example, broiler chicken farmers weigh several chickens manually in addition to the automatic weighing device, and dairy cow farmers visually verify that the cow designated by a detector as being in heat is showing the associated signs before calling the inseminator. The others delegate all responsibility to the equipment. In certain situations, farmers equipped with milking robots continue to carry out certain tasks manually, for example leading a heifer to the robot and attaching the teats in order to accustom the animal to the machine.

The equipment can induce new kinds of contact with the animals when first set up or when new animals arrive. On dairy cow and gestating sow farms, the arrival of new animals appears to be a key period when opportunities exist for the farmer to establish contact with his or her animals and implement habituation strategies (apple juice to tame gilts in quarantine, for example).

Farmer profiles in relation to the profession and the animal also differ with regard to precision livestock farming. Profile A and B farmers distinguish themselves from profile C farmers in their responses concerning precision livestock farming. They most often claim to appreciate working in a modern profession, and consult their computers first thing in the morning before going to see their animals. By contrast, profile C farmers feel that they know their animals better since installing the equipment (milking robots for cows and automated feeders for sows housed in groups). They also say that the human-animal relationship is better. They implement strategies to familiarise the animals with humans and the equipment in order to facilitate their work.

Discussion

The study showed that the farmers entertain a fairly positive image of precision livestock farming. Some of the farmers surveyed mentioned a deterioration in the human-animal relationship, as cited in certain studies (Boivin et al, 2012; Cornou, 2009). However, most are much more positive and say that precision livestock farming, sometimes associated with new farming conditions, has not worsened the relationship but has in fact helped to improve it.

The study enabled diverse profiles to be identified which appear to be fairly generic due to their similarity with those identified in a previous study (Dockès & Kling, 2006) on closeness with animals. Precision livestock farming responds to two areas of interest to farmers: animals and technology.

The study covered a small number of farmers and the findings would benefit from being validated on a larger sample. It would be particularly interesting to survey farmers who had encountered difficulties, for example, farmers who installed a milking robot and did not keep it.

Also of interest would be complementary studies on several parameters that could influence changes in farmers' work in relation to animals and equipment such as sensors and robots, such as gender (in our sample, women are proportionally more numerous in profile C, focused on the animals), farm size, or farm workforce composition (the human-animal relationship is the result of interactions between animals and several people). These parameters can have an influence on both the work and the relationship with animals, and on interest in new technologies.

A comprehensive approach to the human-animal relationship would be multidisciplinary and would combine zootechnical (animal welfare and performance), ethological, ergonomic and sociological approaches (Boivin et al, 2012). Such an approach was not possible within this study but is planned for a new project.

Conclusion and perspectives

Our findings showed broad satisfaction with precision livestock farming among the farmers surveyed. The farmers considered that their work had become easier with sensors and automated machines, and that they had greater control. The majority did not see a deterioration in the human-animal relationship. Instead, they describe a situation in which there are fewer constraints on both themselves and the animals.

The farmers have room to manoeuvre in how they use the equipment; this can be seen particularly in the degree to which tasks are delegated to the equipment, which can be partial or total. Farmers motivated by animals believe that

precision livestock farming has benefits related to the animals, while those who are not much motivated by their profession or animals find technical benefits which are detached from the animals.

New livestock farming conditions such as open buildings instead of individual stalls are providing opportunities to work with animals differently and better. Some farmers implement practices to familiarise animals with people in order to facilitate later human interventions when accustoming the animals to the equipment and over their entire life cycles.

The effect of the development of precision livestock farming on the general public's image of livestock farming was not addressed in this research but also merits detailed examination as society's image of livestock farming is a decisive factor in the evolution of livestock farms.

Acknowledgements

This study was co-funded by GIS Elevage Demain, RMT (a mixed technology network), Travail en élevage and RMT Bien-être animal, supported by MAAF (French Agriculture Ministry).

References

Boivin, X., Bensoussan, S., L'Hotellier, N., Bignon, L., Brives, H., Brulé, A., Godet, J., Grannec, M.-L., Hausberger, M., Kling-Eveillard, F., Tallet, C., and Courboulay, V., 2012. Hommes et animaux d'élevage au travail : vers une approche pluridisciplinaire des pratiques relationnelles. In : *Numéro spécial, Travail en élevage*. Hostiou N., Dedieu B., Baumont R. (Eds). INRA Prod. Anim., **25**, 159-168.

Butler D., Holloway L. and Bear C., 2012.The impact of technological change in dairy farming: robotic milking systems and the changing role of the stockperson. R. Agric. Soc. Engl. **173**, 1–6.

Cornou C., 2009. Automation Systems for Farm Animals: Potential Impacts on the Human-Animal Relationship and on Animal Welfare. *Anthrozoös*, **22**, 213-220

Désire, C. and Hostiou, N., 2015. L'Elevage de Précision : quels changements dans l'organisation du travail et la gestion de données en élevage ? In Idele, eds., *4èmes Rencontres Travail*, Dijon, France, 62-63.

Dockès, A.C., and Kling, F. 2006. Farmers' and advisers' representations of animals and animal welfare. *Livestock Science* **103,** 243-249.

Hostiou, N., Fagon, J., Chauvat, S., Turlot, A., Kling-Eveillard, F., Boivin, X. and Allain, C., 2017. Impact of precision livestock farming on work and human-animal interactions on dairy farms. A review. BASE **21**. http://popups.ulg.ac.be/1780-4507/index.php?id=13706

Jodelet, D., 1989. Les représentations sociales. PUF

Lagneaux, S. and Servais, O. 2014. De la traite robotisée au raid d'avatars. Incorporation et virtualisation. Parcours anthropologiques **9**, 73-101.

Schewe, R. L., and Stuart, D. 2015. Diversity in agricultural technology adoption: How are automatic milking systems used and to what end? *Agric Human Values*, **32**, 199-213.

Waiblinger, S, Boivin, X., Pedersen, V., Tosi, M-V., Janczak A.M., Kathalijne Visser, E., and Jones, B. 2006. Assessing the Human–animal Relationship in Farmed Species: A Critical Review. *Applied Animal Behaviour Science* **101** (3–4) 185–242.

Precision livestock farming: could it drive the livestock sector in the wrong direction?

P. Stevenson
Compassion in World Farming, River Court, Mill Lane, Godalming, Surrey, GU& 1EZ, United Kingdom
Peter.Stevenson@ciwf.org

Abstract

Precision Livestock Farming (PLF) is more likely to be used in large-scale intensive systems in which there is limited potential for delivering satisfactory welfare outcomes. Indeed, PLF may entrench the use of such systems by making them easier to manage. PLF can help prevent poor welfare by identifying early onset of disease and stressful situations, but it may be unable to respond to changing concepts of animal welfare. Mellor (2016) argues it is necessary not only to minimise negative experiences but also "to provide animals with opportunities to have positive experiences" that can arise when animals are kept in "spacious, stimulus-rich environments". Will PLF be able to contribute to such systems?

If PLF is mainly used in the intensive sector, it will be facilitating systems that tend to overproduce and undermine the environment. A Netherlands Presidency paper (2016) states that difficulties in the EU pig and dairy sectors stem from over-production. Intensive livestock production is dependent on feeding cereals to animals which convert them inefficiently into meat. Intensive production's demand for cereals has fuelled intensive crop production which has led to soil degradation, water pollution and biodiversity loss. The FAO (2013) warns that further use of cereals as feed could undermine food security. PLF must shift towards supporting systems that provide positive experiences for animals and primarily use animals to convert inedible materials – grass, by-products, food waste – into food we can eat.

Keywords: precision livestock farming, animal welfare, intensive livestock production, cereals

Introduction

Precision Livestock Farming (PLF) can have a beneficial impact on the health and welfare of animals, for example in enabling early detection of disease or problems such as poor gait score in broilers or malfunctioning of automated

equipment for instance feeder and drinker lines. Such early warning systems allow the timely implementation of mitigation strategies (e.g. Berckmans D, 2014; Ben Sassi et al, 2016).

The literature indicates that PLF technologies are mainly used in intensive livestock systems, particularly in intensive pig, poultry and dairy production (e.g. Berckmans D, 2014; Ben Sassi et al, 2016; Tullo et al, 2016). There is a danger that, in facilitating the management of intensive systems, PLF could entrench the use of systems that have low potential for delivering good welfare outcomes.

Could PLF entrench intensive livestock systems with low potential for good welfare?

Intensive livestock production can be broadly defined as the use of systems in which animals are: (i) confined in cages or narrow stalls or are kept at high stocking densities; (ii) subject to genetic selection for fast growth rates or high yields; and/or (iii) subject to mutilations such as tail docking or beak trimming in order to adapt them to systems that fail to respond to their needs. In intensive systems the performance of normal behaviour is impeded to such an extent that welfare is compromised.

The concept of 'welfare potential' is important in this context. Extensive indoor systems and outdoor systems have the potential, if well-designed and well-managed, to deliver good welfare outcomes. In contrast, even where stockmanship is good, intensive systems have little potential to provide satisfactory welfare; welfare problems are inherent in these systems. For example, the UK Farm Animal Welfare Council (2010), an independent body appointed to advise the government, has suggested that it may not be possible to maintain today's egg output of around 300 eggs in the laying cycle while attaining bone strength sufficient to reduce hens' current high vulnerability to bone fractures.

Research shows the importance for welfare of providing suitable enrichment materials for pigs to allow expression of species relevant behaviours (e.g. Spoolder et al, 2011). However, in intensive pig production growing pigs are often housed on fully slatted floors with no effective enrichment materials. As a result the pigs are unable to perform their natural investigation and manipulation behaviours. The absence of enrichment materials and the resultant inability to perform certain key behaviours is the largest risk for tail biting (EFSA, 2007). PLF may be able to detect the first signs of incipient tail biting but there is a

danger that this could be seen as a substitute for addressing the root causes of tail biting such as housing pigs in barren conditions.

PLF can be used in the dairy sector to detect lameness. This is of course helpful. However, it is possible that this and other applications of PLF will mainly be used in the intensive, high yielding, zero-grazed dairy sector. This sector is highly problematic in health and welfare terms. High yielding cows produce 10,000 litres or more per annum. The European Food Safety Authority (EFSA) has concluded that: "Long term genetic selection for high milk yield is the major factor causing poor welfare, in particular health problems, in dairy cows" (EFSA, 2009). EFSA added: "The genetic component underlying milk yield has also been found to be positively correlated with the incidence of lameness, mastitis, reproductive disorders and metabolic disorders".

High yielding cows tend to be housed indoors all year round even during the grass-growing season. EFSA has stressed that: "If dairy cows are not kept on pasture for parts of the year, i.e. they are permanently on a zero-grazing system, there is an increased risk of lameness, hoof problems, teat tramp, mastitis, metritis, dystocia, ketosis, retained placenta and some bacterial infections" (EFSA, 2009). Other research too has highlighted the health and welfare problems that are associated with zero-grazing (De Vries et al, 2015; Arnott et al, 2017). In a high priority recommendation EFSA stated that "When possible, dairy cows and heifers should be given access to well managed pasture or other suitable outdoor conditions, at least during summer time or dry weather" (EFSA, 2009).

If PLF technologies can support pasture–based dairying, for example by enabling ready detection of lameness in cows kept on pasture, it will indeed contribute to a system that has a high potential for delivering good health and welfare outcomes. If, however, PLF is used to facilitate the management of high yielding, zero-grazing systems it will help embed systems that have very low potential for achieving satisfactory health and welfare outcomes.

PLF can be used to detect high gait scores in broiler facilities (Ben Sassi et al, 2016). While undoubtedly helpful, this tackles the symptoms not the root cause of the high prevalence of leg disorders in broilers. The primary risk factor for broiler leg problems is high growth rate (Knowles et al, 2008). A European Commission report states that EFSA has "pointed out that around 30% of commercial intensively reared broilers presented leg abnormalities. These biomechanical limitations are a likely consequence of the morphological changes such as the rapid growth of breast muscle moving the centre of gravity forwards

and the relatively short legs in relation to the birds' bodyweight. That scientific opinion evidenced how the bones of a fast-growing selected strain are more porous and less mineralised than those of a slower-growing control strain" (European Commission, 2016). EFSA has stressed the need to reduce the proportion of birds with the higher gait scores "even if this objective may require them to reduce growth rate" (EFSA, 2010).

There is a danger that PLF will be used to ameliorate animal welfare within systems that have very limited potential for achieving good welfare and, in so doing, entrench the use of such systems. If that is the case PDF will be failing to respond to Article 13 of the Treaty on the Functioning of the European Union. Article 13 requires the EU and the Member States when formulating and implementing policies on, *inter alia,* agriculture, research and technological development to "pay full regard to the welfare requirements of animals". Legally, the word "full" is of particular importance.

PLF is also poorly equipped to respond to developing concepts of animal welfare. PLF tends to focus on preventing poor welfare rather than on promoting positively good outcomes. However, this minimalist approach is increasingly being queried. There is a growing recognition of the need to take a less narrow view of what constitutes good welfare.

The UK Farm Animal Welfare Council stresses that all farm animals should have 'a life worth living' and a growing number should have 'a good life' (FAWC, 2009). It states that "each farm animal should have a life that is worth living to the animal itself, and not just to its human keeper". It adds that 'a life worth living' requires meeting wants, not just needs.

A recent paper stresses that it is necessary not only to minimise negative experiences but also "to provide the animals with opportunities to have positive experiences" (Mellor, 2016). Such experiences can arise "when animals are kept with congenial others in spacious, stimulus-rich and safe environments which provide opportunities for them to engage in behaviours they find rewarding. These behaviours may include environment-focused exploration and food acquisition activities as well as animal-to-animal interactive activities, all of which can generate various forms of comfort, pleasure, interest, confidence and a sense of control."

Could PLF entrench unsustainable livestock systems?

In primarily supporting intensive production, PLF is furthering systems that are inherently resource-inefficient and that undermine food security and the natural resources on which the future well-being of farming depends. In addition, these intensive livestock systems are dependent on routine preventive use of antibiotics. These aspects will now be examined in detail.

Intensive livestock production is widely assumed to be efficient in part because of its ability to raise a large number of animals in a relatively small space. However, intensive livestock production is inherently inefficient due to its dependence on feeding human-edible crops to animals.

Intensively raised animals are mainly fed on concentrates which are predominantly made up of cereals and vegetable proteins such as soybean meal. For pigs farmed intensively nearly all the feed is concentrates (Mekonnen & Hoekstra 2012). The same is true for intensively produced broiler chickens and laying hens in most regions. In intensive broilers and layers, and in pig production, grains contribute more than 50% of total dry matter (DM) intake, while oil seed cakes range from 9-25% of DM intake (Mottet et al, 2017).

Grain comprises a high proportion of the diet of intensively raised cattle. Data from DairyCo (2013) in the UK shows that high-output cows receive 2629 kg DM/cow/year of non-forage feed while cows at grass receive much less – 1087 kg DM/cow/year. In U.S. beef feedlots the usual practice is to gradually decrease the proportion of forage in the feed over time, eventually reaching rations that can be as high as 90% grain (Shields & Orme-Evans, 2015). In feedlot systems in OECD countries, grains account for 72% of dry matter intake (Mottet et al, 2017).

Substantial quantities of cereals and soy are used as animal feed. European Commission (2017) data show that 55% of EU cereal production is used as animal feed. Globally the figure is 36% (Cassidy et al, 2013). 98% of global soybean meal is used as animal feed (Soyatech, 2017).

Animals convert cereals very inefficiently into meat and milk. Smil (2000) and Lundqvist et al (2008) calculate that on average 1700 calories/capita/day are fed to animals globally but of these only 500 calories/ capita/day are delivered for human consumption as meat and dairy products. This means that for every 100 calories fed to animals in the form of human-edible crops, we receive just 30 calories in the form of meat and dairy products.

A report by the United Nations Environment Programme (2009) suggests that the conversion rate may be even lower. It estimates that a kilo of cereals provides six times as many calories if eaten directly by people than if it is fed to livestock. This indicates that for every 100 calories fed to animals in the form of human-edible crops we receive just 17 calories in the form of meat and dairy products.

Cassidy et al (2013) have calculated calorie and protein conversion rates for different types of animal products when human-edible grain is fed to animals. Their study found that for meat the conversion efficiency is poorer than the 17-30% indicated by earlier studies. It concludes that for every 100 calories of grain fed to animals, we get only about 40 new calories of milk, 22 calories of eggs, 12 of chicken, 10 of pork, or 3 of beef. Similarly for every 100 grams of grain protein fed to animals, we get only about 43 new grams of protein in milk, 35 in eggs, 40 in chicken, 10 in pork, or 5 in beef.

Alexander et al (2017) report that, due to poor conversion rates of crops into meat and milk, livestock production is the largest contributor to losses from the food system of the energy and protein embodied in harvested crops. This study shows that the use of human-edible crops as livestock feed is responsible for greater losses of energy and protein than consumer waste. Mottet et al (2017) show that extensive ruminant grazing systems use less human-edible feed by unit of nutrition produced than industrial monogastric systems or feedlot cattle productions.

The sheer scale of the losses entailed in feeding cereals to animals means that this practice is increasingly being recognised as undermining food security. The United Nations Food and Agriculture Organisation (FAO) (2011) states: “When livestock are raised in intensive systems, they convert carbohydrates and protein that might otherwise be eaten directly by humans and use them to produce a smaller quantity of energy and protein. In these situations, livestock can be said to reduce the food balance”. The FAO (2013) warns that further use of cereals as animal feed could threaten food security by reducing the grain available for human consumption. While PLF can improve the poor conversion rates of intensive livestock production, it is simply making an inherently inefficient system somewhat less inefficient.

Intensive livestock production’s huge demand for cereals has led to the intensification of crop production which, with its monocultures and agro-chemicals, has led to the pollution and overuse of water (Mekonnen & Hoekstra, 2012), soil degradation (Edmonson et al, 2014; Tsiafouli et al, 2015) and

biodiversity loss (World Health Organization and Secretariat of the Convention on Biological Diversity, 2015).

Recent studies argue that the only efficient role of livestock is to convert materials that we cannot consume - such as grass, by-products, crop residues and unavoidable food waste - into edible food (Bajželj et al, 2014; Schader et al, 2015). The latter write that "environmental pressures from livestock production could be reduced by focusing on grassland-based ruminant production and by reducing the amount of primary feedstuffs derived from cropland in both ruminant and monogastric feeding rations".

PLF aims to improve product yields in intensive livestock systems (Berckmans, 2014). However, important parts of the EU's intensive livestock sector are suffering from overproduction which tends to depress prices and so undermine farmers' livelihoods. A Netherlands Presidency paper (2016) states that difficulties in the EU pig and dairy sectors stem from over-production.

A Joint Scientific Opinion by EFSA and the European Medicines Agency (2017) states that "the stress associated with intensive, indoor, large scale production may lead to an increased risk of livestock contracting disease." PLF mainly operates in the intensive sector which tends to depend on routine use of antimicrobials to prevent the diseases that are common in the high density, stressful conditions of intensive production (European Medicines Agency, 2006; O'Neill, 2016). PLF may be able to reduce the use of antimicrobials by identifying individual sick animals at an early stage (Berckmans, 2014) but it is questionable whether it can reduce antimicrobial use to the much lower levels that are the norm in extensive systems (e.g. Danish Ministry of Agriculture, 2014). Data from Denmark show that, although antimicrobial use has been much reduced in Denmark's intensive pig sector, it remains very much higher than in Denmark's organic pig sector.

Conclusion

PLF mainly operates in the intensive sector. By alerting farmers to problems at an early stage it can to a degree improve animal welfare and system efficiency. However, such improvements are made within a system that has inherently low potential for good welfare and is inherently inefficient due to its dependence on feeding human-edible cereals to animals. PLF may primarily be used to enhance the viability of intensive livestock production, to make it more feasible to keep very large herds or flocks in stressful, high density conditions with poor levels of welfare. PLF needs to find a role for itself in supporting an increased uptake of

extensive farming which has much greater potential for delivering food security, environmental sustainability and good animal welfare than the intensive model.

References

Alexander P., Brown C., Arneth A., Finnigan J., Moran D., and Rounsevell M. 2017. Losses, inefficiencies and waste in the global food system. Agricultural Systems 153: 190–200.

Arnott G., Ferris C.P., and O'Connell N.E. 2017. Review: welfare of dairy cows in continuously housed and pasture-based production systems. *Animal* 11(2): 261-273.

Bojana Bajželj B., Richards K.S., Allwood J.M., Smith P., Dennis J.S., Curmi E., and Gilligan C.A. 2014. Importance of food-demand management for climate mitigation. Nature Climate Change 4: 924-929

Ben Sassi N., Averós X., and Estevez I. 2016. Technology and poultry welfare. *Animals* 6,62.

Berckmans D. 2014. Precision livestock farming technologies for welfare management in intensive livestock systems. *Rev. sci. tech. Off. int. Epiz.*, 2014, 33 (1), 189-196.

Cassidy E.S., West P.C., Gerber J.S. and Foley J. A. 2013. Redefining agricultural yields: from tonnes to people nourished per hectare. *Environmental Research Letters* 8: 1-8.

DairyCo. 2013. Managing costs: second Milkbench+ report p11

Danish Ministry of Agriculture. 2014. Fødevareministerens besvarelse af spørgsmål nr. 495 (FLF alm. del) stillet den 28. august 2014 efter ønske fra Per Clausen (EL). http://www.ft.dk/samling/20131/almdel/flf/spm/495/svar/1156714/1401964.pdf Accessed 22 April 2017.

De Vries, M., Bokkers, E. A. M., Van Reenen, C. G., Engel, B., Van Schaik, G., Dijkstra, T. and De Boer, I. J. M. 2015. Housing and management factors associated with indicators of dairy cattle welfare. *Preventive veterinary medicine*. *118*, 80-92.

Edmondson J.L., Davies Z.G., Gaston K.J. and Leake J.R. 2014. Urban cultivation in allotments maintains soil qualities adversely affected by conventional agriculture. *Journal of Applied Ecology* 51: 880–889.

European Commission. 2016. Report on the impact of genetic selection on the welfare of chickens kept for meat production. Brussels, COM(2016) 182 final.

European Commission 30 March 2017 EU market: cereals supply & demand http://ec.europa.eu/agriculture/cereals/balance-sheets/cereals/overview_en.pdf

European Food Safety Authority. 2007. Scientific Opinion and Report of the Panel on Animal Health and Welfare on a request from Commission on the risks associated with tail biting in pigs and possible means to reduce the need for tail docking considering the different housing and husbandry systems. *The EFSA Journal* (2007) 611, 1-98.

European Food Safety Authority. 2009. Scientific Opinion of the Panel on Animal Health and Welfare on a request from European Commission on welfare of dairy cows. *The EFSA Journal* 2009 1143, 1-38.

European Food Safety Authority. 2010. Scientific Opinion on the influence of genetic parameters on the welfare and the resistance to stress of commercial broilers. The EFSA Journal 2010; 8 (7):1666.

European Medicines Agency. 2006. Reflection paper on the use of fluoroquinoles in food-producing animals in the EU.

European Medicines Agency & EFSA. 2017. EMA and EFSA Joint Scientific Opinion on measures to reduce the need to use antimicrobial agents in animal husbandry in the European Union, and the resulting impacts on food safety. *EFSA Journal* 2017; 15(1):4666.

Farm Animal Welfare Council. 2009. Farm animal welfare in Great Britain: past, present and future, London, UK.

Farm Animal Welfare Council. 2010. Opinion on Osteoporosis and Bone Fractures in Laying Hens, London, UK.

Food and Agriculture Organization. 2011. World Livestock 2011: livestock in food security, Rome Italy.

Food and Agriculture Organization. 2013. Tackling climate change through livestock, Rome Italy.

Knowles T. G., Kestin S. C., Haslam S. M., Brown S. N., Green L. E., Butterworth A., Pope S. J., Pfeiffer D. and Nicol C. J.2008. Leg disorders in broiler chickens: prevalence, risk factors and prevention. *Plos One* 3 (2)

Lundqvist J., de Fraiture C. and Molden D. 2008. Saving Water: From Field to Fork – Curbing Losses and Wastage in the Food Chain. Stockholm International Water Institute Policy Brief.

Mekonnen M.M. and Hoekstra A.Y. 2012 A global assessment of the water footprint of farm animal products, supplementary materials Appendix IV. *Ecosytems* Volume 15 (3): 401–415

Mellor D. J. 2016. Updating Animal Welfare Thinking: Moving beyond the "Five Freedoms" towards "A Life Worth Living". *Animals* 2016, 6(3), 21.

Mottet A., de Haan C., Falcuccia A., Tempioa G., Opioa C., and Gerbera P. 2017. Livestock: On our plates or eating at our table? A new analysis of the feed/food debate. In press: Global Food Security.Netherlands Presidency. 2016. Discussion paper: Food of the future – the future of food.

O'Neill. 2016. The Review on Antimicrobial Resistance: Tackling drug-resistant infections globally: final report and recommendations.

Schader S., Muller A., El-Hage Scialabba N., Judith Hecht J., Isensee A., Erb K-H.,

Smith P., Makkar H.P.S., Klocke P., Leiber F., Schwegler P., Stolze M., and Niggli U. 2015. Impacts of feeding less food-competing feedstuffs to livestock on global food system sustainability. J. *R. Soc. Interface* 12: 20150891. Shields S. and Orme-Evans G. 2015. The impacts of climate change mitigation strategies on animal welfare. *Animals* 2015, 5, 361-394.

Smil V. 2000. Feeding the world: a challenge for the twenty-first century. MIT Press

Soyatech. 2017. http://www.soyatech.com/soy_facts.htm accessed 19/04/2017.

Spoolder H., Bracke M., Mueller-Graf C., and Edwards S. 2011. Preparatory work for the future development of animal based measures for assessing the welfare of pigs, Report 2: Preparatory work for the future development of animal based measures for assessing the welfare of weaned, growing and fattening pigs including aspects related to space allowance, floor types, tail biting and need for tail docking. Technical report submitted to the European Food Safety Authority.

Tsiafouli M.A., Thebault E., Sgardelis S.P., De Ruiter P.C., Van Der Putten W.H., Birkhofer K., Hemerik L., De Vries F.T., Bardgett R.D., Brady M.V., Bjornlund L., Jorgensen H.B., Christensen S., D'Hertefeldt T., Hotes S., Gera Hol W.H., Frouz J., Liiri M., Mortimer S.R., Setala H., Tzanopoulos J., Uteseny K., Pizl V., Staray J., Wolters V. and Hedlund K. 2015.Intensive agriculture reduces soil biodiversity across Europe. Global Change Biology 21: 973–985.

Tullo E., Fontana I., Gottardo D., Sloth K.H., and Guarino M. 2016. Technical note: Validation of a commercial system for the continuous and automated monitoring of dairy cow activity. *Journal of Dairy Science.* Volume 99 (9), 7489-7494.

United Nations Environment Programme. 2009. The environmental food crisis – The environment's role in averting future food crises.

World Health Organization and Secretariat of the Convention on Biological Diversity. 2015. Connecting global priorities: biodiversity and human health.

Precision Livestock Farming and animal welfare

I. Veissier[1], H. Blokhuis[2], I. Halachmi[3], S. Klimpel[4], B. Meunier[1], M.-M. Mialon[1], P. Nielsen[5], T. Norton[6], A. Peña Fernández[6], M. Silberberg[1], K. Helle Sloth[7] (alphabetic order except 1st author)
[1]*Université Clermont Auvergne, INRA,VetAgro Sup, UMR herbivores, F-63122 Saint-Genes-Champanelle, France*
[2]*SLU, Box 7068, Uppsala 750 07, Sweden*
[3]*Volcani, Israel*
[4]*GEA Farm Technologies GmbH, Siemensstrasse 25-27, 59199 Bönen, Germany*
[5]*University of Copenhagen, Grønnegårdsvej 8, 1870 Frederiksberg C, Denmark*
[6]*KUL, Kasteelpark Arenberg 30, Leuven B – 3001, Belgium*
[7]*GEA Farm Technologies GmbH, Nørsskovvej 1B, DK-8660 Skanderborg, Denmark*
isabelle.veissier@inra.fr

Abstract

Precision Livestock Farming (**PLF**) is often perceived as an instrumentation of animals in order to make more profitable 'industrial farms'. By contrast, one could argue that animal welfare can be better ensured if they are closely monitored with state of the art technology, enabling rapid feedback by the farmer. We will start from the main dimensions of animal welfare, as defined in the Welfare Quality® approach, to analyse how PLF can help to ensure the health and the comfort of animals, to promote appropriate behaviour, and to avoid distress. Examples will be mainly based from our own experience gained by the use of a Real Time Locating System that allows inferring the animal behaviour in real time. Not only the time a given animal spent in each activity or the distance it travels per day can help understanding whether this animal is functioning normally (e.g. spends sufficient amount of time resting or eating, or moves enough) but also the organisation of activities during the day or in relation to specific events (i.e. circadian rhythms, reactions to human approach) can give indications on subtle changes that reflect health or behavioural problems. We do not conclude that PLF is necessary for animal welfare nor that animal welfare is always promoted by PLF techniques but rather that including animal welfare considerations in the development and use of PLF techniques is essential to obtain profit for all: the farmer, the animal, and the society.

Key-words: PLF; animal welfare; behaviour; RTLS

Introduction

Precision Livestock Farming (**PLF**) is often perceived as an instrumentation of animals in order to make more profitable 'industrial farms'. Although the initial drive might be profitability and reduction of farmers' workload, we argue that PLF can also help to ensure animal welfare. PLF technology can detect anomalies in the environment and thereby offers the possibility to take remedial actions quicker. For instance, if the temperature is getting too hot in a poultry house, then cooling systems can be turned on, thereby restoring normal feeding behaviour of the animals and ensuring good welfare as well as an optimal production. Likewise, if the feed intake of a cow can be monitored precisely together with its weight and milk production, then this cow can be given the exact amount of food it needs to keep her in a good condition and to avoid waste (Halachmi *et al.*, 2016).

In this paper, we will start from the operational definition of animal welfare from Welfare Quality®: 12 criteria of welfare have been defined, grouped into 4 principles (Welfare Quality®, 2009):

- Good feeding: Absence of prolonged hunger; Absence of prolonged thirst
- Good housing: Comfort around resting; Thermal comfort; Ease of movement
- Good health: Absence of injuries; Absence of disease; Absence of pain induced by management procedures
- Appropriate behaviour: Expression of social behaviours; Expression of other behaviours; Good human-animal relationship; Positive emotional state

Then, we will discuss how PLF can help meet these principles. We will largely base our argumentation on our own experience within the European project EU-PLF (http://www.eu-plf.eu/).

PLF and good feeding

PLF technologies have been developed to precisely control the amount of food eaten by animals. In herbivores, not only the amount of concentrates but also that of forage can be measured individually. Combined with an analysis of feeds quality and animal needs (depending on their production level, their individual characteristics, the environment, etc.), this can serve to check whether animals are fed according to their needs. In addition, the time spent eating is now also available thanks to specific devices (time spent at the trough or time spent chewing or ruminating). Indirect measures can also be used. For instance, the

frequency of the sounds emitted by broilers are inversely proportional to their weight (Fontana *et al.*, 2015). This could be used to check whether the growth of broilers is normal and if not, one may suspect an inadequate diet or a health disorder. The amount of water drunk by animals may be monitored at group level by water counters on drinkers; It can also be estimated in cattle by the variations in the temperature of the rumen. All this information can be used to check whether the principle 'Good feeding' is fulfilled.

PLF and good housing

There are several areas where PLF can help to ensure good housing to animals. In poultry, image analysis can be used to analyse the spread of animals in a poultry house and detect overcrowded spots; similarly in cattle, Real Time Locating Systems (**RTLS**) can help to detect problems in the flow of animals in a barn, e.g. 'traffic jams' or 'bottle neck'.

The time spent lying down can be detected with accelerometers fixed on animals' legs, at least in large animals. The time spent in the lying area can also be detected thanks to RTLS, with tags positioned on an animal's neck and antennas in the barn. The time spent resting or using the lying area could reflect the comfort of the lying area. Moreover, combining these two sets of information, that is the time spent in the lying area and the actual lying of cows, one could estimate the time spent by an animal to lie down once in the lying area; this information is especially important in case of cattle barns with cubicles: a long delay between entering the lying area and lying down can reflect a poor design of cubicles, with animals colliding against cubicle partitions.

PLF and good health

The welfare of animals is impacted by health problems, especially in case of painful disorders such as lameness. Several monitoring systems have been proposed to detect lameness, based on the way animals balance the weights on their four feet, the regularity of their walking movement or the time spent walking during a day (e.g. Maertens *et al.*, 2011). In broilers, leg health could be predicted based on activity changes, measured with image analysis techniques, after the passage of an observer through the flock (Silvera *et al.*, 2017). All these indicators are of prime importance because lameness is both a common and often very painful condition.

The welfare of animals can also be impaired by illness, even if the disease is not painful. Animals can not only be ill but also feel ill; this is observed through behavioural changes such as drowsiness, hypophagia, social withdrawal,… (Aubert, 1999, Dantzer *et al.*, 2008). At the moment, much work is done into detecting such sickness behaviour with PLF techniques. We used a RTLS system to analyse the time budget of dairy cows and analysed the circadian rhythm in

activity. The first results show that anomalies in the circadian rhythm may precede the mastitis or lameness symptoms detected by the farmer (Veissier *et al.*, 2017). A combination of behavioural and performance data can also be used to diagnose finely health disorder after calving (Steensels *et al.*, 2016).
PLF can therefore help to detect health disorders at an early stage so that they are more easily cured by the farmer.

PLF and appropriate behaviour

Animal behaviour often reflects the state of mind of an animal and thus its welfare. For a long time animal behaviour was not specifically taken into account neither in daily husbandry practice, nor really taught in farming courses. However, farmers observe the behaviour of their animals and use – possibly in an informal way – behavioural parameters in their management decisions. Many PLF systems are measuring animal behaviour: time spent eating, moving, lying, position in a barn, etc. They can monitor behaviour in a detailed and continuous way. It can thus be checked if animals display a normal time-budget, or whether some activities are under- or over-expressed. One can easily imagine that the time spent grooming is detected thanks to sensors on brushes provided to animals (especially cattle) or the time spent using enrichment devices (now compulsory in pigs) is measured to check that these devices are effective. One could also imagine detecting aggression between animals, thanks to e.g. high pitch vocalisations in pigs or specific positions of animals in regard to each other's. Similarly, the response to humans could be measured automatically by measuring the distance between animals and a stockperson walking through a group of animals using RTLS or video imaging (Johansson *et al.*, 2015).

Conclusion

Although PLF techniques cannot tell us the exact animal mental state, they offer a wide range of possibilities to approach animal welfare through manifestations of animal behaviour. We believe these possibilities are still underexplored. We do not conclude that PLF is necessary for animal welfare nor that animal welfare is always promoted when PLF techniques are used, but rather that including animal welfare considerations in the development and use of PLF techniques is essential to obtain profit for all: the farmer, the animal, and the society.

References

Aubert A 1999. Sickness and behaviour in animals: a motivational perspective. *Neuroscience and Biobehavioral Reviews* **23**, 1029-1036.

Dantzer R, O'Connor JC, Freund GG, Johnson RW and Kelley KW 2008. From inflammation to sickness and depression: when the immune system subjugates the brain. *Nat Rev Neurosci* **9**, 46-56.

Fontana I, Tullo E, Butterworth A and Guarino M 2015. An innovative approach to predict the growth in intensive poultry farming. *Computers and Electronics in Agriculture* **119**, 178-183.

Halachmi I, Ben Meir Y, Miron J and Maltz E 2016. Feeding behavior improves prediction of dairy cow voluntary feed intake but cannot serve as the sole indicator. *Animal* **10**, 1501-1506.

Johansson A, Blokhuis HJ, Berckmans D and Butterworth A 2015. Development of an automatic method to assess human-animal relationship in broilers on flock level. In *Precision livestock farming '15,* Milan, Italy, pp. 195-201.

Maertens W, Vangeyte J, Baert J, Jantuan A, Mertens KC, De Campeneere S, Pluk A, Opsomer G, Van Weyenberg S and Van Nuffel A 2011. Development of a real time cow gait tracking and analysing tool to assess lameness using a pressure sensitive walkway: The GAITWISE system. *Biosystems Engineering* **In Press, Corrected Proof**.

Silvera AM, Knowles TG, Butterworth A, Berckmans D, Vranken E and Blokhuis HJ 2017. Lameness assessment with automatic monitoring of activity in commercial broiler flocks *Poultry Science* **pex023. doi: 10.3382/ps/pex023**.

Steensels M, Antler A, Bahr C, Berckmans D, Maltz E and Halachmi I 2016. A decision-tree model to detect post-calving diseases based on rumination, activity, milk yield, BW and voluntary visits to the milking robot. *Animal* **10**, 1493-1500.

Veissier I, Mialon M-M and Sloth KH 2017. Short communication: Early modification of the circadian organization of cow activity in relation to disease or estrus. *Journal of Dairy Science* **100**, 3969-3974.

Welfare Quality® 2009. *Welfare Quality® assessment protocol for cattle (fattening cattle, dairy cows, veal calves).* Welfare Quality® Consortium, Lelystad, The Netherlands.

Session 21

Emissions

Data extraction method for enteric methane measurements from a hand-held Laser Methane Detector®

T. Bruder[1], B. Rouillé[1], M. G.G. Chagunda[2]
[1]*Institut de l'Elevage, Service Productions Laitières, Monvoisin – BP 85225 – 35652, LE RHEU Cedex, France*
[2]*Future Farming Systems Group, Scotland's Rural College (SRUC), Edinburgh, EH9 3JG, Scotland, UK*
benoit.rouille@idele.fr

Abstract

This study aimed to develop the framework for extracting features and signals which characterise biologically meaningful data from individual time-series enteric methane measurements in breath cycles captured using the hand-held Laser Methane Detector (LMD). Ruminants account for approximately 39% of total greenhouse gas (GHG) production in agriculture (FAO, 2013). One of the most potent GHG produced by ruminants is methane. Enteric methane eructation indicates inefficiencies in feed utilisation. One of the difficulties in developing effective mitigation strategies is the inability to collect enough measures from a large number of animals. The application of traditional techniques such as metabolic chambers at applied research level is very limited. The LMD is a gas detector and determines methane gas density along the path of the beam and allows remote and fast measurements without disturbing the animal. Results from previous work on the LMD have shown strong correlation with results from respiratory chambers ($r = 0.80$; Chagunda and Yan, 2011). To date, the LMD has been used in experimental setups and hence no global data extraction method is in place. To contribute to addressing this gap, data from a 5-week study in an intensively monitored group of 71 dairy cows were used in the current analysis. To test the optimal measurement time, five different recording windows of 60, 120, 180, 240 and 300 seconds were created. Methane measurements from each measurement window were used to calculate the overall average. The measurement time affected the estimated averages ($p<0.001$). Differences between individual window measurements indicated that measurements over 120, 180 and 240s were not significantly different from each other. However, the most significant difference was between 60s and 240s ($p=0.049$) and between 60s and 300s ($p=0.018$). Measurements in the 60s window gave the lowest overall average, indicating missed eructation episodes in the breath cycles. The study demonstrated the importance of measurement duration in methane data extraction methodology.

Keywords: laser methane detector, ruminants, enteric methane

Introduction

Agriculture faces considerable challenges to limit global warming. Livestock plays an important role in greenhouse gas emissions (GHG), especially in terms of methane. Livestock farming represents 14.5% of the total anthropogenic GHG. Cattle are the main emitters, contributing 65% of the sector's total output (FAO, 2013). Of that, enteric methane produced during digestion is the largest component. Enteric methane emissions reflect inefficiencies in feed utilisation. These emissions can be reduced either by modifying the feed ration and intake or through genetic improvement of livestock and plants. However, one of the difficulties in developing effective mitigation strategies is the inability to collect enough measures from sufficient numbers of animals. The application of traditional scientific techniques at applied research level is very limited. Techniques such as respiration calorimetric chambers and the tracer gas method (SF6) are used to estimate methane emission. Due to the need to measure methane emissions directly on the farm, one technique is becoming more and more popular: the GreenFeed. These techniques, although effective and reliable, are however expensive and/or time consuming. Novel approaches should allow measurements to be taken at a farm level, in large numbers and without disturbing the animals. For example, using breath as the measurement platform is an attractive proposition, not least because 80 to 85% of enteric methane is exhaled. The Laser Methane Detector (LMD), suggested for the first time by Chagunda *et al.* (2009) is a promising and practical tool. The LMD is a gas detector which determines methane gas density along the path of the beam and allows remote and fast measurements without disturbing the animal. Results from measurements taken simultaneously from the LMD and respiratory chambers have shown a strong correlation (r = 0.80) (Chagunda and Yan, 2011). However, being a novel procedure, there is no joined-up protocol covering all aspects, including data collection, data extraction, data handling and estimating methane volume from the measured concentration. The current study aimed to develop the framework for measuring and extracting appropriate features from individual time-series measurements from LMD data.

Materials and methods

The LMD is a hand-held methane detector which measures instantly and is specific to measuring methane. It was developed by Tokyo Gas Engineering Co. and is distributed by Crowcon Ltd. It is generally used in places where methane leaks can occur, for example in gas transportation networks, mine pits and

landfill sites. It can detect methane concentrations between 10 and 50 000 ppm-m, up to a distance of 100 m and through glass. It operates at between 0 and 40°C and for a humidity range of 20-90%. Detection speed is about 0.1s. Methane measurements from the LMD are based on infrared absorption spectroscopy: it emits an infrared light and analyses the light that is reflecting back. The laser wavelength is specific of methane. Concentrations are obtained in ppm-m as the gas density along the path of the beam. It is then related to the concentration itself but also the length of the methane plume.

For each measure, the distance between the laser beam and the nostril of the cow was estimated as 1 m. Measurements lasted 4 to 5 minutes. For each individual time-series measurement, time of recording and the cow's tag number was recorded. Time of recording will make it possible to identify the LMD data and link it with the specific cows from which methane was measured.

A dataset obtained from an intensively recorded group of 71 dairy cows over 5 weeks was used in the study. Measurements were conducted over a period of 5 weeks. In each week, measurements were taken on 3 consecutive days from 15 different cows at the feed fence after midday milking.

Data was collected on an Android device as a .csv file. As soon as recording started, a measure was taken every 0.5s and data were lined up depending on timestamp, not on measurement time. Each animal was measured once a day and each measure lasted between 4 and 5 minutes. This window – or individual time-series – of 4-5 min represents a unique recording. Calculation of the exact measurement time for each of these windows is needed. The dataset was broken down into specified groups of time measurements for further processing. Five datasets were created in order to calculate a gross average of methane emissions relative to 60s, 120s, 180s, 240s and 300s of measurement duration. The first dataset contained all the measurements taken between 0s and 60s, i.e. the first values up to 60s; the other ones are on the same pattern but for 120s, 180s, 240s and 300s. Methane measurements from each measurement window were used to calculate gross average and standard deviation. The recommendation of Chagunda *et al.* (2011) was a 4-minute measure for each window. 1075 single data were validated and used in this study (Table 1) ranging from 38 to 340 ppm-m, with a mean value of 144 ppm-m.

Table 1: Distribution of enteric methane concentration form the cows in the study

In ppm-m	Mean	Standard Deviation
Minimum	38.18	13.74
1st quantile	108.74	86.19
Median	143.18	114.08
Mean	144.11	116.90
3rd quantile	171.99	140.29
Maximum	340.77	291.72

Analysis of variance applying a mixed model was used to identify potential differences between time classes. In the analysis, fixed effects of parity, lactation stage, age and genetic line were accounted for and the individual cow effect was used as a regression factor. The ANOVA and a multiple comparison of means performed on the data make it possible to validate the time window required, with small adjustments.

Results and discussion

Initial results showed that the data used for the analysis had more than 200 data points for each time window. This is important considering that measurements were taken for a maximum of 5 minutes per measurement window. This means that the total collection represents more than 70 hours of data. Further analysis showed that the longest measurement time also corresponded with the highest value of methane measurement in ppm-m. For example, methane concentration values that ranged from 135 to 149 ppm-m had a measurement window that ranged from 60 seconds up to 300 seconds. Furthermore, the standard deviation reduced as time of measurement increased, indicating less variation with an extended measurement window.

Table 2: Means and standard deviations of enteric methane concentration for different time windows

Time window	Window name	Number of data	Mean in ppm-m	SD in ppm-m
[0s;90s]	60s	215	135.78	50.46
[90s;150s]	120s	215	143.42	46.32
]150s;210s]	180s	219	144.73	44.89
]210s;270s]	240s	222	147.51	42.08
]270s;300s]	300s	204	149.23	39.18

Individual window measurements indicated that measuring for 240 seconds was not significantly different from 120s, 180s and 300s (Table 3). The most significant difference was between 60s and 240s (p=0.049). There was also a difference between 60s measurements and 300s measurements (p=0.019). Measurements carried out over a period of 60s had the lowest concentrations, indicating missed eructation episodes in the breath cycles. However, there is no significant difference between 240s and 300s. These results indicate that there may not be a serious need to take measurements for a longer duration than 240 seconds.

Table 3: ANOVA of the methane concentration comparing different time windows

Comparison of time window	Mean difference	P value
120 versus 60	7.64	0.39
180 versus 60	8.95	0.23
240 versus 60	**11.73 ***	**0.049**
300 versus 60	**13.44 ***	**0.019**
180 versus 120	1.31	0.99
240 versus 120	4.09	0.88
300 versus 120	5.81	0.67
240 versus 180	2.78	0.97
300 versus 180	4.50	0.84
300 versus 240	1.72	0.99

For the shorter measurement duration, results indicated that enteric methane concentrations from measurement windows of 120s to 240s were not significantly different (p=0.88). However, in practical terms, measurements should be taken for more than two minutes to avoid getting unrealistic averages and variation.

It is estimated that eructation episodes in breath cycles take place every one to three minutes. By measuring for less than 4 minutes, there is a risk of missing eructation episodes and being more exposed to unnecessary variability. For this reason, we agree with the proposition that measurements should be taken for at least 4 minutes per measurement window in order to obtain biologically meaningful results.

Conclusion

The LMD demonstrates the potential to provide a robust proxy for measuring enteric methane emissions in cows. This current study has shown and confirmed the importance of measurement duration in generating reliable and useful data.

Acknowledgement

This study was funded by Idele.
SRUC receives support from the Scottish Government.

References

Chagunda, M.G.G and Yan T. 2011. Do methane measurements from a laser detector and an indirect open-circuit respiration calorimetric chamber agree sufficiently closely? Animal Feed Science and Technology, 165:8-14

Chagunda, M.G.G., Ross, D and Roberts, D.J. 2009. On the use of a laser methane detector in dairy cows. Computers and Electronics in Agriculture 68:157–160

FAO, 2013. Tackling climate change through livestock. A global assessment of emissions and mitigation opportunities. FAO report, 139 pages.

Influences of feeding behaviour and forage quality on diurnal methane emission dynamics of grazing cows

Y. Blaise[123], A.L.H. Andriamandroso[12], B. Heinesch[13], Y. Beckers[12], E. Castro Muñoz[234], F. Lebeau[13], J. Bindelle[12]
[1]*TERRA Teaching and Research Center, AgricultureIsLife*
[2]*AgroBioChem, Precision Livestock and Nutrition Unit*
[3]*Biosystems Dynamics and Exchanges, Gembloux Agro-Bio Tech, University of Liege, Passage des Déportés 2, 5030 Gembloux, Belgium*
[4]*Facultad de Ciencias Agrícolas, Universidad Central del Ecuador, Universitaria, Quito, 170129, Ecuador*
yblaise@ulg.ac.be, jerome.bindelle@ulg.ac.be

Abstract

This study aimed to evaluate diurnal methane (CH_4) emission dynamics of grazing cattle and highlight their relationships with biotic factors such as the feeding behaviour as well as seasonal changes in pasture characteristics.
Existing methods to assess grazing ruminants' daily CH_4 emissions provide useful insights to investigate mitigation strategies relying on feeding and genetic selection. Nonetheless such methods based on tracer gases (SF_6) or feeding bins equipped with sniffers (e.g. GreenFeed) can hardly cover diurnal CH_4 emission fluctuations which can influence the accuracy of total CH_4 production estimations. Previous studies in barns showed that emission dynamics strongly vary during post feeding time, leading to a possible bias in estimates of daily CH_4 emissions as high as 100%. To investigate whether such fluctuations are also taking place on pasture, a portable device was designed with infrared CH_4 and CO_2 sensors measuring concentrations in the exhaled air at a high sampling rate (4 Hz). Six grazing dry red-pied cows were equipped with the device and motion sensors during runs of 24h to monitor CH_4 and CO_2 emissions and detect their feeding behaviours (grazing, rumination and other behaviours), respectively. This experiment was performed in summer and fall in order to cover seasonal changes in pasture forage quality. Methane emission was estimated from the CH_4:CO_2 concentration ratio and the metabolic CO_2 production of the cows. As for barn studies, variations were observed in total daily CH_4 emission due to the seasons and diurnal variations were also observed due to animal behaviours. Relationships between animal feeding behaviour and CH_4 emissions patterns on pasture were also unravelled.

Keywords: cattle, methane emission, pasture heights, grazing, behaviour.

Introduction

Livestock holds an important share of the anthropogenic greenhouse gases emissions. In cattle, rumen fermentation contributes significantly to this burden through the production of methane (CH_4). Methane is less prevalent in the atmosphere (1851 ppb in 2017) than carbon dioxide (CO_2) (407 ppm in 2017) but has a global warming potential 72 times greater than CO_2 over a 20-year period (IPCC, 2007; NOAA, 2017). Over the past decade, the concentration of CH_4 in the atmosphere grew faster than ever before and some name the expansion of cattle that increased from 1.3 billion heads in 1994 to 1.5 billion heads in 2014 as one of the major causes. There is an urgent need to develop adequate measure to reduce methane emissions or at least mitigate their effects and therefore develop techniques that allow measuring CH_4 emissions at different scales and under different production systems, including the individual level for grazing animals (Saunois et al., 2016). Grazed pastures are indeed important agroecosystems for the multiple ecosystems services they provide. In Belgium, a grazing cattle in a cow-calf operation produces about 50kg of CO_2 eq /year (Dumortier et al., 2016) but the whole pastoral agroecosystem works rather as a carbon sink (Gourlez de la Motte et al., 2016). While CH_4 affects climate change, for animal nutritionists, CH_4 production is also a sign of feed inefficacies. On average, 6% of the energy consumed by cattle is lost as methane (Johnson and Johnson 1995). CH_4 is released from the rumen mainly during eructations (87%) (Saunois et al., 2016).

The monitoring of CH_4 fluxes is usually carried out in metabolic chambers, i.e. in a controlled environment. It is regarded as the standard method (Storm et al., 2012). For grazing cattle, the chamber is not adequate. On pasture, three techniques can be used to estimate CH_4 production: (1) the eddy covariance method allowing the measurement of the CH_4 production of an entire herd and over time steps of 30 min (Dumortier et al., 2016); (2) the tracer method involving sulphur hexafluoride allowing the measurement of one individual's methane production over periods of, typically, 1 to 5 days (Hammond et al., 2016); and (3) short infra-red CH_4 and CO_2 measurements of the air exhaled that are achieved on individual animals and used to estimate their daily CH_4 production. In the latter, measurements are performed in a feeding bin and last for a few minutes. They can be repeated for a same individual between two to four times per day (Madsen et al., 2010 Garnsworthy et al., 2012). Such short term measurements can induce a bias when quantifying CH_4 production if there is important diurnal variation pattern in the dynamics of CH_4 emission that are possibly related to the behavioural phases of the cows (Velazco et al., 2016). In

barns, cows fed on a restricted diet displayed strong fluctuations of their CH_4 emission rates according to the post-feeding time (Blaise et al., 2017). On pasture, the feeding behaviour is different since animals realise longer and more frequent meals and forage intake rate during the meals is lower (Andriamandroso et al., 2017). Hence, in order to contribute to management practices which could limit the CH_4 emissions of grazing cattle, an experiment was designed to measure how CH_4 emission rates of grazing cows vary along the day and whether such variations depend on the animal's behaviour and the changes in pasture characteristics across the seasons.

Material and methods

The experiment was run on the *AgricultureIsLife* experimental farm of TERRA Teaching and Research Centre of Gembloux Agro-Bio Tech in Gembloux, Belgium (50°33'59.06"N 4°42'07.97"E). All the experimental procedures and handling of the animals were approved by the Animal Care Committee of the University of Liege [protocol n°14-1627].

Experimental set up

Six dry red-pied Holstein cows between 4 and 7 years old and weighing 697.3 ± 82.9 kg were used during two data acquisition sessions: one in the summer (July 2016) and the second during the fall (September 2016). The herd was set to graze a permanent ryegrass (*Lolium perenne*) and white clover (*Trifolium repens*)-based pasture and water was freely available to the animals. The pasture was divided in adaptation and measurement paddocks whose size and grass height allowed to reach forage allowances letting cows graze ad libitum. During both measurement campaigns i.e. in summer and fall, animals were grazing the same pasture and forage allowance (approx. 17 kg/100 kg BW/d) was similar, as measured using a rising plate pasture meter. After one week of adaptation to the sensors and to the pasture in an adaptation paddock, the cows wearing the equipment described below were placed in a measurement paddock for a measurement period that lasted 24 hours. The experimental scheme was performed in summer and repeated in fall.

Sward and ingestion characteristics

Before each measurement periods on a paddock, grass height (n=20) was measured and grass was sampled by randomly cutting eight quadrats of 30 × 30 cm^2. This grass was taken for chemical composition and nutritive value determination. Faeces were collected individually by rectal grabbing for faecal near-infrared reflectance spectrometry (F-NIRS) analysis. Faecal and grass samples were oven dried at 60°C. After moisture determination, samples were

ground at 1 mm in a hammer mill (Cyclotec, FOSS Electric, Hillerød, Denmark). Each sample of ground forage and faeces were read by a NIRS-system 5000 monochromator spectrometer (XDS Rapid Content Analyser XM-1100 Serie, FOSS Electric, Hillerød, Denmark) (Decruyenaere et al., 2015). The absorption spectrum of each sample was recorded as log 1/R for wavelengths ranging from 1100 to 2498 nm, every 2 nm (WINISI 1.5, FOSS Tecator Infrasoft International LCC, Hillerød, Denmark). Prediction equations used to convert spectral data were provided by the Reference Laboratory Network REQUASUD (Wallonia, Belgium). Prediction by F-NIRS for CP, OM, NDF, ADF, ADL and DMI were considered as good since the standardized Mahalanobis distance (H) which evaluates the correspondence between the faeces spectra and the F-NIRS database was always lower than 3, ensuring an accurate prediction.

Sensors

Three types of sensors were worn by the animals and synchronized for further data processing: (1) gas sensors, (2) movement sensors and heart rate (HR) belt (3) (Figure 1).

Gas Sensor. A pump (24V DC Pump Gascard NG Models) sucked at a flow rate of 0.5 l/min the exhaled gas in a flexible PVC hose (1.85 m, inner ø 4mm) in front the nostril. The gas measurement sensors were placed on the animal's back (Figure 1), the CH4 infra-red sensors coming upstream from the CO_2 infra-red sensor (NG Gascard® 0-1 % CH4 and Gascard® NG 0-10% CO_2, respectively; Edinburgh Sensors, Livingston, UK). A 1-µm filter ensured the protection of both sensors. The concentrations of CH_4 and CO_2 were recorded at 4 Hz on a SD-card connected to a microcontroller.

Motion Sensors. **C**ows were fitted with a halter on which an iPhone (4S Apple Inc., Cupertino, CA, USA) was attached at the level of the neck of the animal (Figure 1). The built-in inertial measurement unit (IMU) was used to record head and jaw position and movements and converted into a behaviour matrix via an open-source algorithm to differentiate grass intake, ruminating and other behaviours (Andriamandroso et al., 2017).

Heart rate sensor. A transmitter heart rate (HR) belt was placed around the cows' chest (Equine H7 heart rate, Polar, US). Contact areas were moistened with water and electrocardiography gel. The transmitter belt communicated via Bluetooth with a dedicated application (Heart Rate Variability Logger, HRV, available on Apple Store) of an iPhone placed on the animal which recorded the HR in a CSV format at 1 Hz.

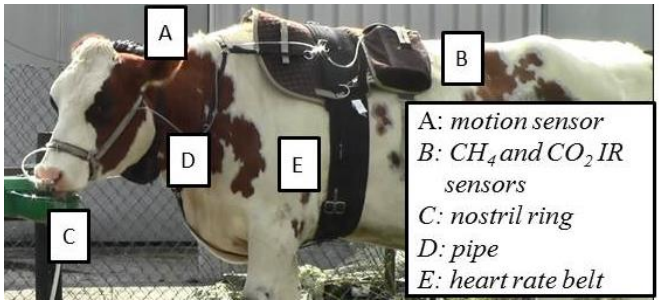


Figure 1. Equipment installed on a grazing cow. The motion sensor of an iPhone 4S is placed inside a waterproof box (A) attached on a halter on the top of the neck. The opening of the pipe (D) is attached to a nostril ring (C) to pump the gas exhaled (A). At the exhaust pipe there are two IR gas sensors to measure CH_4 and CO_2 concentrations.

Signal analysis

Data from the IMU were used to classify the cows' behaviour by time windows of 60 seconds in MatLab R2014a (MathWorks, Natick, MA, USA). MatLab R2014a was also used for the processing of the HR and the analysis of the gas concentration. All these data were synchronized during the processing analyses. HR was averaged over 60 seconds. The calculation of CH_4 DER (daily emission rate, L/day) as described by Madsen et al. (2010) was calculated for each 60-s time windows. For this purpose, every minute, the minimum CH_4 and CO_2 values were considered as background concentrations and subtracted from all the other raw values. Then, CO_2 and CH_4 concentrations were averaged over 60 s. Subsequently, all values below 400 ppm of CO_2 were discarded to avoid samples with very low concentration of breath (Haque et al., 2014). Such rejection (6%) of data was mainly ascribed to clogging of the pipe with grass or water. The technique to estimate the CH_4 DER consisted in using metabolic CO_2 as an internal tracer and multiplying it by the ratio between CH_4 and CO_2 (Equation 1 and 2) (Madsen et al., 2010). The total daily metabolic CO_2 produced by the animal is calculated from the daily heat production (Equation 4). For a dry and non-pregnant cow, the heat production is estimated according to the BW (Equation 3) (Haque et al., 2014).

$$CH_4{:}CO_2 = \frac{\left([CH_4]_{\text{exhaled air}} - [CH_4]_{\text{background}}\right)}{\left([CO_2]_{\text{exhaled air}} - [CO_2]_{\text{background}}\right)}, \qquad Equation\ 1$$

$$CH_4PMR\ (L/day) = \left(CO_{2_{metabolic}}\right) \times CH_4{:}CO_2, \qquad Equation\ 2$$

$$\text{HP} = 5.6 \times BW^{0.75}, \qquad Equation\ 3$$

$$CO_{2_{metabolic}}(L/day) = HPU \times 180 \times 24, \qquad Equation\ 4$$

where:

$[CH_4]$ and $[CO_2]_{\text{in exhaled air}}$	are the concentrations of gas in the air, ppm;
$[CH_4]$ and $[CO_2]_{\text{background}}$	are the minimum concentrations in each time window, ppm;
HP	is the heat production from the animals, watt (W);
BW	weight of the animals, kilograms (kg);
HPU	is the heat producing unit (HP/1000);
180	L of CO_2/HPU/h.

Statistical analyses

The CO2, CH4 concentrations, CH_4:CO_2 ratios, CH_4 DER, HR were compared using PROC MIXED in SAS (SAS Institue, Inc., Cary, NC, USA) in a general linear model where the fixed effect of behaviours (grazing, rumination, other), season (fall and summer) and their interaction were tested and the individual cow was used as a random variable. Each time window served as experimental unit. The chemical composition of the faeces (CP, OM, NDF, ADF, ADL) and the DMI of the cows (N=6), as well as forage allowance and the nutritive values of the grass (N=20) (Table 1) in summer and fall were also compared using an one-way ANOVA model in SAS.

Results and Discussion

Pasture nutritive values

The cows grazed the same pasture in summer and fall, but, as expected the characteristics of the forage changed (Table1). While forage allowance remained similar (approx. 17 kg/100 kg BW/d), the nutritional value decreased between the summer and fall as highlighted by an increase in fibre contents and a decrease in crude protein and energy (Table1).

Table 1: Pasture forage allowance and nutritive value in summer and fall.

		Seasons	
	unit	Summer	Fall
DM[1]	g/kg	233.8±23.2[b]	338.0±36.2[a]
FA[2]	kg DM/100 kg BW/d	17.2±7.3[a]	17.3±6.7[a]
Ash	g/kg DM	81.6±6.0[a]	98.7±9.3[a]
Ca	g/kg DM	5.37±1.42[a]	7.19±2.79[a]
P	g/kg DM	3.33±0.17[a]	3.62±0.39[a]
NDF[3]	g/kg DM	388±15.9[b]	570.5±25.3[a]
ADF[4]	g/kg DM	233±9.9[a]	366.8±20.4[a]

ADL[5]	g/kg DM	19.9±3.6[b]	31.7±1.7[a]
DOM[6]	g/kg DM	794.4±7.98[a]	666.8±14.85[b]
DCP[7]	g/kg DM	66.21±11.2[a]	52.44±11.24[b]
VEM[8]	g/kg DM	1054±13.73[a]	847.8±23.46[b]
DVE[9]	g/kg DM	89.6±1.85[a]	64.83±4.3[b]
OEB[10]	g/kg DM	-43.3±9.42 [a]	-35±8.01[a]

[1]DM = dry matter; [2]FA = forage allowance; [3]NDF = neutral detergent fibre; [4]ADF = acid detergent fibre; [5]ADL = acid detergent lignin; [6]DOM = digested organic matter; [7]DCP = digested Crude protein. [8]VEM = Dutch standard for NEL (1 VEM = 6.9 kJ of NEL); [9]DVE = truly digested protein in the small intestine; [10]OEB = degraded protein balance calculated as the difference between the amounts of microbial proteins synthesized in the rumen as a function of the nitrogen inputs and the energy inputs. According to the Dutch Feed Evaluation Scheme (Tamminga et al., 1994).
[a b] means within a line with different superscript letters differ.

Results displayed in Table 2 indicate a shift across the seasons in the faeces characteristics, which contained more fibre and less protein during the fall, matching with the changes observed in forage quality (Table 1). During the fall, the animals ate less, probably as a consequence of the increase in NDF content and the decrease in CP, making the grass less digestible and reducing rumen passage time. Another possible explanation might be due to the increase in selectivity or as an additional consequence of the higher fibre content of the forage, an increase in the difficulty for animals to perform defoliation bites required to fulfil easily their daily forage intake.

Table 2: Bodyweight of the cows and chemical composition of the cows faeces and dry matter intake of grazing cows according to the seasons as estimated by F-NIRS.

period	Bodyweight	CP[1]	OM[2]	NDF	ADF	ADL	DMI[3]
	kg	g/kg DM	g/kg DM	g/kg DM	g/kg DM	g/kg DM	g DM/kg BW
Summer	697.3±82.9[a]	198±12[a]	773±20[a]	402±21[b]	227±17[b]	102±11[a]	25.7±2.2[a]
Fall	696.8±70.8[a]	154±6[b]	814±5[a]	533±12[a]	299±3[a]	100±3[a]	18.3±1.3[b]

[1] total protein content; [2] organic matter; [3] dry matter intake.
[a b] means within a row with different superscript letters differ.

Behaviour and diet/season effect on average methane emission

Table 3 illustrates the impact of season (summer and fall) and behaviours (grazing, ruminating and all other behaviours called "other") on different items: the HR, the CH_4:CO_2 ratio measured continuously in the animal's breath, the CH4 DER estimated from the ratio and the metabolic CO_2 and the CH_4 DER corrected by the DMI of individual cow estimated from the F-NIRS. The values were comparable to Madsen et al. (2010) who observed ratio between 0.06 and 0.1 using typical Danish feeding levels. Whereas, Martin et al. (2016) calculated on dairy cows in milk higher values for methane production per unit of feed intake with 32.7 l CH_4 DER / kg of DMI. The cows used in this study were dry.

Table 3: Measurement and estimation of the HR (beat per minute), the CH_4:CO_2 ratio, the CH_4 DER estimated and the CH_4 DER per Kg of DMI.

	Main effects	N	HR	CH_4 : CO_2	CH_4 DER	CH DER/ DMI
Seasons	Behaviour		Bpm	-	l/day	l/kg/DMI
Summer	Grazing	1110	93.7±15.3^{b}	0.055±0.033^{c}	179±104^{d}	10.0±6.0^{c}
	Rumination	635	73.6±8.7^{d}	0.056±0.040^{c}	187±132^{d}	10.3±7.0^{c}
	Other	5694	80.7±17.9^{c}	0.055±0.037^{c}	180±120^{d}	10.1±6.7^{c}
Fall	Grazing	1304	97.0±22.7^{a}	0.095±0.075^{a}	276±212^{a}	23.1±18.6^{a}
	Rumination	782	73.9±12.4^{d}	0.072±0.044^{b}	211±129^{c}	17.7±10.9^{b}
	Other	3164	95.5±26.7^{ab}	0.077±0.061^{b}	233±178^{b}	18.8±15.1^{b}
Standard error of the mean			0.26	4.5 ^{E}-4	1.34	0.11
Source of variation						
	Season × Behaviour		<0.001	<0.001	<0.001	<0.001
Variance parameter estimates						
	Cow		67.4	1.96^{E}-4	1073	9.5
	Residual		305	22.4^{E}-4	21027	116

$^{a\,b\,c\,d}$ Means within a row with different superscript letters differ.

This work shows a combined effect of season and behaviours on CH_4 emissions, but the part of the variance due to individual cows is low. Indeed, the SD for the CH_4 emissions is important, reflecting a variability of the emission during the day whatever the individual. In summer, there is no difference according to the feeding behaviours, whereas there are differences in the CH_4 production per day and per kg of DMI during fall. In fall, the animals produced more CH_4 during grazing. As the heartbeat rate varies, systematically, within a season according to the behaviour, the HR being higher during grazing than during ruminating, one cannot rule out an additional interaction with CH_4 estimates as metabolic CO_2

production might increase with higher HR, reducing the CH_4 estimates by decreasing the CH_4:CO_2 ratio.

During the summer, regardless of the behaviour, CH_4 emissions were smaller. The grass is richer in energy and proteins and the cows ate more but the feed probably stayed less longer in the rumen. Longer residency times in the rumen are associated with higher CH4 emissions. It is indeed well documented that a diet that is richer in NDF decreases DMI and increases CH_4 production (Hammond et al., 2016).

On pasture studying the impact of specific behaviour is not easy, because the animals achieve many small behavioural sequences. This is why, it is difficult to observe the impact of a specific behaviour on CH_4 emission or to analyse precisely the impact of the post-feeding time on CH_4 kinetics. In stable-fed animals, with a restricted diet given twice a day, during and after the meal a rapid increase of the emission is observed (Blaise et al., 2015). In this study, during fall, CH_4 emission is higher during grazing. As cows spent less time grazing during fall, the impact of post-feeding on CH_4 emission is detectable because the impact of a meal on ruminal fermentation is more pronounced. Lockyer and Champion (2001) also found that CH_4 emission rates tended to follow the feeding activity whereas emission rate fell during ruminating. They explained that CH_4 is emitted when the rumen is congested, so when feed enters the rumen, CH_4 production continues during rumination but in smaller quantities and decreases gradually as the fermenting rumen content gets progressively drained. Hegarty (2013), also reported variations in CH_4 emission rates with an increase matching with grazing bouts.

With this tailor-made device, CH_4 emission of grazing cow at each moment could be monitored. Howerer, the technique is an mere estimation of the CH_4 emission because the method is based on the assumption that the emission of the internal tracer (CO_2) is stable. In this experiment, cows on pasture express grazing cattle behaviours and have physical activities. Hence, a higher HR during grazing than during other behaviours is noticed. As stated before, it means that metabolic CO_2, and hence CH_4 DER, may be undervalued during grazing and overestimated during more quite phases.

Conclusions

This paper shows the possibility of improving the estimation of enteric CH_4 emission monitoring on pasture. Combining this innovative technique to a device monitoring animal behaviour at a high-frequency showed that emissions displayed diurnal evolution that is linked to behaviours and, for the present study, particularly in fall. The CH_4 emission is higher during grazing. The main explication is the impact of immediate post-feeding CH_4 production which

occurred when grass reach the rumen. A seasonal evolution was also present, with emissions increasing from summer to fall. This increase was due to a lower forage quality that compensated for the decrease in dry matter intake.

Acknowledgements

This research was funded by an ARC grant for Concerted Research Actions, financed by the French Community of Belgium (Wallonia-Brussels Federation), and relied on the Terra Teaching and Research Centre experimental platforms of Gembloux Agro-Bio Tech. The electro-mechanical expertise of M. Rudy Schartz (Biose department) is deeply acknowledged.

References

Andriamandroso, A.L.H., Lebeau, F., Beckers, Y., Froidmont, E., Dufrasne, I., Heinesch, B., Dumortier, P., Blanchy, G., Blaise, Y., Bindelle, J. 2017. Development of an open-source algorithm based on inertial measurement units (IMU) of a smartphone to detect cattle grass intake and ruminating behaviors. Computers & Electronics Agriculture 139:126–137

Blaise, Y., Lebeau, F., Andriamandroso, A., Beckers, Y., Heinesch, B., Bindelle, J. 2016. High rate monitoring CH4 production dynamics and their link with behavioral phases in cattle. In EAAP–67 th Annual Meeting, Belfast 2016.

Decruyenaere, V., Planchon, V., Dardenne, P., Stilmant, D. 2015. Prediction error and repeatability of near infrared reflectance spectroscopy applied to faeces samples in order to predict voluntary intake and digestibility of forages by ruminants. Animal Feed Science and Technology, 205, 49–59.

Dumortier, P., Aubinet, M., Beckers, Y., Chopin, H., Debacq, A., Gourlez de la Motte, L., Heinesch, B. 2017. Methane balance of an intensively grazed pasture and estimation of the enteric methane emissions from cattle. Agricultural and Forest Meteorology, 232, 527–535.

Garnsworthy, P. C., Craigon, J., Hernandez-Medrano, J. H., Saunders, N. 2012. Variation among individual dairy cows in methane measurements made on farm during milking. Journal of Dairy Science, 95(6), 3181–3189.

Gourlez de la Motte, L., Jérôme, E., Mamadou, O., Beckers, Y., Bodson, B., Heinesch, B., Aubinet, M. 2016. Carbon balance of an intensively grazed permanent grassland in southern Belgium. Agricultural and Forest Meteorology, 228–229, 370–383.

Hammond, K. J., Jones, A. K., Humphries, D. J., Crompton, L. A., Reynolds, C. K. 2016. Effects of diet forage source and neutral detergent fiber content on milk production of dairy cattle and methane emissions determined using GreenFeed and respiration chamber techniques. Journal of Dairy Science, 99(10), 7904–7917.

Haque, M. N., Cornou, C., Madsen, J. 2014. Estimation of methane emission using the CO2 method from dairy cows fed concentrate with different carbohydrate compositions in automatic milking system. Livestock Science, 164(1), 57–66.

Hegarty, R. S. 2013. Applicability of short-term emission measurements for on-farm quantification of enteric methane. Animal : An International Journal of Animal Bioscience, 7 Suppl 2, 401–8.

IPCC. 2007. Climate change 2007: the physical science basis. Intergovernmental Panel on Climate Change, 446(7137), 727–8.

Johnson, K. A., Johnson, D. E. 1995. Methane emissions from cattle. Journal of Animal Science, 73(8), 2483–2492.

Madsen, J., Bjerg, B. S., Hvelplund, T., Weisbjerg, M. R., Lund, P. 2010. Methane and carbon dioxide ratio in excreted air for quantification of the methane production from ruminants. Livestock Science, 129(1–3), 223–227.

Martin, C., Ferlay, A., Mosoni, P., Rochette, Y., Chilliard, Y., Doreau, M. 2016. Increasing linseed supply in dairy cow diets based on hay or corn silage: Effect on enteric methane emission, rumen microbial fermentation, and digestion. Journal of Dairy Science, 99(5), 3445–3456.

NOAA, 2017. Trends in Atmospheric Carbon Dioxide [Online] .Available: https://www.esrl.noaa.gov/gmd/ccgg/trends_ch4/

Saunois, M., Bousquet, P., Poulter, B., Peregon, A., Ciais, P., Canadell, J. G., … Zhu, Q. (2016). The Global Methane Budget: 2000-2012. Earth System Science Data Discussions, (June), 1–79.

Storm, I. M. L. D., Hellwing, A. L. F., Nielsen, N. I., Madsen, J. 2012. Methods for measuring and estimating methane emission from ruminants. Animals. 2:160–183

Tamminga, S., Van Straalen, W. M., Subnel, A. P. J., Meijer, R. G. M., Steg, A., Wever, C. J. G., Blok, M. C. 1994. The Dutch protein evaluation system: the DVE/OEB-system. Livestock Production Science, 40(2), 139–155.

Velazco, J. I., Mayer, D. G., Zimmerman, S., Hegarty, R. S. 2015. Use of short-term breath measures to estimate daily methane production by cattle. Animal, 1–9.

Evaluation of a cost-effective ammonia (NH_3) analyser in pig house

S. Zhuang[1], P. Van Overbeke[1], J. Vangeyte[1], B. Sonck[2,3], P. Demeyer[1]
[1]*Technology and Food Science Unit, Flanders Research Institute for Agriculture, Fisheries and Food (ILVO), Burg. van Gansberghelaan 115, 9820 Merelbeke, Belgium*
[2]*Animal Sciences Unit, Flanders Research Institute for Agriculture, Fisheries and Food (ILVO), Scheldeweg 68, 9090 Melle, Belgium*
[3]*Department of Biosystems Engineering, Faculty of Bioscience Engineering, Ghent University, Coupure links 653, 9000 Ghent, Belgium*
Peter.Demeyer@ilvo.vlaanderen.be

Abstract

Ammonia is one of the major gaseous pollutants in pig production. Although the issue is recognized in environmental policies and development of emission reduction techniques, there is a lack of suitable tools to provide sufficient monitoring. Measuring ammonia poses several technical challenges due to the physiochemical properties of the gas and the complexity of indoor air composition in pig housing. Standard ammonia measurement techniques are either too costly or labour intensive. A more efficient solution is required to improve the monitoring efficiency in pig farms. In this study a commercially available cost-effective tuneable-diode laser spectroscopy (TDLS) analyser was evaluated in both laboratory and field conditions, compared with a Fourier transform infrared spectroscopy (FTIR) analyser and a cavity ring-down spectroscopy (CRDS) analyser. The results suggested that the tested ammonia analyser can be applied for a relatively low cost ammonia monitoring system in pig houses.

Keywords: ammonia (NH_3), gas analyser, tuneable-diode laser analyser, pig housing

Introduction

Ammonia (NH_3) is one of the major gaseous pollutants produced in pig farming. The gas poses considerable risks to health and welfare in both human (National Research Council U.S., 2008) and farm animals (Jones *et al.*, 1996) due to its pungent smell, corrosivity and toxicity. After releasing into the atmosphere, NH_3 rapidly reacts with water and surrounding gases of other species, and then deposits back to the local environment. These processes vastly contribute to acidification, eutrophication and subsequent impact in local ecosystems.

Action plans of reducing NH_3 emission are incorporated in environmental policies, such as National Emission Ceilings Directive 2001/81/EC (NECD), Gothenburg Protocol (1999) and Directive on Integrated Pollution Preventions and Control (96/61/EC). In Europe agriculture is responsible for 93.7% of NH3 emission (EEA, 2012), and pig husbandry is one of the major sources (Groot Koerkamp *et al.*, 1998). A number of emission reduction techniques are recommended to pig farming in the Best Available Techniques (BAT) reference document (EU Commission, 2017). Techniques like air scrubbers are also certified by independent institutes, such as BWL in the Netherlands and DLG in Germany, for their emission reduction efficiencies.

A reliable tool is required for monitoring both the emission process and tracking the effectiveness of emission reducing measures. Nonetheless, measuring NH_3 is technically challenging due to its physicochemical property. The gas is sticky and can be absorbed by variant materials, known as the wall effect. Consequently measurement approaches that rely on gas sampling processes have to either risk underestimation or prolong the sampling time (Calvet *et al.*, 2013; Mosquera *et al.*, 2014). Open-path measurements are not affected by the wall effect, whereas the approaches are dependent on the transparency of the gas mixture. Chemically NH_3 is highly reactive. The gas can dissolve in and react with water. It also reacts with acidic gas species and converts to ammonium compounds.

Although a wide range of measuring principles and approaches are available for measuring airborne NH_3 (Ni and Heber, 2008; Liu *et al.*, 2012), only a few are reliable enough to be regarded as standard reference methods (VERA Secretariat, 2011; EU Commission, 2017). However, the reference methods are either labour intensive, *e.g.* wet chemical method, or too costly, *e.g.* Fourier transform infrared spectroscopy (FTIR) and photoacoustic spectroscopy (PAS). Applying those methods and techniques for general emission monitoring can be infeasible (EU Commission, 2017).

The presented study aimed to explore the potential of a cost-effective commercially available analyser in monitoring NH_3 concentration in pig houses.

Material and Methods

TDLS gas measurement

Tuneable diode laser spectroscopy (TDLS) is an optic technique for gas measurement using a narrow linewidth laser bean in infrared region (IR). Many gas species have distinctive light absorption spectrums. By focusing on a

spectrum region where a target gas has the least overlap with other gas species, TDLA is able to achieve very high selectivity. A trade-off is that the technique is limited to single-gas measurement. As the source light attenuates while transmitting through an absorptive medium, the concentration can be estimated using Beer–Lambert law

$$\log_{10} \frac{I_0}{I} = \epsilon \cdot L \cdot c \tag{1}$$

where,
I_0 is the intensity of incident light,
I is the intensity after transmitting through a medium,
ϵ is an absorptivity coefficient of the absorbing species,
L is the transmission distance through the medium,
c is the concentration of the absorption species in the medium.

In this study a LGD F200-A NH_3 TDLS analyser (Axetris® AG, Kaegiswil, Switzerland) was evaluated. The analyser (also referred as LGD F200 hereafter) incorporates a single-mode tuneable diode laser. The emitted light bean travels through a 20cm measurement cell and is reflected once, yielding a total transmission distance of 40cm. Gas measurement is taken continuously while a gas stream is flowing through the measurement cell. The tested analyser was factory calibrated for 0~100ppm_v ammonia measurement. Sampling rate of 1Hz was applied in all the presented experiments.

Laboratory condition test

The laboratory performance tests were conducted in an indoor environment where the operation conditions were in accordance with the LGD F200 user guide. An hour warming-up time was given to the analyser prior to the tests. Gas measurement set-up included all the necessary parts needed for a field test (Figure *1*). Inline flowrate and pressure were manually adjusted via a pressure reducer and two needle valves; the flowrate was fixed at 1.5 Nl/min, and the inline pressure was adjusted to approximately 1.0 atmosphere unless otherwise specified. All parts were connected with 4mm I.D. Teflon tubes. Most of the tubing were fixed with stainless-steel compression tube fittings. Exceptionally, push-in fittings were used on the water filter, barometer, vacuum pump and between the pressure reducer and the first needle valve.

Certified gas cylinders containing 0, 5.03(±0.15), 14.51(±0.44), 28.12(±0.84) and 68.8(±2.1) ppm_v NH_3 dilutions in nitrogen (N_2) were used to evaluate the sensor performance. In addition, 1.6, 2.0, 2.4 and 3.0 bar (abs.) inline pressure was applied on three of the concentrations to investigate pressure dependencies.

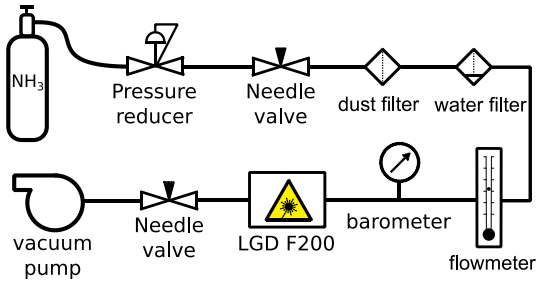


Figure 1 schematic of a typical set-up of NH_3 measurement using LGD F200 analyser.

Accuracy and precision of the LGD F200 were evaluated under both laboratory and practical conditions. The accuracy and precision were quantified by root-mean-square error (RMSE) with respect to respectively the applied reference concentration and sample mean. Ammonia mixture of each concentration was applied two times to the analyser as a step input of at least 5 minutes. To estimate accuracy and precision, a subset of one-minute measurements were taken 30 seconds before switching from NH_3 mixture to background.

Analyser response time was tested in laboratory condition and was indicated by T_{90}, *i.e.* the amount of time that the analyser took to reach 90% of the applied concentration. As measurement noise may potentially result in an underestimated response time, T_{90} was measured based on central moving average of the raw analyser output.

Field performance test

The field performance of LGD F200 was evaluated in two conditions. The first condition was in a fattening pig house, where two tests were conducted. In the first test NH_3 measurements were taken continuously at a ventilation exhaust for 24 hours. Similar sampling set-up as the laboratory (Figure *1*) test was used except that there was no gas cylinder or pressure reducer. Air flow was solely driven by a vacuum pump, and the flowrate was set at 1.5 Nl/min, and the inline pressure was approximately 850 mbar (abs.). Reference NH_3 concentrations were measured at a rate of one cycle per 54 minutes by a Gasmet™ CX4000 Fourier transform infrared spectroscopy (FTIR) analyser (Gasmet Technologies Oy, Helsinki, Finland), which was factory calibrated for 0~150ppm_v NH_3 measurement. In each cycle three consecutive measurements with 1 minute interval were taken by the FTIR. Air samples to the two analysers were drawn from separate lines, where the distance between the sampling location was < 2cm.

In the second test LGD F200 and FTIR were sequentially connected, such that an air sample would flowed through both analysers. In this test air samples were taken from eight sampling lines which lead to eight compartments in the pig house. Leakages, *i.e.* contaminating the sampled air with ambient air, were intentionally induced in two of the sampling lines. Switching between sampling lines were performed manually. Measurement interval of the FTIR was set to 2 seconds.

The second test condition was in a beef cattle barn. Reference concentrations of NH_3 were measured every 5 seconds by a Picarro G2103 cavity ring-down spectroscopy (CRDS) analyser (Picarro, California, United States), which was factory calibrated for 0~5ppm$_v$ NH_3 measurement. Air samples were taken from eight locations via a multichannel gas sampler. The sampled air sequentially passed through the LGD F200 and the CRDS analyser for NH_3 measurement. At such a low concentration level the sensor noise could be overwhelming. Thus the LGD F200 was configured to apply an exponential filter on the sensor outputs for a better precision.

Results and Discussion

Laboratory test

The average accuracy and precision of LGD F200 was respectively 0.68 and 0.50ppm$_v$ (Table 1). Both indicators showed no dependency on the NH_3 concentrations. The accuracy on 28.12ppm$_v$ was worse than the others. This might associate with the fact that the gas cylinder was almost empty at the time of the experiment. One the other hand, as the uncertainty in the reference gas cylinders were larger for higher concentrations, the estimated error might differ from the ground truth.

One way to improve the accuracy and precision is via smoothing. For example, the two indicators was improved to 0.34 and 0.08ppm$_v$ respectively after implementing a 30-point moving average. Further potential improvement can be done by adjusting the calibration curve especially for the concentration range of interest.

Table 1 Accuracy and precision of the LGD F200 measurements on different ammonia concentrations in two repeats.

Reference concentration (ppm_v)	**Accuracy**		**Precision**	
	Repeat 1	Repeat 2	Repeat 1	Repeat 2
0	0.50	0.57	0.43	0.56
5.03±0.15	0.56	0.50	0.46	0.49
14.51±0.44	0.64	0.68	0.57	0.48
28.12±0.84	0.98	0.99	0.45	0.43
68.8±2.1	0.51	0.87	0.47	0.62

Average response time T_{90} was 37 seconds at 1.5 Nl/min flow rate for most concentrations (Figure *2*). Nonetheless, T_{90} with 5.03 ppm cylinder was more than 2 minutes. The reason for this long response time was unclear. A possible explanation was that the low concentration is associated with prolonged saturation time due to the wall effect (Rom and Zhang, 2010). Although Teflon tubing is generally recommended in NH_3 measurement, it was reported to cause approximately 1 ppm_v NH_3 underestimation regardless of tube length or inlet concentration (Mukhtar *et al.*, 2003). Another possibility was that leakages occurred after changing a gas cylinder, and this caused the ambient air being mixed into the gas samples.

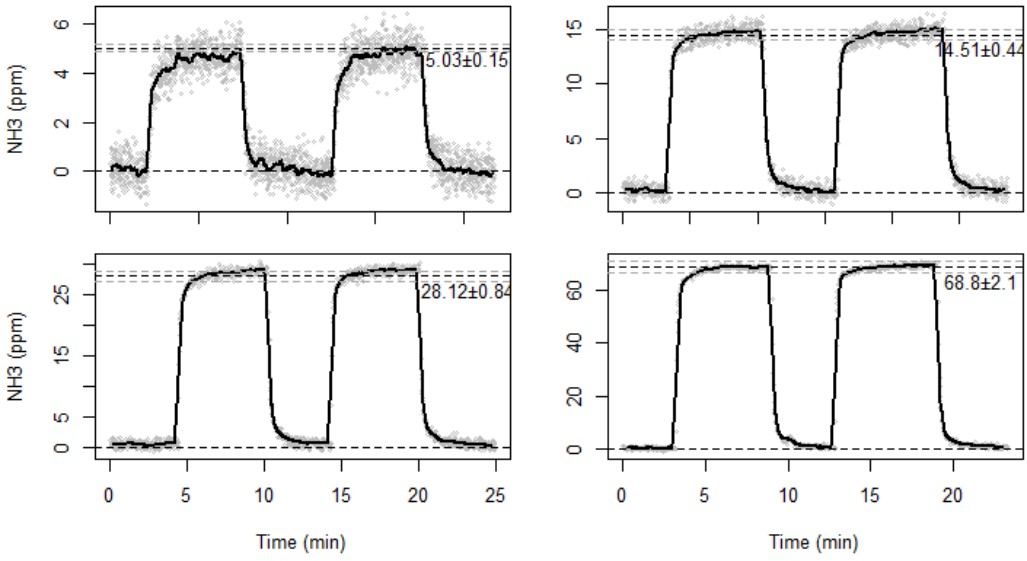


Figure 2 Ammonia measurement by LGD F200 on gas cylinders. The grey dots are the raw analyser output, black bold lines are central moving average over a 30-second window. The black dashed lines indicate reference values and baseline, and the grey dashed lines denote the confidence interval of the mixture.

Pressure is an important factor in TDLS gas measurement due to the pressure broadening effect (Hodgkinson and Tatam, 2013). On LGD F200 overpressure resulted in significant underestimation of the NH_3 concentration (Figure *3*Figure *6*). This behaviour is in contradiction to the ideal gas law that gas concentration and pressure are directly proportional at fixed temperature. Sensor precision also seemed to decrease with inline pressure. It was unclear if this instability was related to the sensor characteristics or turbulence due to leakage.

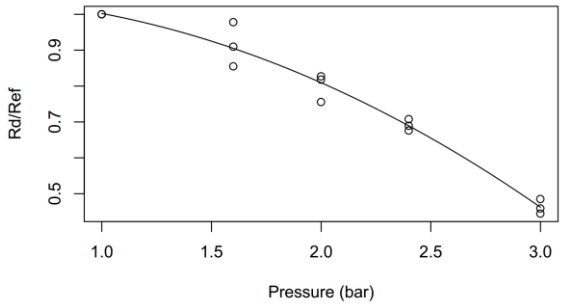


Figure 3 Relationship between inline pressure and sensor reading/reference ratio in LGD F200.

Field test vs FTIR

Ammonia measurements of 24 hours were taken from a fattening pig house using LGD F200 and FTIR analyser (Figure *4*). The R^2 between the two analyser measurements was 0.82. This degree of correlation fell in the observed range of an earlier reported inter-agreement between different analysers in field measurement (von Bobrutzki *et al.*, 2010). However, the LGD F200 on average reported 0.8ppm_v higher than FTIR. Randomness of the residuals was verified by a normality check and autocorrelation function, suggesting that the estimation difference between LGD F200 and FTIR was a systematic error. A similar phenomenon was once observed in the same set-up, where FTIR underestimated NH_3 concentration by 4 ppm_v due to a severe leakage in the sampling line.

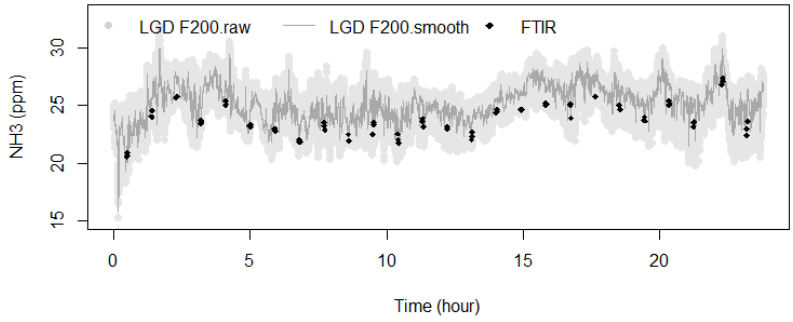


Figure 4 Ammonia concentration measured by Axetris LGD F200 and Gasmet FTIR gas analyser.

In the second test LGD F200 and FTIR measured the same gas sample and were subjected to the some systematic flaws, if any, in the sampling process. The measured concentrations and degree of fluctuation were in general similar between the two analysers (Figure *5*). When leakages (subtest 6 and 8) or unknown events (subtest 2 and 10) happened in the sampling process, LGD F200 responded in the same way as FTIR. Notice that LGD F200 occasionally measured either higher (subtest 2 and 10) or lower concentrations (subtest 1). Since such phenomenon was not consistently observed, it was likely caused by external factors that were exclusive to these subtests.

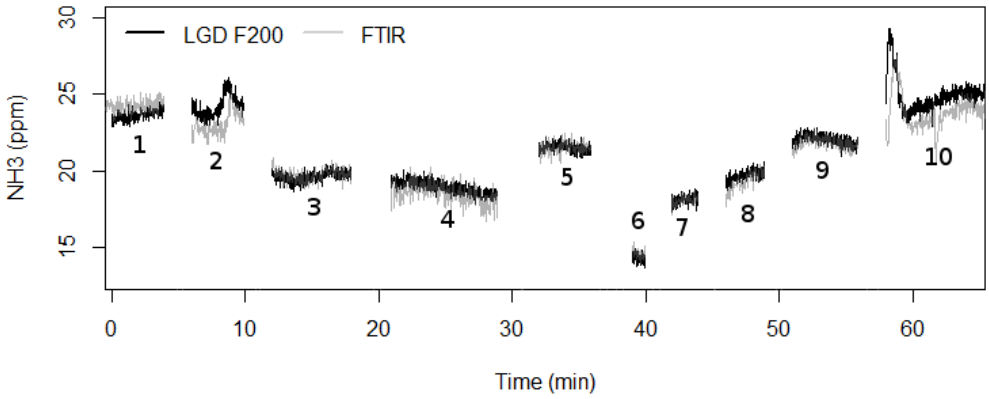


Figure 5 Ammonia measurement by Axetris LGD F200 and Gasmet FTIR in 10 subtests marked by numbers. Measurements collected during manual manipulation of the sampling lines were discarded. The sampled air flowed sequentially through LGD F200 and FTIR.

Filed test vs Picarro

LGD F200 was tested in a beef cattle barn where the ammonia concentration varied between 2~3.5ppm$_v$ (Figure *6*). The raw LGD F200 outputs showed a decent match with Picarro, but still consisted of low frequency fluctuations. The measurement data were further processed with a low pass filter, and eventually yielded an RMSE of 0.09ppm$_v$ with respect to the Picarro. This performance was better than which of the laboratory test, and it was possibly because that the measurement condition suited the requirement of LGD F200. This suggests that, while being provided with an optimal operation condition, the analyser may also suited for, for instance, cattle barns and pasture where the NH_3 concentration is generally low. Nonetheless, LGD F200 is unlikely capable of ppb$_v$ level measurement due to its short transmission length. Distance of several tens of metres is required in TDLS techniques at this concentration level (Werle, 2004).

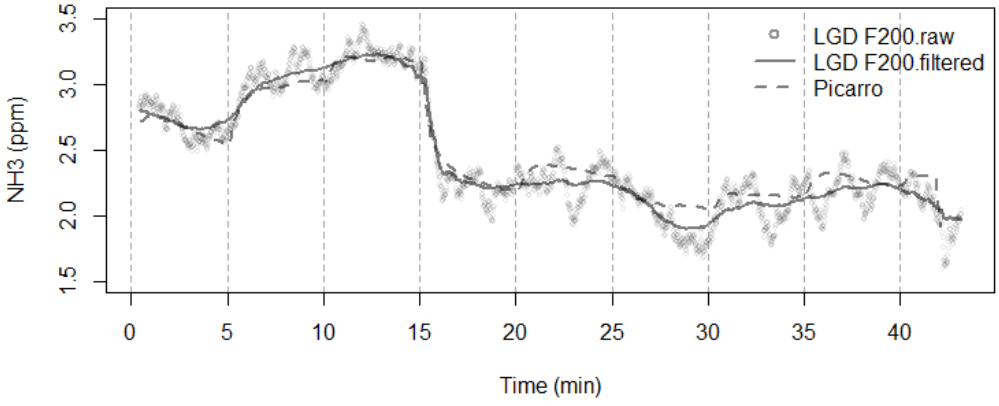


Figure 6 Ammonia measurement by Axetris LGD F200 and Picarro G2103 in a beef cattle barn. The vertical dashed lines denote the moment in changing sampling locations. Ammonia concentration at each sampling location was measured for 5 minutes.

Cost and usability

The LGD F200 analyser showed a comparable performance to the reference equipment in ammonia measurement, with a cost of 5~20 times less. The analyser nevertheless is designed for OEM purpose and does not incorporate any gas sampling functionality. It should be either merged into a standalone gas monitoring system such as the BPEX system (Demmers, 2015), or coupled with a separate gas sampling system. Although extra costs are needed for building a sampling system, they will unlikely be significant enough to make up the cost difference between a LGD F200 and a reference devices.

Conclusions

A promising performance of a commercially available tuneable diode laser spectroscopy (TLDS) based analyser for airborne ammonia monitoring in pig house was presented. The analyser was capable of producing similar measurement outcome as a Fourier transform infrared spectroscopy (FTIR) and a cavity ring-down spectroscopy (CRDS) analyser. On the other hand, optimal sampling processes also played an important role in acquiring reliable measurements. The evaluation of the TDLS analyser is not completed at this stage. Additional primary sensor characteristics and the influence of external factors will be further investigated.

References

von Bobrutzki, K., Braban, C. F., Famulari, D., Jones, S. K., Blackall, T., Smith, T. E. L., Blom, M., Coe, H., Gallagher, M., Ghalaieny, M., McGillen, M. R., Percival, C. J., Whitehead, J. D., Ellis, R., Murphy, J., Mohacsi, A., Pogany, A., Junninen, H., Rantanen, S., Sutton, M. A. and Nemitz, E. 2010. Field inter-comparison of eleven atmospheric ammonia measurement techniques, *Atmospheric Measurement Techniques*, 3(August), pp. 91–112.

Calvet, S., Gates, R. S., Zhang, G., Estellés, F., Ogink, N. W. M., Pedersen, S. and Berckmans, D. 2013. Measuring gas emissions from livestock buildings: a review on uncertainty analysis and error sources, *Biosystems Engineering*, 116(3), pp. 221–231.

Demmers, D. 2015. Verification of the BPEX Multi-Channel Analyser system against the ‘ Gold Standard ’ ammonia analyser under field conditions

EU Commission 2017. Commission implementing decision (eu) 2017/302 of 15 february 2017

Groot Koerkamp, P. W. G., Metz, J. H. M., Uenk, G. H., Phillips, V. R., Holden, M. R., Sneath, R. W., Short, J. L., White, R. P. P., Hartung, J., Seedorf, J., Schröder, M., Linkert, K. H., Pedersen, S., Takai, H., Johnsen, J. O. and Wathes, C. M. 1998. Concentrations and emissions of ammonia in livestock buildings in northern europe, *Journal of Agricultural Engineering Research*, 70(1), pp. 79–95.

Hodgkinson, J. and Tatam, R. P. 2013. Optical gas sensing: a review, *Measurement Science and Technology*, 24(1), p. 012004.

Jones, J. B., Burgess, L. R., Webster, A. J. F. and Wathes, C. M. 1996. Behavioural responses of pigs to atmospheric ammonia in a behavioural responses of pigs to atmospheric ammonia in a chronic choice test, *Animal Science*, 63(3), pp. 437–445.

Liu, X., Cheng, S., Liu, H., Hu, S., Zhang, D., Ning, H. and Engineering, I. 2012. A survey on gas sensing technology, *Sensors*, 12(7), pp. 9635–9665.

Mosquera, J., Edouard, N., Guiziou, F., Melse, R. W., Riis, A. L., Sommer, S. and Brusselman, E. 2014. Decision document on the revision of the VERA protocol on air cleaning technologies: Measuring techniques for the determination of the removal efficiency for ammonia. Wageningen

Mukhtar, S., Rose, A. J., Capareda, S. C., Boriack, C. N., Lacey, R. E., Shaw, B. W. and Parnell Jr., C. B. 2003. Assessment of ammonia adsorption onto teflon and ldpe tubing, *CIGR Journal of Scientific Research and Development*, V(December), pp. 1–13.

National Research Council U.S. 2008. Acute Exposure Guideline Levels for Selected Airborne Chemicals. Washington, D.C.: National Academies Press

Ni, J. Q. and Heber, A. J. 2008. Sampling and measurement of ammonia at animal facilities, *Advances in Agronomy*. Edited by D. Sparks, 98(08), pp. 201–269.

Rom, H. B. and Zhang, G. Q. 2010. Time delay for aerial ammonia concentration measurements in livestock buildings, *Sensors*, 10(5), pp. 4634–4642.

VERA Secretariat 2011. Test protocal for Livestock Housing and Management Systems. Denmark

Werle, P. W. 2004. Diode-laser sensors for in-situ gas analysis, in *Laser in Environmental and Life Sciences*. Springer Berlin Heidelberg, pp. 223–244.

Poster Session

French virtual prototype of a broiler precision building integrating innovations to meet the specific needs of each farmer

P. Créach[1], E. Pigache[2], G. Amand[1], P. Robin[3], M. Hassouna[3], C. Nicolas[4], J.P. Prigent[5], A. Keita[6]
[1]*ITAVI 41, rue de Beaucemaine, 22440 Ploufragan, France*
[2]*Chambre Régionale d'Agriculture des Pays de la Loire - 49105 Angers, France*
[3]*INRA, UMR SAS – 35000 Rennes, France*
[4]*Chambre Régionale d'Agriculture de Bretagne - 29270 Carhaix, France*
[5]*Avipôle Formation – 22440 Ploufragan, France*
[6]*ANSES, Seleac – 22440 Ploufragan, France*
creach@itavi.asso.fr

Abstract

The poultry house is an important vector for the broiler production sector, in areas as varied as zootechnical performance, animal health and welfare, quality of work for the farmer, yield and product quality for slaughterhouses and consumers, and environmental impacts. Given the loss of competitiveness of the French poultry production sector in comparison with other major producing countries in Europe, an inventory of poultry buildings showed less specialisation, a modest average size of conventional barns and less modern facilities. Based on these observations, the Mixed Technological Network ("Livestock Buildings of Tomorrow") has been working on a virtual prototype of a broiler farm in France that can be viable, competitive and modern.
Poultry experts working in different specialisms met to define the virtual prototype in terms of the design, construction and use of this future building. New avenues will be explored for next generations of buildings.

This paper will focus on the potential contribution of precision livestock farming in achieving energy savings at farm level (efficient insulation, cost-effective lighting, optimum climate control inside the building, air exchangers), minimising the environmental impact (use of a biomass heating device allowing indirect combustion, solar panels) and ensuring the health and welfare of broilers. It also seeks more precise input and production monitoring (feed, water, energy, broiler growth and activity, indoor environmental control) to guarantee the zootechnical performance, health and welfare of broilers.
With this prototype building, breeders will be able to implement the necessary combinations to meet specific needs. The recent development of connected management devices should facilitate the introduction of new technologies and the response to the expectations of the poultry sector and society in general.

Integration of these new technologies into the current building stock and into the breeder's knowledge should facilitate professionalisation of rearing facilities, improve the profitability of investments and make livestock breeding attractive to the next generation.

Keywords: Precision Livestock Farming (PLF), broiler, building, technologies, innovations, specifications

Introduction

Between 1998 and 2008, the production of poultry meat in France decreased by about 20%. This decrease is largely due to a decline in exports, including within Europe, and an increase in imports. These concerns gave rise to an inventory of poultry buildings in France and a comparison with other European countries which are large poultry producers with better competitiveness. It was observed that French poultry farming is poorly specialised and of modest size. Indeed, about 80% of farms have another activity (cattle production or cereal cultivation, for example), poultry production being a supplementary activity. Furthermore, the average size of a French poultry farm is about 1700 m2, compared with 4000 to 5000 m2 in Germany and the Netherlands. The buildings in France are less modern with, for example, clay soils in most cases, while the floors of buildings in other comparable countries are concrete. Based on these observations and within the framework of the Mixed Technological Network (RMT in French) "Livestock Buildings of Tomorrow", a group a poultry experts worked on a virtual prototype of a meat-producing poultry farm in France which can be viable, competitive and modern. The main objective of this virtual prototype was to design poultry buildings in France that meet farmers' and society's expectations in terms of respect for the environment, animal health and welfare, productivity and working conditions. This article discusses how the virtual prototype was developed, focusing on the contribution of precision livestock farming to achieving the set objectives.

Materials and methods

The virtual prototype referred to above was designed and structured on the basis of data from poultry experts with different specialisms (precision livestock farming, thermal and fluid dynamics, building management, equipment, control of energy consumption and provision of training in the poultry sector). These eight experts from different organisations met under the Mixed Technological Network (RMT in French) "Livestock Buildings of Tomorrow" to define the virtual prototype in terms of the design, construction and use of this future

building. This RMT is based on partnerships between certain people involved in agricultural, development and education research and promotes exchanges of information on topics related to livestock buildings. The aspects discussed are based on the results of studies and feedback from each of the experts.

The priority of this prototype is based on precision livestock farming, given the growing importance of this activity and its significant prospects in the poultry sector. Precision livestock farming (PLF) is defined as the coordinated use of technologies to measure different indicators, on animals and their environment, to improve livestock monitoring and management. PLF allows real-time management of different types of data (data from the animals, their feed consumption, the atmosphere in the house, etc.) (Creach et al., 2017). The building will focus on precision equipment which has a direct impact on the design and/or organisation and/or use of livestock buildings, the installation of such equipment or management of the information they generate. According to the rules set by the RMT when considering this prototype, it will be possible to explore avenues which are not necessarily viable, especially from an economic point of view. The return on investment of the innovations and technologies discussed is not yet known. The economic aspect should not be a barrier to innovation (RMT, 2017).

Important objectives of this prototype must be to save inputs (animal litter, water, energy), to produce energy from renewable sources and to provide good insulation, heating, ventilation and low-energy lighting. In addition, it is important to treat and utilise the manure by providing sufficient land for spreading or by carrying out collective or non-collective composting. Moreover, the attractiveness of the farmer's work (mechanisation, outsourcing some tasks) must be improved with the aim of attracting more young people to the profession.

I. Results and discussion

1. General specifications of the French prototype

The experts chose broiler chicken production because it is the dominant form of poultry production, and is also the sector where the French industry must regain its competitiveness. In this context, one of the main issues and objectives is to increase the average size of buildings and farms (compared to the current situation) in order to achieve economies of scale and encourage automation. For example, the average size of a professional French broiler farm is 30,000 birds, compared with 60,000 in Germany and more than 90,000 in the United Kingdom.

The optimal average size of French farms, in terms of the workforce involved, would be 6000 to 8000 m² of poultry buildings per farm, with four buildings between 1500 and 2000 m2. This would allow economies of scale. Indeed,

beyond 2000 m² per building, there is no economy of scale because there are more health problems and less social acceptance. Beyond 2000 m², the size of the building increases significantly (width greater than 20 m) and consequently the cost of the infrastructure also rises. In terms of the workforce, the prototype could work either with a farmer and external workers (service delivery) or alternately with permanent employees. This means that the farmer is either working alone with the help of external help or working with a permanent employee.

2. PLF specifications at farm level and integration of technological innovations using existing equipments

Energy saving

In terms of energy saving, the farm must be equipped with efficient insulation materials in order to limit heat loss and overcome the external climatic conditions. Indeed, ineffective insulation will increase heating energy consumption. Insulation must be reinforced in roofing and substructures, primarily for the thermal comfort of animals rather than issues related to the loss of energy.

LEDs (Light-Emitting Diodes) can also contribute to energy savings because their high output (70 to 95 lumens per Watt) can be combined with an appropriate lighting programme (Photos 1 and 2). LED devices are also attractive because of their longevity.

Photos 1 and 2 : LED (Light-Emitting Diode) in broiler barn (photo credit: ITAVI)

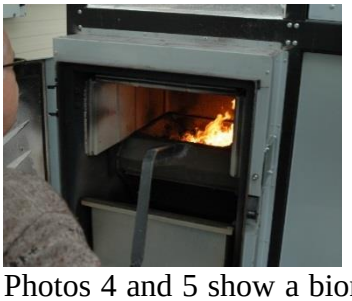
The future French farm prototype will use natural light with photocells in a semi-clear building (i.e. with both natural and artificial lighting systems) (Photo 3). These cells can maintain a selected lighting level depending on the natural light input by automatic monitoring of the window shutters. They also help to save energy and ensure broiler welfare.

Photo 3: Natural light in a broiler barn (photo credit: ITAVI).

Currently, new ventilation technologies are being developed for optimum climate control of buildings. They use fresh air supply systems and fans for air extraction. The inlet flap can consist of several parts (discontinuous flaps), allowing precise adjustment of the air intake. On the other hand, companies also sell economical and progressive fans which better match the animal's air renewal needs. These new technologies therefore allow farmers to use lateral ventilation with progressive fans at chick placement (fewer stop phases, more stable ventilation and uniform supply of fresh air) while longitudinal extraction is used at the end of the growing period.

Preserving the environment

For a circular economy, the prototype will use a biomass boiler (using mainly wood pellets) in order to reduce propane gas consumption for heating (Photos 4 and 5). Innovative systems are being developed to use manure for heating. Other advantages of the system are the lower cost of raw materials and an average drop in relative humidity of about 20 % during the heating period (ITAVI 2016).



Photos 4 and 5 show a biomass heating device using wood pellets (photo credit: ITAVI)

This will enable farmers to reduce consumption of fossil fuels. Moreover, this system involves indirect combustion which does not inject steam into the building, unlike direct combustion systems (e.g. propane gas heaters).

Heat exchangers allow heat recovery by means of an air exchanger (calories transferred from the hot (extracted) air to the (entering) cold air) and can thus reduce the farmer's energy bill and production costs (Photos 6 and 7). Indeed, gas used for heating represents nearly 30% of the variable costs (costs excluding chicks and feed consumed). According to ITAVI (2016), heat exchangers help to improve the climate inside the building by reducing dust (in 43% of cases), ammonia (observed in 83% of cases) and relative humidity (11% decrease). Moreover, they also ensure thermal comfort for the animals.


Photos 6 and 7: Heat exchangers for a broiler barn (photo credit: ITAVI).

Indirect combustion and biomass heating devices may have other advantages. They can help to reduce carbon dioxide concentrations inside the building compared with a system without heat exchangers and indirect combustion.

Installation of solar panels on the roof of the farm building will make it possible to produce electricity which can be used on the farm or sold. This preserves the environment while also improving the profitability of the farm.

Other sustainability aspects must also be taken into account: recycling of building materials, profitability of manure management, reducing emissions (ammonia, greenhouse gases, dust), thereby creating a building that will be fit for use by several generations of farmers, with good integration of the buildings into the landscape.

Ensuring the health and welfare of broilers

The virtual building will be equipped with biosecurity facilities. A specific route for equipment, vehicles and people will be defined, for example by first visiting the birds which are least at risk, followed by those which are most at risk. It is

important to isolate the farm area using a fence and install a parking area. It is also important to have a central facility for the farm where all personnel who access the different buildings must change their clothes and shoes. Another point is to create concrete areas in front of doors and gates, and to recover the wash water from the buildings. Inside the buildings the floors will be concreted in order to facilitate cleaning and disinfection.

As discussed above (section 2: energy saving), optimum building climate control is necessary to provide a safe atmosphere for the chickens and ensure good broiler health and welfare. Climate control is currently based only on the temperature and relative humidity inside the building. The next step will probably be to also take account of carbon dioxide measurements which are a good indicator of air renewal.

Feeding with precision

To know the state of feed stocks and estimate average consumption by the animals, each silo can be equipped with a strain gauge (Photos 8 and 9). This type of device allows monitoring of the stock of feed in order to manage and to optimise deliveries (photos R and T). It is also possible to measure water and feed consumption precisely and in real time and to monitor animal weight to provide better management of the broiler batch and better weight prediction at slaughter (Photo 10).

Automatic weighing device with PESbox (developed by Tuffigo- (photo credit: ITAVI).

Photos 8 (photo credit: Tuffigo-Rapidex) and 9 (photo credit: Sodalec): examples of strain gauges.

Photo 10: suspended tray Rapidex)

Facilitating the farmer’s work

Automation / mechanisation of hard work through automatic feed distribution and automatic triggering of misting when high temperatures occur in the house are tools which can reduce the farmer’s workload. A connected electronic

controller with a touchscreen allows farmers to centralise large amounts of data. These electronic controllers make it easier to monitor flow performance and health and to control the atmosphere parameters in the house, providing farmers with effective alerts. They also enable farmers to transmit data to partners.

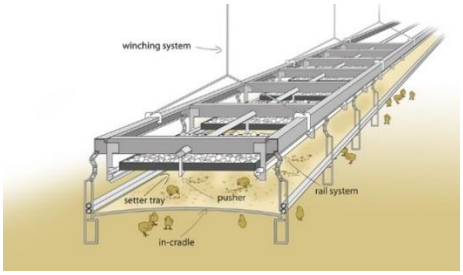
3. Prospects

Many PLF technologies can be applied in the poultry sector to help farmers by making their work easier and improving productivity.
Technology such as connected glasses represents an interesting tool for farmers and could make it possible to initiate actions verbally, thus freeing the hands. Potential applications in broiler production include assisting practitioners (e.g. training, procedures) and following up on implemented measures (e.g. pododermatitis scoring) (Creach et al., 2017).

In the future, algorithms will allow automatic, continuous and quantitative monitoring of broiler behaviour and welfare by image analysis (barns equipped with cameras, Photo 13). Image analysis could detect abnormalities by examining animal distribution or movement and could establish early warning thresholds to alert farmers promptly in the event of health or animal welfare problems (Creach et al., 2017).

Photo 13: Camera image of a broiler flock in the barn (photo credit : ITAVI).

The X-treck system recently developed by Vencomatic allows in-barn hatching. Trays with 18-day incubated eggs are placed on a rail system in the barn (Photos 11 and 12). On incubation days 19 and 20 the chicks hatch in the barn. With this system, the eggs are transported and not the live animals. After hatching, chicks have direct access to water and food. They are already in their living environment so there is no thermal variation after hatching. The X-treck system appears to produce good results in terms of broiler performance (boosts intestinal development and the immune system [information from Vencomatic]) and should be studied in more detail.



Photos 11 and 12: X-treck system developed by Vencomatic in a broiler barn (photo credit: Vencomatic)

In the future, by contrast to whole-flock management, sentinel animals could be equipped with micro-sensors (thermometer, pedometer, accelerometer, RFID chips, etc.) to provide information at individual scale. Recording and processing of sounds in the barn could be promising technology for detecting health, stress or growth issues. For example, the University of Leuven has studied food intake of broilers using audio technology for continuous, automatic monitoring. Under experimental conditions, a correlation was found between ingested feed and broiler feed pecking sounds (Berckmans et al., 2015). Moreover, a recent study by Fontana et al. (I. Fontana et al., 2016) shows that the vocalisation frequency and patterns changed as the age and weight of the broilers increased. This result shows that there is potential for audio monitoring.

PLF technologies generate a large quantity of data. These data can ensure and improve product traceability. Indeed, it is possible to trace the life cycle of a product from the breeder to the consumer.

Conclusions

The design of this prototype makes it possible to analyse the benefit of combining known equipment and technological innovations in order to better respond to the priorities of specific rearing situations. It aims to save energy at farm level, preserve the environment, ensure the health and welfare of broilers, allow more precise input and production monitoring and provide real-time data transmission to farmers and their partners. All the equipment incorporated into the virtual prototype will be connected and centralised, and all the information obtained will be used to create an efficient dashboard and warning system for the farmer.

With this prototype building, breeders will be able to implement the necessary combinations to meet specific needs. Combining these investments in modern livestock facilities will encourage professionalisation, improve the profitability of investments and attract new generations. As well as improving productivity,

PLF will also help to make the farmer's work easier (ergonomics, safety, pain) and enhance the modernity and attractiveness of the profession.

Acknowledgements

The author gratefully acknowledges all her co-authors for their investment in the success of this study.

References

Berckmans.D et al., 2015, Elevage de précision : l'intérêt pour l'éleveur du futur ; communication orale 15ème journée d'étude des productions porcines et avicoles à Beez.

Creach.P, Doutart.E, Bouvarel.I ; 2017. Precision livestock farming and big data: a new challenge for poultry sector. Journées de la recherche avicole et palmipèdes à foie gras.

Fontana.I, Tullo.E, Scrase.A and Butterworth.A, 2016. Vocalisation sound pattern identification in young broiler chickens. Animal, volume 10, issue 9, pp. 1567-1574.

ITAVI and CIPC, 2014. Les nouveaux modèles d'élevage avicole. 24 pages.

ITAVI, 2016. Les échangeurs récupérateurs de chaleur. Plaquette réalisée avec la contribution financière de l'ADEME à travers du POBE et de la région Rhône-Alpes à travers le PEP avicole.

RMT (the Mixed Technological Network in english) "Livestock Buildings of Tomorrow", 2017. 3 priorities of the RMT "Livestock Buildings of Tomorrow" [on line : http://www.rmt-batiments.org/IMG/pdf/RMT-batiments-de-demain_Note-introductive-3-thematiques_23-01-2017.pdf]

AWARTECH Project: An overview

V. Fitas da Cruz[1], A. Neves[2], D. Pires[3]
[1]*Rural Engineering Department, Évora University, Portugal,*
[2]*Equiporave Ibérica Lda*
[3]*Hexastep*
vfc@uevora.pt

Abstract

In a world that is increasingly demanding high-quality food, produced with proper respect for animal welfare, ethical principles and social and environmental responsibility, special attention to must be paid to cost rationalisation and increased efficiency in the use of production factors and value chains. Pig production is an important sector in the Portuguese farming economy. The need to change, grow, resize and reorganise makes pig farming an excellent case study for challenges in animal welfare and its potential to create wealth, employment and sustainable land use, in harmony with environmental goals. Efficient pig meat production, taking account of animal welfare and environmental conditions, is essential if we are to achieve economically viable and sustainable results and good market access. The Alentejo region, where half of the national swine herd is located and also where the climate variables are most extreme, requires efficient monitoring of environmental and physiological variables to ensure sustainable and safe production.

The main objective of the AWARTECH (Animal Welfare Adjusted Real Time Environmental Conditions of Housing) project, which started in September 2016 with EU financial support through the Portugal2020 programme, is to create and develop an innovative tool for precision livestock farming which will support and reinforce the pig value chain in a multidimensional context. This paper describes the main activities of the project, starting with the development of a small lab prototype which will serve as the basis for the living lab phase where the “Awartech Smart Sensing” technological platform will be developed.

Keywords: Precision livestock farming, animal welfare, real time, environmental control, swine

Introduction

Nowadays, the world is becoming increasingly demanding with regard to food quality, expecting food that is produced in compliance with animal welfare regulations, ethical principles and social and environmental responsibilities. This requires special care with the rationalisation of costs and increased efficiency in the use of production factors and value chains.
On the one hand, intensifying production by pursuing self-supply or higher competitiveness objectives may lead to a decline in animal welfare conditions; on the other hand, the lack of attention paid to animal welfare is a factor which contributes to lower productive efficiency and, as a consequence, a drop in economic performance and a loss of competitiveness.

In addition, animal welfare is also a growing concern for society and consumers, who are looking for quality and not price in differentiated products, and demanding humane treatment of animals during production, transport and slaughter.

One of the most important livestock sectors in Portugal is pig farming, which represents approximately 25% of the gross animal product and 10% of the gross agricultural product. This sector is undergoing change, with a need to grow, reorganise and resize, reflecting current global trends. In this way, it will become a generator of employment and wealth, contributing to sustainability and employment in rural areas, in harmony with the interests of the territory and the environment. It is therefore necessary to create new projects with ambitious and innovative ideas that are based on the principle of good production practices and consider animal and worker welfare, food safety and respect for the environment.

During the growing and fattening stages, in addition to their nutritional and health needs, pigs have other requirements which ensure that animal productivity is not compromised. Engineering and environmental control are essential in order to provide the necessary environmental conditions.

Climatic (environmental) factors such as temperature, relative humidity and air velocity have a significant influence on the animals, with an impact on their behavioural, physiological and immunological status (Cruz, 1997). This type of production requires an appropriate environmental control system which maximises the welfare and productivity of animals and extends the lifespan of the infrastructure (Baêta e Souza, 2010; cited in Fournel, 2017).

Environmental modification is usually achieved by means of ventilation (natural or mechanical), supplementary heaters for cold conditions and cooling

equipment for high-temperature conditions (Baêta and Souza, 2016; cited in Fournel, 2016).

This equipment is designed to control environmental variables such as temperature, humidity, air velocity and airborne contaminants. However, the ideal environmental conditions vary according to the local climate, the design of the building, the number of animals and the production phase. The ventilation and heating or cooling needs for control of environmental conditions within the livestock installation, are determined based on production of heat and humidity (Baêta e Souza, 2010; cited in Fournel, 2017).

The indoor environmental conditions of a building are a key factor in the success of a farm and must guarantee animal welfare and appropriate production conditions, leading to economic profitability. To assess whether the animals are housed under good welfare conditions, it is necessary to study and understand some indicators which can express the adjustment capacity (biological needs) or failure (stress/suffering, low performance and abnormal behaviour) in their adaptation to the environment provided (Arbel and Cruz, 2006), such as: physiological, behavioural, health-related and production indicators.

Automatic control of the microenvironment in a livestock installation is a process which is generally based on feedback from the indoor air temperature measured in a building (Fournel, 2017). This assessment presents inherent problems, since it is not interactive with the needs of the animals. Air temperature does not represent the environment as a whole, because it also includes environmental factors such as humidity (especially in hot conditions), radiation (in poorly insulated buildings), type of floor and floor conditions (dry and/or wet), behavioural changes, changes in the nutritional status and health of the animals (Pandorfi et al., 2012).

Over the past two decades, a number of new technologies have become available to support environmental conditioning systems in livestock buildings, and limited progress has been made in the development of control algorithms. In order to obtain greater benefit from the new technologies available, it is necessary to integrate more knowledge about the interaction between animal responses and control actions into the algorithms applied (Banhazi, et al., 2009).

In this context, it is important to monitor animal welfare conditions in pig housing, using the innovations provided by precision livestock farming. These could serve as the basic concept for development of an advanced control system based on automatic monitoring, at an appropriate frequency of environmental, physiological and behavioural variables.

The main objective of the AWARTECH (Animal Welfare Adjusted Real Time Environmental Conditions of Housing) is to create and develop an innovative

tool for precision livestock farming which controls and monitors, in real time, the environmental and welfare conditions that lead to economic and productive sustainability of farms. This differentiates this project from other, already existing projects.

Materials and methods

The purpose of this project is to measure, monitor and control environmental and animal (physiological and behavioural) parameters in real time, at any place and at any time.
This project is divided into several phases, starting with preparation activities for the entire project management component, logistics, preparation of work teams and the project office.

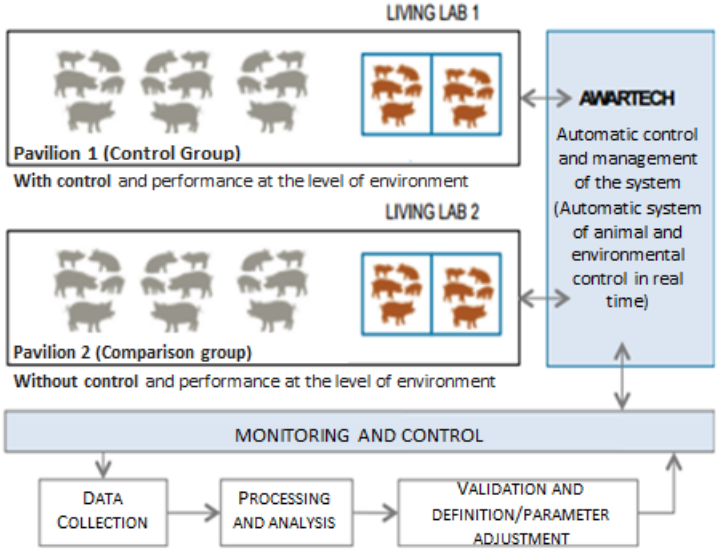


Figure 1 - Simplified diagram of the functional prototype "Living-Lab"

The next step is the preliminary study and investigation phases, with the involvement of all the collaborators, to characterise the parameters and collect the data for “AWARTECH”, namely in a living-lab and small-lab-prototype.
In the “living-lab” environment we defined two groups of animals: the control group and the comparison group. These groups will be housed in pavilions, each measuring approximately 90 x 20 m. We considered two areas of approximately 4.0 m x 4.0 m for monitoring. Each area will house 15 animals. Thus, the final configuration is composed of four areas measuring 4.0 m x 4.0 m, with a total of 60 animals undergoing simultaneous monitoring. Two feeders will be installed in each pavilion (one per area, four in total), with capacity for 15 animals per

machine. At the feeder each animal will be recognised by viachiprfid passive identification.
For the "small-lab-prototype" we will use a small control group of animals (maximum of 6 animals) in a laboratory environment with a controlled environment room measuring approximately 12 x 12 m.

The information collected in these environments will be static, i.e. based on indicators (animal performance records) and dynamic, i.e. provided by the external and internal (outdoor and indoor) environment, and by the animals through behavioural (image analysis) and physiological records (using technology that does not stress animals).

PARAMETERS		DATA COLLECTION
Environmental	Outdoor (temperature, humidity, atmospheric pressure, CO_2, NH_3, H_2S, wind (speed and direction).	Automatic and continuous.
	Indoor (temperature, atmospheric pressure, noise, CO_2, NH_3, H_2S, CH_4).	Automatic and continuous
Physiological	Surface temperature.	Automatic, near the feeder; image recording; thermal vision camera.
	Body temperature; surface temperature; blood pressure; respiratory frequency; blood count; cortisol; α-amylase.	Measurement and periodic collection.
Behavioural	Lying/animals together: location and duration; number of visits and time spent in the feeder; animal sounds.	Automatic, through video camera, and read data from the feeder/ID chip on the animal.
Production	Initial, final and intermediate weights; feed and water intake; mortality rate; unproductiveness rate.	Measurement and periodic collection.

After data collection, we will proceed to the prototyping phase, where all the elements produced will be interconnected and their correct functioning validated. This will also be supported by the subsequent testing and experimental phase. To this end, the software platform to be developed is a technological platform which allows decentralised interoperability by connecting the various infrastructures and devices and their AWARTECH environments, integrating and centralising all the information at a central point.
The technological platform known as "Awartech Smart Sensing" will interconnect physical objects by exploiting data capture, allowing the insertion of data collected by various means into different environments and locations, communicating with the central system through Ethernet and/or 3G/4G. A smart-sensing platform allows not only remote monitoring and supervision of various environments and sensory devices, but also automatic remote updating of equipment, specifically the environmental regulation equipment in the Living-Lab pavilion. It will be possible not only to know the parameters that are being collected by various means in the various locations and environments in real-time, but also to collect all data automatically and continuously. This platform will also allow access and operate remotely, through the internet. The system will be compatible with a wide variety of commercially available brands and models of sensors, communication devices and infrastructures, as well as any computer equipment and operating systems. It will be characterised by a high degree of autonomous data capture capability, event transfer, connectivity and network interoperability. Finally, it will be able to integrate with existing Living-Lab environment control systems, and possibly with others in the future, and to integrate with data analytics systems for statistical treatment and data analysis.

Results and discussion

As mentioned above, the AWARTECH project aims to analyse housing conditions and minimise their impact on animal welfare in real time. This purpose fits with the structural priorities of regional development and the priorities for intervention by the funds, in the framework of Alentejo 2020 and Portugal 2020, either by promoting sustainable production and animal welfare or by improving the competitiveness of the value chain and, consequently, the competitiveness of the regional and national economy.
The use of adequate environmental conditioning on pig farms contributes to improvements in animal welfare and production patterns (Cruz, 2005; Arbel and Cruz, 2006; cited in Perissinotto et al., 2008). The thermal environment is an important and permanent factor in pig welfare (physiology, behaviour and productivity) during the growth and fattening phase (Cruz, 1997; Olczak et al., 2015, cited in Soerensen and Pedersen, 2015). Modern technology offers a range

of possibilities to control the environment through appropriate environmental conditioning techniques, namely thermal insulation of the enclosure, ventilation systems and heating and cooling systems.
Verstegen et al. (1982) estimated that 400 kJ /°C of metabolisable energy should be provided daily, as a supplement, to a pig weighing 25 kg to 100 kg and housed under temperature conditions below the lower critical temperature. Several scientific articles show the effect of high temperatures on the growth and fattening performance of pigs (Banhazi et al., 2009). In extreme situations, animals decrease their food intake so drastically that they experience decreases in live weight (Cruz et al., 2000).
On the other hand, animal welfare is evaluated through welfare indicators. These measurements are preferable since they provide a better practical evaluation of well-being (Manteca et al., 2013). The validity, repeatability and feasibility of all the adopted criteria are considered in the evaluation of animal welfare under the Welfare Quality® (2009) protocol. The collection of information should not take too much time, should prioritise data obtained directly from the animals, be universal and applicable to any production system and should result in a final combination which assigns a global welfare score (Welfare Quality ®, 2009; Temple et al., 2011a; Velarde and Dalmau, 2012; cited in Manteca et al., 2013). All the measures proposed in the Welfare Quality protocol (2009) use non-invasive methodologies (Velarde and Dalmau, 2012): collected saliva for disease detection and animal health monitoring (Huang et al., 2014); evaluation of animal behaviour through image capture and processing; identification of sounds and vocalisations emitted by pigs which indicate changes in the environment, such as temperature and relative air humidity; and also early detection of diseases (Rushen et al., 2012; cited in Vandermeulen et al., 2015), with the aid of computer programs, etc.
Sensor development is constantly evolving, with sensors which can gather an increasing volume of information: animal weight and behaviour, physiological and environmental variables, noise, gases and odours (Costa, 2014). Automatic electronic identification systems can aid in disease detection and measurement of food intake, behavioural activity and physiological response to stress, among other things (Pandorfi et al., 2012), so they are a very useful tool for managing animal welfare remotely and in real time. The radio frequency identification technique is already widely used to monitor animal feeding behaviour, so this can be considered an indicator of non-invasive animal welfare.

Conclusions

This project aims to link information collected either automatically or manually to an analytical system which allows operators to correlate data in order to

provide predictive analysis and create simulation models with the objective of improving animal welfare and the productive efficiency of each individual holding. This will allow operators to make decisions according to the data collected.

Currently, there are no systems available on the market which solve this problem; therefore, this project is completely innovative in nature. As positive impacts we consider: relations with other companies, since it is probable that this concept will transmitted either upstream or downstream of the company presenting the project as a result of positive contagion; at the level of the consumer, since this project could raise awareness and encourage consumers to buy meat produced according to animal welfare standards; at the distributor level, with the possibility that production will achieve greater bargaining power and, later, a segment of consumers concerned about animal welfare; in production and in the value chain, since better economic results in production, greater efficiency in production, cost reduction and value creation can be beneficial to all stakeholders in the value chain; and expansion of the study to other animal species and contexts, with the help of precision livestock farming which can create and develop a tool to support the sustainability of the value chain, and can be replicated, with some adjustments, for other species and regions.

References

Arbel, A.; Cruz, V.F. (2006) – Mitigation actions. In: I.A. Näas & D.J. Moura (eds.), Animal Housing in Hot Climates: A multidisciplinary view, CIGR Working Group Report. 2006. Published by DIAS, Denmark, pp: 23-39.

Baêta, F.C., Souza, C.F., (2010) Ambiência em edificações rurais – conforto animal, editora ufv 2010 2ª edição

Banhazi, T. M., Thuy, H., Pedersen, S., Payne, H., Mullan, B., Berckmans, D., et al. (2009). Review of the consequences and control of high air temperatures in intensive livestockbuildings. Australian Journal of Multi-disciplinary Engineering, 7(1), 63e78

Costa, D. S. Medidor de frequência cardíaca e temperatura cutânea para pequenos ruminantes. 2014. Dissertação (Mestrado) - Universidade Federal do Vale do São Francisco.

Cruz, V.F. Influência da estação do ano sobre as performances do porco em fase de crescimento e acabamento. Sua relação com a densidade de alojamento e a concentração energética da dieta. 1997. Tese de Doutoramento. Universidade de Évora, Évora.

Cruz, V.F. Novas Filosofias para a Planificação de Instalações Pecuárias. Revista de Ciências Agrárias. 2005, vol. XXVIII n.º 3/4, pp. 329-340.

Huang, Y. Weifeng, L., Chao, Y., Ce, L.; Ruqian, Z.; Chiaojing., Y. Response to lipopolysaccharide in salivary components and the submandibular gland of pigs. Livestock Science. ISSN 18711413. 167:1 (2014) 323–330. doi: 10.1016/j.livsci.2014.06.013.

Manteca, X.; Silva, C.A.; Bridi, A.M.; Dias, C.P. Bem-estar animal: Conceitos e formas práticas de avaliação dos sistemas de produção de suínos. Semina:Ciencias Agrarias. . ISSN 16790359. 34:6 SUPPL. 2 (2013) 4213–4230. doi: 10.5433/1679-0359.2013v34n6Supl2p4213.

Olczak K, Nowicki J, Klocek C. Pig behaviour in relation to weather conditions – a review. Ann. Anim. Sci. 2015; 15: 601–10

Pandorfi, H.; Almeida, G.; Guiselin, C.. Zootecnia de precisão: princípios básicos e atualidades na suinocultura. Revista Brasileira de Saúde e Produção Animal, 2012; v. 13, n. 2, 2012.

Perissinotto, M.; Moura, D.J.; Fitas da Cruz, V. Applied Intelligent System for Environmental Control in Dairy Housing. In. Proceedings of the ILES VIII International Livestock Environment Symposium, Foz do Iguaçu. ASAE e SBEA . 2008 I: 47-52

Rushen, J.; Chapinal, N.; Passilé, A. M. Automated monitoring of behavioural-based animal welfare indicators. Animal Welfare. 2012. 21:3 339–350. doi: 10.7120/09627286.21.3.339. ISSN 09627286.

Soerensen D.D., Pedersen L.J. Infrared skin temperature measurements for monitoring health in pigs: a review. Acta Veterinaria Scandinavica 2015; 57:5. DOI 10.1186/s13028-015-0094-2

Temple, D. Dalmau, A., Ruiz de la Torre, J.L., Manteca, X. e Velarde, A. Assessment of animal welfare through behavioural parameters in Iberian pigs in intensive and extensive conditions. Applied Animal Behaviour Science. 131:1-2 (2011) 29–39. doi: 10.1016/j.applanim.2011.01.013. . ISSN 01681591

Vandermeulen J, Bahr C, Tullo E, Fontana I, Ott S, Kashiha M, Guarino M, Moons CP, Tuyttens FA, Niewold TA, Berckmans D. Discerning pig screams in production environments. PLoS One. 2015 Apr 29; 10(4):e0123111. doi: 10.1371/journal.pone.0123111. eCollection 2015.

Velarde, A.e Dalmau, A. - Animal welfare assessment at slaughter in Europe : Moving from inputs to outputs. 92:2012) 244–251. doi: 10.1016/j.meatsci.2012.04.009.

WELFARE QUALITY ® - Welfare Quality ® Assessment protocol for pigs (sows and piglets, growing and finishing pigs). (2009) 1–123.

Novel activity monitoring system based on smart collar and variational Bayesian learning of multivariate autoregressive hidden Markov models

A. Ayastuy Rodriguez[1], P. Record[1], F. Kenyon[2]
[1]*Heriot-Watt University Edinburgh Campus, Edinburgh Scotland, United Kingdom*
[2]*Moredum Research Institute, Pentland Research Park, Bush Loan, Edinburgh*
ara4@hw.ac.uk

Abstract

Current demographic trends push livestock production toward more intensive farming while reducing environmental impact and maintaining a high grade of animal welfare. Under this new scenario, farmers need to be provided with tools to manage their farm more efficiently. Currently the health status of small ruminants is monitored by farmers using mostly visual inspection however this become ineffective for larger stock numbers.
This piece of work presents a new machine learning algorithm based on autoregressive hidden Markov model to analyse triaxial accelerometer data to classify sheep behavioural patterns. The algorithm creates a model of animal's activity directly from raw data from the sensors and was specifically design for running on embedded devices.
This approach allows the model, when used on the initial healthy animal, to be automatically tuned for each individual which subsequently provides a normal reference for abnormal detection.
Finally, a set of experiments were performed where a sheep was fitted with the collar prototype over two days. The animal under study was maintained in a shed with two other sheep. The result of this experiment shows that algorithm achieved an average of 93.40±0.09% accuracy when determining the animals' activities using only the accelerometer data which is comparable to more computer expensive classifying techniques.

Keywords: Smart collar, accelerometer, sheep, activity monitoring, hidden Markov model, variational Bayesian inference

Introduction

Current economic and demographic trends are pushing livestock production toward more intensive farming. Meanwhile consumers and regulators are increasing their concern about food quality and animal welfare. As a result, the livestock sector needs to cope with the new market requirements by increasing

its efficiency. Currently, small ruminants are usually monitored by farmers using mostly visual inspection, however this is becoming ineffective for larger herds and certain diseases e.g. production limiting diseases, which can subtly affect animal behaviour and therefore tend to be usually neglected by the farmer until more severe symptoms are present. The aim of this research is to develop a new technique that can be used by farmers for long term monitoring of their sheep stock and specially focuses in creating computational efficient algorithms that can analyse animal's behavioural pattern with high accuracy and low power consumption.

Accelerometers have become increasingly popular to monitor livestock health status and tracking production performance e.g. oestrus detection in dairy cattle. The working principle of this methodology is based on measuring the acceleration of the animal's movements on the position where the sensor is attached and correlating this information with animal's health status. Accelerometers have been applied among other things to measure animal's activity levels (Müller & Schrader, 2003), classifying behavioural patterns (González, Bishop-Hurley, Handcock, & Crossman, 2015; Nadimi, Jørgensen, Blanes-Vidal, & Christensen, 2012; Robert, White, Renter, & Larson, 2009), analysing locomotion patterns, monitoring grazing and rumination (Moreau, Siebert, Buerkert, & Schlecht, 2009; Watanabe, Sakanoue, Kawamura, & Kozakai, 2008), etc.

Accelerometers collars, halter or leg-band can be an effective and non-invasive solution for detecting early symptoms of several conditions e.g.: tracking animal activity and detecting health conditions such as ketosis, lameness or milk fever (Helwatkar, Riordan, & Walsh, 2014).

In addition, these sensors are especially effective for this mission because they are cost-effective, power efficient, light-weight and small sized. In addition, it can be sampled at slow speed (1-100Hz). Nevertheless, acceleration data gathered with these sensors are difficult to correlate with the animal's health status. For this reason several methods have been developed which relies on control theory such as Kalman filter (Nadimi & Søgaard, 2009), on heuristics or on Machine Learning (ML) techniques, e.g.: Classification trees (Nadimi, Søgaard, & Bak, 2008), Artificial Neural Networks (ANN) (Nadimi et al., 2012), Support vector machines (SVN) (Martiskainen et al., 2009) or ensemble method (Dutta et al., 2015).

These algorithms need to detect complex patterns in signals with low signal to noise ratio under the constrains of this application which are limitation in memory, communication bandwidth and computational power. Additionally, the algorithm complexity finally affects the battery consumption which tends to further constrain in embedded device in long term monitoring infrastructures.

In this work, a new algorithm is presented for analysing 3 axial accelerometer data resulting from a smart collar to classify sheep behavioural patterns. The algorithm is based on a modification of the classical hidden Markov model (HMM) (Rabiner & Juang, 1986) which uses a multivariate linear autoregressive model as observation models and a variational Bayesian training algorithm (Beal, 2003, Chapter 2) with stick-breaking prior. This allows the training algorithm to tune the model complexity (number of states, number of observation models and their order) to adapt to the signal complexity which finally impact into the application performance reducing the computational complexity cost and hence increasing the battery life.

Material and methods

Experimental procedure

A set of experiments where performed in Moredun Research Facilities in Penicuik, Scotland, UK where a sheep was fitted with the prototype collar for two days. The animal understudy was keep indoors in a pen with two other sheep during the whole experiment. In order to provide a ground truth for the animal's behaviour the experiments were video recorded using a Foscam C1 Lite 720P wireless camera. It had a large angle of view the camera (120 degrees), so it could capture the complete pen area when placed in one of the corner at 2.5 meters high over ground level except for a small area under the camera. The video was streamed using Wi-Fi to Raspberry Pi 3 where the video was stored in a hard drive and timestamped. The Raspberry Pi ran a Zoneminder 1.30 server to manage the video recording and to allow later expansion of the system with extra cameras or sensors.

A custom sensor was manufactured for this application consisting of a STM32L476RTG microcontroller, Invensense MPU6000 inertial measurement unit that contains a triaxial accelerometer and gyroscope, and microSD memory card to record the data produced by the IMU for posterior analysis. The sensor was powered by a 1000 mAh lithium battery which allows the sensor to run continuously for approximately 48 hours although the battery lifetime of the sensor can be extended for final application by sampling in small epoch of a few second and remaining in low power mode for most the time. The sensor was attached to the animal using a collar made out of a nylon strap of two centimeters' width and adjustable release buckle that allows to adjust the collar length to fit the animal's neck.

Model definition

The algorithm proposed relies on a variation of the classical hidden Markov model where the observation model are linear autoregressive models called

uncertain order multivariate autoregressive stick-breaking hidden Markov model (UOmAR-SBHMM). It consists in double stochastic processes which are characterised by an underlying non-observable process that follows a Markov chain and an observable process modelled by the observation models. The Markov chain consist of a series of states x^t whose dynamics are characterised by the transition probabilities $p(x^t|x^{t-1})$ and initial probabilities $p(x^0)$ that follow a categorical distribution. Whereas, the observation models which are linear autoregressive models follows a distribution $\left(y^t\middle|\{y^t\}_{t-p}^{t-1},\theta^Y,z^t\right)$. The outputs are produced in each time step by selecting an observation model z^t. This selection is characterised by the emission probability $p(z^t|x^t)$ which follows a categorical distribution as well.

$$y^t|y^{t-1},y^{t-2}\dots y^{t-p},z^t \sim f\left(y^t\middle|\{y^t\}_{t-p}^{t-1},\theta^Y,z^t\right)$$
$$x^0 \sim Cat(\pi)$$
$$x^t|x^{t-1} \sim Cat\left(A_{x^{t-1}}\right)$$
$$z^t|x^t \sim Cat\left(B_{x^t}\right)$$

Where, y^t is the output at time t, Cat stand for categorical distribution, A,B,π are the parameters of the hidden Markov model and θ^Y are the parameters of the observation models. The UOmAR-SBHMM complexity is characterised by the number of states n, the number of observation models and the orders of the observation models (mAR) p.

The multivariate linear autoregressive model (mAR) used for emitting the output in each state are defined by the following recurrent formula:

$$y^t = \sum_{k=1}^{p} \phi_k y^{t-k} + \phi_0 + w \qquad w \sim N(0;\Sigma)$$

In addition, unlike classical approach the order of the autoregressive model is consider an unknow parameter which will be inferred in the training procedure. The sample are grouped in δ steps to reduce the algorithm complexity since the mAR dynamic tend to be quicker than the underlying chain model. The likelihood of the observation model can then be expressed as follows:

$$f\left(y^t\middle|\{y^t\}_{t-p}^{t-1},\theta^Y,z^t\right) = \left(\frac{1}{(2\pi)^d\left|\Sigma^{\mathrm{p,z^t}}\right|}\right)^{\frac{\delta}{2}} \exp\left(-\frac{1}{2}\left\|y^t - \sum_{k=1}^{r}\phi_k^{\mathrm{p,z^t}} y^t - \phi_0^{\mathrm{p,z^t}}\right\|^2_{\Sigma^{\mathrm{p,z^t}}}\right)$$

Where d is the dimension of the output, p is the order of the mAR.

<u>Training and decoding procedure</u>

The training algorithm used a variational Bayesian (VB) approach and hence treats the parameters and hidden variables as random variables (Beal, 2003, Chapter 2). The objective of these methods is to approximate

the posterior distribution of the joint distribution of the parameters and hidden variable given the data using a variational calculus approach. In most scenarios the model studied, the posterior joint distribution cannot be inferred and an independence assumption need to be made $q(x,\theta) \approx q(x)q(\theta)$.

$$\log p(y|m) \geq \iint q(x,\theta) log\left(\frac{p(y,x,\theta|m)}{q(x,\theta)}\right) d\theta dx$$
$$\approx \int\int q(x) log\left(\frac{p(y,x,\theta|m)}{q_x(x)}\right) dx + log\left(\frac{p(\theta|m)}{q_\theta(\theta)}\right) q(\theta) d\theta$$
$$= F_m\big(q_x(x), q_\theta(\theta)\big)$$

It can be proved that by maximizing the free-energy the Kullback–Leibler (KL) divergence between the approximate posterior distribution of the parameters and hidden variable, the actual posterior is minimized and therefore converge to the actual posterior solution. The optimization process is performed by alternatively optimizing with respect to the hidden variable (VB expectation step, VBE) and with respect to the parameters (VB maximization step, VBM) which is known as VB expectation maximization.
The Bayesian approach assumes some previous knowledge in the parameter distribution or prior knowledge. Stick-breaking processes were chosen as prior distribution for the underlying Markov chain parameters. This process approximates a hierarchical Dirichlets process and force the training algorithm to converge to a model with a small number of states. Whereas, the parameters prior distribution of the linear multivariate autoregressive models follows a matrix normal distribution for ϕ^{p,z^t}, an inverse-Wishart distribution for Σ^{p,z^t} and a categorical distribution for p. The relationships between the hidden variables, parameters and hyper-parameters of the model are summarized in figure 1.

$$\phi^{p,z^t} \left| \Sigma^{p,z^t}, z^t, p \sim MN_{d\times(pd+1)}\left(M_0^{p,z^t}, S_0^{p,z^t}, \Sigma_0^{p,z^t}\right)\right.$$
$$\Sigma^{p,z^t}|z^t, p \sim iW_d\left(V_0^{p,z^t}, \nu_0^{p,z^t}\right)$$
$$p\big|z^t \sim Cat\big(\mu_0^{z^t}\big)$$

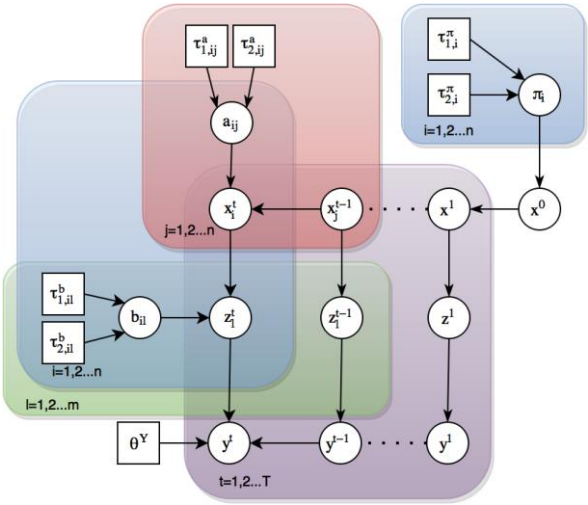


Figure 1: Plate diagram of the UOmAR-SBHMM

Signal processing

The signal processing consists of several stages. Firstly, the video recordings were manually annotated in various activities which were previously defined. If the animal behaviour was unclear or the camera vision of the animal understudy was obstructed by other animals the behaviour was annotated as unknown and was not used for neither the training or the validation stage of the process. Secondly, the sensor data was pre-processed. The acceleration data gathered by the sensors consists of 3 acceleration measurements with 16 bit of resolution in three perpendicular axes and 4g range. The data was time-stamped using a real-time clock module presented in the ST microcontroller and sampled at 50 Hz rate. The acceleration data was then synchronized with the video recording using both the timestamps of the data and the recording, divided in chunks with the same annotated behaviour and finally subdivided in smaller epochs of 14 seconds each for creating the dataset for each behaviour. For the training process, each dataset was first divided in training and validation dataset by selecting randomly at most 30% (overall 8%) of the epochs as training datasets and the remaining was used for validation. No features were calculated for the datasets since the algorithm can process automatically the raw data from the sensor.

Then, the variational Bayesian expectation maximization (VBEM) training procedure was then applied to each of the training datasets to create a model for each of the behaviours. A maximum number of states and observation models of seven was selected and a maximum order of eight for the autoregressive model was chosen.

Next a modification of the classical Viterbi algorithm was applied to each of the validation sample epochs to calculate the likelihood for the most probable state sequence for each model and the most probable model was selected. This

solution coincides with the maximum posterior choice when every model has the same prior probability. Finally, the predictions were compared with the actual behaviour to calculate the algorithm performance.

Results and Discussion

A set of performance metrics has been defined to evaluate the algorithm such as accuracy (ACC), Specificity (SPC) or F1 score, which are defined as follow:

$$SEN = \frac{TP}{TP + FN} \quad PRE = \frac{TP}{TP + FP}$$

$$ACC = \frac{TP + TN}{TP + FP + TN + FN} \quad F1 = \frac{2 \cdot SEN \cdot PRE}{SEN + PRE}$$

where TP, FP, TN, FN stand for true positive, false positive, true negative and false negative. The results show an overall accuracy of 93.40±0.09% and F1 scored of 80.21±2.32% in classifying six different behaviors. (see table 1).

Table 1**:** Behavioural classification performance of the proposed algorithm

Behaviour	Sensitivity	Precision	Specificity	Accuracy	F1
Coughing	100.00±42.85	37.50±22.69	99.10±0.57	99.11±0.57	54.55±37.00
Grazing	91.29±1.18	90.94±1.17	91.92±1.05	91.62±0.56	91.12±2.35
Laying	83.33±2.92	77.27±2.68	94.55±0.69	92.51±0.56	80.19±5.48
Running	100.00±47.33	40.00±30.37	99.46±0.57	99.47±0.57	57.14±46.32
Standing	64.46±2.36	81.25±3.08	95.91±0.72	89.13±0.56	71.89±5.86
Walking	59.42±3.99	53.25±3.53	92.68±0.64	88.59±0.56	56.16±8.49
Total:	80.21±0.54	80.21±0.54	96.04±0.11	93.40±0.09	80.21±2.32

This piece of work presented a new algorithm the UOmAR-SBHMM which consist of a variational Bayesian approach to the multivariate linear autoregressive hidden Markov Model. This algorithm allows the analysis of the raw sensor data with no parameter tuning and automatically adapts the model complexity to the training dataset by inferring the model topology during the training (number of states and observation models, and their orders). In addition, unlike similar approaches e.g. UOAR-SBHMM proposed by (Morrell, Ruxton, & James, 2010) it shares the observation models across the states reducing the model complexity by reusing them when possible. The model can be efficiently decoded using a modification of the classical Viterbi algorithm with a complexity order of $O\big(T(d^2pm + mn + n^2)\big)$ where T is the number of samples.

The performance of the different methodology followed in literature can be challenging to compare because of the different experimental setups and signal processing design choices e.g. the animal involved in the experiments, the attachment of the sensor, the type and characteristics of the sensors and factors related with the signal processing e.g. the sampling rate, the number of behaviors classified.

Most of the published work so far focuses on cattle stocks and normally uses accelerometers mounted on collars although other attachment have been tested e.g. Leg-band (Robert et al., 2009) or halters (Giovanetti et al., 2017; Watanabe et al., 2008). In addition, it has been proposed to use multiple sensors e.g. Combination of GPS and accelerometer. (Dutta et al., 2015; González et al., 2015). However, GPS based sensors usually have a high battery consumption therefore they tend to be impractical for long term monitoring and require bulky batteries.

Several signal processing methods have been proposed, classification trees being the most popular one. One of the most successful techniques in cattle has been reported by (Dutta et al., 2015) using bagging ensembles with a tree learner, achieving an accuracy of 96.00%, however this technique requires a high computational cost since it entails running several standard machine learning techniques on the data and selecting the prediction by majority. The performances of the different published techniques are summarized in table 2.

Table 2: Accuracy of the different techniques published in literature

Publication	1	2	3	4	5	6	7	8	9	10	11	AVG
This Work		91.62			88.59	99.47		99.11	89.13	92.51		93.40
Giovanetti2017	96.45			94.23						95.12		95.27
Alvarenga2015		93.38			98.48	99.31			90.77	89.12		94.21
Dutta2015	93.00	98.00		97.00			92.00			97.00		96.00
Gonzales2015	94.13			91.32	98.86					89.69	96.96	94.19
Nadimi2012		83.80			73.80				71.80	83.20	68.50	76.20
Martiskainen2009		96.27		92.16	98.86				86.60	84.21		94.48
Moreau2009	77.70	66.01	81.28									77.03
Robert2009					67.80				98.00	99.20		88.33
Watanabe2008		95.90		96.10						85.40		94.10

Note: 1. Foraging, 2. Grazing, 3. Eating, 4. Ruminating, 5. Walking, 6. Running, 7. Scratching, 8. Coughing, 9. Standing, 10. Resting, 11. Other, AVG. Overall

Conclusions

A new algorithm based on hidden Markov model has been proposed to analyse the data produced by a triaxial accelerometer to classify sheep behavioural patterns (UOmAR-SBHMM). This algorithm presents several advantages over standard techniques e.g. it can directly process raw sensor data, it adapts the

complexity of the model to the signal complexity and can be easily retrain by using stabilised forgetting. The algorithm has shown an accuracy of 93.40±0.09% which is the same range of more complex techniques which require higher computation power or uses additional sensors e.g. GPS.

Acknowledgements

This project was funded by Engineering and Physical Science Research Council (EPSRC) and Moredun Research.

References

Beal, M. J. (2003). *Variational algorithms for approximate bayesian inference*. *The Gatsby Computational Neuroscience Unit University College London*. University of London.

Dutta, R., Smith, D., Rawnsley, R., Bishop-hurley, G., Hills, J., Timms, G., & Henry, D. (2015). Dynamic cattle behavioural classification using supervised ensemble classifiers. *Computers and Electronics in Agriculture*, *111*, 18–28. https://doi.org/10.1016/j.compag.2014.12.002

Giovanetti, V., Decandia, M., Molle, G., Acciaro, M., Mameli, M., Cabiddu, A., … Dimauro, C. (2017). Automatic classi fi cation system for grazing , ruminating and resting behaviour of dairy sheep using a tri-axial accelerometer. *Livestock Science*, *196*(December 2016), 42–48. https://doi.org/10.1016/j.livsci.2016.12.011

González, L. a., Bishop-Hurley, G. J., Handcock, R. N., & Crossman, C. (2015). Behavioral classification of data from collars containing motion sensors in grazing cattle. *Computers and Electronics in Agriculture*, *110*, 91–102. https://doi.org/10.1016/j.compag.2014.10.018

Helwatkar, A., Riordan, D., & Walsh, J. (2014). Sensor Technology For Animal Health Monitoring. *8th Internacional Conference on Sensing Technology*, 2–4.

Martiskainen, P., Järvinen, M., Skön, J.-P., Tiirikainen, J., Kolehmainen, M., & Mononen, J. (2009). Cow behaviour pattern recognition using a three-dimensional accelerometer and support vector machines. *Applied Animal Behaviour Science*, *119*(1–2), 32–38. https://doi.org/10.1016/j.applanim.2009.03.005

Moreau, M., Siebert, S., Buerkert, A., & Schlecht, E. (2009). Use of a tri-axial accelerometer for automated recording and classification of goats' grazing behaviour. *Applied Animal Behaviour Science*, *119*(3–4), 158–170. https://doi.org/10.1016/j.applanim.2009.04.008

Morrell, L. J., Ruxton, G. D., & James, R. (2010). Spatial positioning in the selfish herd. *Behavioral Ecology*, *22*(1), 16–22. https://doi.org/10.1093/beheco/arq157

Müller, R., & Schrader, L. (2003). A new method to measure behavioural activity levels in dairy cows. *Applied Animal Behaviour Science*, *83*(4), 247–258. https://doi.org/10.1016/S0168-1591(03)00141-2

Nadimi, E. S., Jørgensen, R. N., Blanes-Vidal, V., & Christensen, S. (2012). Monitoring and classifying animal behavior using ZigBee-based mobile ad hoc wireless sensor networks and artificial neural networks. *Computers and Electronics in Agriculture*, *82*, 44–54. https://doi.org/10.1016/j.compag.2011.12.008

Nadimi, E. S., & Søgaard, H. T. (2009). Observer Kalman filter identification and multiple-model adaptive estimation technique for classifying animal behaviour using wireless sensor networks. *Computers and Electronics in Agriculture*, *68*(1), 9–17. https://doi.org/10.1016/j.compag.2009.03.006

Nadimi, E. S., Søgaard, H. T., & Bak, T. (2008). ZigBee-based wireless sensor networks for classifying the behaviour of a herd of animals using classification trees. *Biosystems Engineering*, *100*(2), 167–176. https://doi.org/10.1016/j.biosystemseng.2008.03.003

Rabiner, L., & Juang, B. (1986). An introduction to hidden Markov models. *IEEE ASSP Magazine*, *3*(January), Appendix 3A. https://doi.org/10.1109/MASSP.1986.1165342

Robert, B., White, B. J., Renter, D. G., & Larson, R. L. (2009). Evaluation of three-dimensional accelerometers to monitor and classify behavior patterns in cattle. *Computers and Electronics in Agriculture*, *67*(1–2), 80–84. https://doi.org/10.1016/j.compag.2009.03.002

Watanabe, N., Sakanoue, S., Kawamura, K., & Kozakai, T. (2008). Development of an automatic classification system for eating , ruminating and resting behavior of cattle using an accelerometer. *Grassland Science*, *54*(4), 231–237. https://doi.org/10.1111/j.1744-697X.2008.00126.x

Identification of key factors for dust generation in mechanically and naturally ventilated broiler houses

G. Park[1], K. S. Kwon[2], I.-B. Lee[1]
[1]*Department of Rural Systems Engineering, Research Institute for Agriculture and Life Sciences, College of Agriculture and Life Sciences, Seoul National University, 599, Gwanakno, Gwanakgum Seoul 08826, Republic of Korea*
[2]*Animal Environment Division, National Institute of Animal Science, 1500, Kongjwipatjwi-ro, Jeollabuk-do, 55365, Republic of Korea*
kskwon0512@korea.kr

Abstract

The evaluation of dust level is of concern because it can result in poorer indoor air quality (IAQ) within livestock houses, which is associated with the respiratory welfare of both livestock workers and animals. To create an adequate IAQ inside broiler houses, an understanding of the mechanisms of dust generation according to a complicated combination of variables is very important. However, most investigations conducted to date have focused on the single correlation between dust concentration and environmental factors. There have been few comprehensive and detailed studies that have statistically investigated various dust generation factors simultaneously. In this study, intensive dust monitoring was carried out for 13 months in mechanically and naturally ventilated broiler houses. For the multiple regression analyses to evaluate the key factor for dust generation, various factors were also simultaneously monitored. Among them, the ventilation rate of the facilities was numerically evaluated using computational fluid dynamics with tracer gas decay (TGD). The observations showed that dust concentrations which were seven times higher than normal occurred when farmers entered the facility, due to an increase in broiler activity. In terms of the applicability of each variable under practical conditions, controlling the humidity level was the significant factor in the generation of inhalable dust. However, increased humidity in the facility is strongly related to the proliferation of micro-organisms. Therefore, careful approaches are needed to ensure biological safety with regard to the outbreak of animal disease.

Keywords: aerosol, broiler house, inhalable dust, PM10, respirable dust, TSP

Introduction

Organic dust generated in livestock production facilities is the major factor causing environmental degradation for both animals and workers. The dust is

mainly generated by feed, hair, faeces and bedding materials inside the livestock house (Hartung & Saleh, 2007). Substances attached to the surface of the dust, such as micro-organisms, endotoxins and toxic gases, can cause negative health effects for both livestock and workers. High dust concentrations could decrease productivity by causing allergic reactions, and carry livestock disease pathogens such as HPAI or Newcastle disease (Hugh-Jones et al., 1973; Power, 2005). Many studies have reported that workers on livestock farms have a high prevalence of respiratory symptoms, such as allergic rhinitis, chronic decline in lung function, organic dust toxic syndrome (ODTS) and bronchitis (Tucker, 2000; Rosentrater, 2004). The dust generation rate inside the livestock house is influenced by various factors, including animal species, age, rearing density, ventilation, micro-climatic conditions, feeding method and so on. However, most existing studies have shown a single correlation between the measured aerial dust concentration and one experimental environmental factor. Only a few have conducted comprehensive and detailed studies with statistical analysis of multiple dust generation factors simultaneously. Banhazi et al. (2008) conducted a statistical investigation to determine the key factors for the generation of airborne pollutants in pig houses. However, there is insufficient long-term and comprehensive research on poultry facilities. In this study, dust concentration and environmental conditions were monitored and statistically analysed to determine key dust generation factors inside broiler houses.

Materials and methods

Experimental broiler houses

Mechanically and naturally ventilated broiler houses on a farm located in Jeongeup city, South Korea, were selected for the experiment. For the mechanically ventilated (MV) broiler house, a tunnel ventilation system with 14 tunnel exhaust fans (1.27 m diameter, 26,500 CMH) and two plate openings (24.45 m long, 1.58 m high) was used during the summer, and a cross-ventilation system using three side fans (0.88 m diameter, 33,000 CMH) and slot-openings (1.25 m long, 0.43 m high) during the winter. The experimental MV broiler house was 15 m wide, 85 m long, 3.2 m high at the eaves and 6.3 m high at the ridge, and a total of 30,000 broilers were raised in the facility.

The naturally ventilated (NV) broiler house used a combination of natural ventilation with two winch curtain openings (85.5 m long, 1.2 m high) and mechanical ventilation with eight exhaust fans (0.51 m diameter, 6,020 CMH) during the summer. During the winter and the early stages of broiler rearing, mechanical ventilation with exhaust fans and pipe inlets (0.1 m diameter, 1.95 m long) along the roof slope was used. The of the experimental NV broiler house was 11 m wide, 85.5 m long, 1.5 m high at the eaves and 4.5 m high at the ridge,

and a total of 25,000 broilers were raised in this facility. Schematic diagrams of the experimental broiler houses are shown in Figure 1.

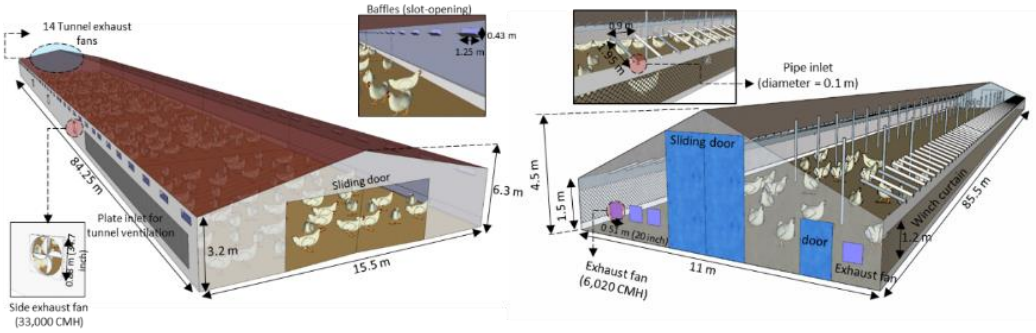


Figure 1: Schematic diagram of the experimental mechanically ventilated broiler house (left) and naturally ventilated broiler house (right)

Experimental equipment

A polytetrafluoroethylene (PTFE) membrane filter (SKC Inc., Eighty Four, PA, USA, 2.0 µm pore size, 37 mm diameter) was used to sample aerial TSP and PM10. PTFE membrane filters were inserted into a 3-stage polystyrene cassette (SKC Inc.) for TSP while a Personal Environmental Monitor (PEM) (SKC Inc.) sampler was used for PM10. Aerial dust was collected using an air sampler (AirChek XR5000; SKC Inc.), which was connected to the 3-stage polystyrene cassette and PEM sampler. Gravimetric measurement of the filters with sampled dust particulates was carried out using an electronic balance device (Ohaus Discovery balance DVG214C; Ohaus Co.).

An Aerosol spectrometer (Model 1.109; GRIMM Aerosol Technik GmbH & Co.) was used to measure the concentration and particle numbers of inhalable and respirable dust based on a laser light scattering method. Dust was measured in the range of 0.001~100 mg/m3, with a detection sensitivity of 0.001 mg in real time. Measurements of the dust concentration and the particle numbers were taken every 6 seconds.

For comprehensive analyses of dust generation inside the livestock houses, various experimental instruments for monitoring the environmental factors were also used. T-type thermocouples (Omega Engineering Inc., Stamford, CT, USA) and a data-logger (GL-820; Graphtec Inc., Jessup, MD, USA) were used to record the internal thermal distributions of the experimental broiler houses. HOBO sensors (UX100-003; Onset Computer Co., Bourne, MA, USA) were used to measure indoor air temperature and relative humidity in the experimental livestock houses. A portable weather station (WatchDog 2700; Spectrum Tech, Inc., Aurora, IL, USA) was used to monitor outdoor environmental conditions

such as wind speed, wind direction, solar radiation, rainfall, air temperature and humidity near the experimental livestock buildings.

Experimental procedure

In this study, long-term and intensive monitoring of aerial dust including TSP, PM10, and inhalable and respirable dust was conducted regularly in a mechanically ventilated broiler house and naturally ventilated broiler house, respectively. To investigate any correlation between the dust concentration and various experimental variables, indoor and outdoor climates were also measured. Monitoring in the experimental facilities took place 12 times, according to the rearing stage of the broilers, over 13 months from September 2013 to September 2014.

PTFE filters were fully desiccated for 24 hours and the pre-weighed and measured filter was then housed in a 3-stage polystyrene cassette for TSP while sampling PM10 in the PEM. The flow rates for TSP and PM10 sampling were 2 and 4 l/min for 8 hours, respectively. Dust sampling instruments were installed at a height of 1.5 m above the broiler zone to reflect the average height of a broiler farmer's respiratory intake. Five experimental regional sampling locations were selected for each experimental broiler house. When sampling was complete, the filters were completely desiccated again for 24 hours in the laboratory and then weighed to determine the particle mass based on the gravimetric method.

The concentration of inhalable and respirable dust was measured using the Aerosol spectrometer at a height of 0.2 and 1.5 m, reflecting the average respiratory height of broilers and farmers. Measurements were taken at locations near the entrance and in the middle of the facility. The concentration of these occupational dusts was measured in two experimental situations: i) when broilers were very calm and ii) when broilers showed active and vigorous movement due to the work activity of the staff. Measurements of the target dust concentration in the MV broiler house are shown in Figure 2.

Figure 2: Measurement of TSP and PM10 (left) and inhalable and respirable dust (right) concentration in an experimental mechanically ventilated broiler house

Results and discussion

Results of TSP concentration monitoring

The monitoring results for TSP concentration are shown in Figure 3. The results for PM10 show a similar tendency. Measured mean values for TSP from each broiler house showed similar concentrations and tendencies according to the age in weeks and seasonal changes, except in the experimental situations with broiler ages of 2 and 4 weeks in the cold season. On the other hand, the mean TSP concentrations measured in the NV broiler house during the summer were generally higher than those in the MV broiler house (92~176%). The reasons for these differences in dust concentration could be: i) unfavourable air exchange through winch curtain openings due to the relationship between wind direction and building arrangement, ii) increase in broiler activities where a brighter light environment could be created due to the broad winch curtain openings and incoming sunlight (Hessel & Van den Weghe, 2007) and iii) dehumidification effects of incoming sunlight on bedding materials in the NV broiler house; when winch curtain openings were used, the water content of the bedding materials was lower than in the MV broiler house (62~99%).

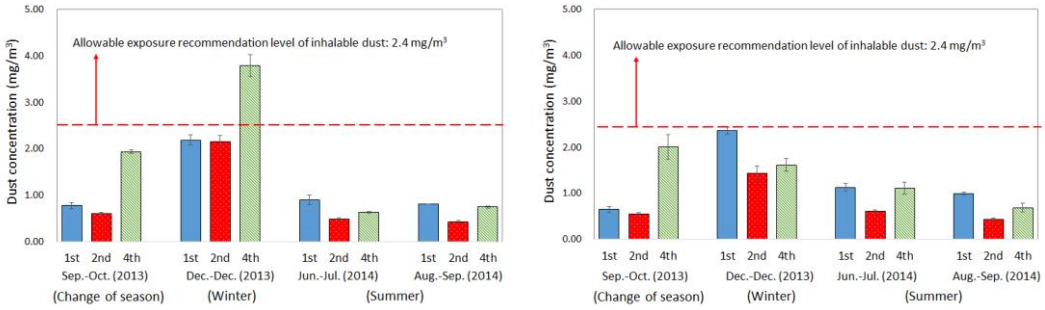


Figure 3: Monitoring results for TSP concentration in a mechanically ventilated broiler house (left) and naturally ventilated broiler house (right)

Result of inhalable dust concentration monitoring

Figure 4 shows the inhalable dust concentration measured at broiler height in the MV and NV broiler house, respectively. As shown in Figure 4, relatively higher concentrations of inhalable dust were found in the NV broiler house than in the MV broiler house. These observations could be explained by the following facts: i) a higher rearing density (113%) than in the MV broiler house, ii) dehumidification effects of bedding materials due to excessive heating in the cold season. In interviews with farmers, the heating cost for the NV broiler house was generally 1.5~2.0 times higher than for the MV broiler house to compensate for heat loss from leakage through the winch curtain opening. iii) effects of incoming sunlight in summer and the change of season. When winch curtain

openings were used, sunlight coming through openings could desiccate the surface of the bedding materials, therefore increased dust potential could be expected as mentioned above. An increase in animal activity was also identified in a brighter environment, as reported in previous studies (Hessel & Van den Weghe, 2007); the increase in animal activity is strongly related to high concentrations of pollutants inside the facility.

Like the results for TSP, some results for inhalable dust in both experimental broiler houses decreased temporarily as the broiler age increased from 1 to 2 weeks, and relatively higher dust concentrations were observed at 4 weeks old; these tendencies were not found in the summer, especially in NV broiler house where natural ventilation was prominent. These observations could be explained by the unbalanced relationship between the dust emission rate and the decontamination rate of the ventilation system according to the rearing stage, as mentioned earlier. In other words, irregular dust concentration tendencies measured at the age of 2 weeks during the summer might be inferred from the following facts; i) ineffective air exchange rate through winch curtain openings during the summer and ii) increase in broiler activity due to incoming sunlight. Some results for inhalable dust concentration, usually measured during the change of season and winter, exceeded the recommended level for animals of 3.7 mg/m3 (CIGR, 1994). In particular, a 148 and 214% excess was observed at the age of 4 weeks during the winter season in the MV and NV broiler house, respectively.

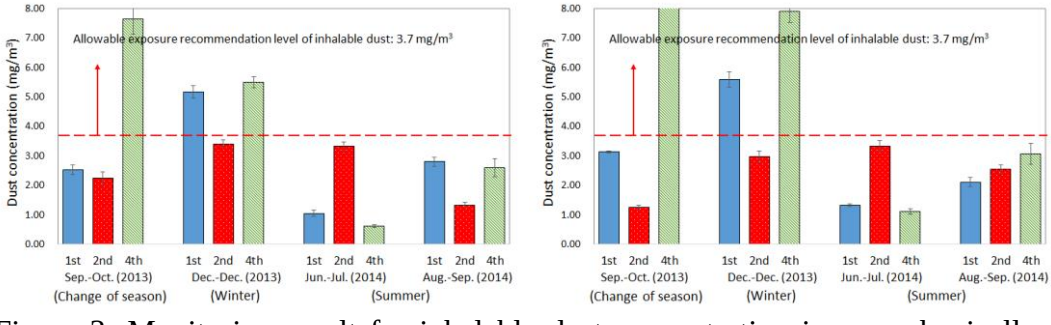


Figure 3: Monitoring result for inhalable dust concentration in a mechanically ventilated broiler house (left) and naturally ventilated broiler house at broiler height

<u>Multiple regression analysis of measured occupational dust</u>

Multiple regression analyses were conducted on the basis of the measured inhalable ($C_{Inhalable}$; mg/m³) and respirable dust concentration ($C_{Respirable}$; mg/m³) at broiler height and environmental conditions. To ensure the independence of the experimental variables, correlation tests and multi-collinearity tests were carried out. From the result, the independent variables

selected were broiler age (Age; days), CFD computed ventilation rate (VR; AER/min), outdoor absolute humidity level (AH_o; kg/kg-da), indoor air temperature (T_i; ℃), indoor absolute humidity level (AH_i; kg/kg-da), water content of bedding materials (WC; %), and activity status of broilers (Ac). The activity status was a nominal factor, which reflects the effect of broiler status in relation to the entry of workers and work activities. Additionally, a backward elimination process was applied to select predictive variables for each regression model. Following a normality test using the Shapiro-Wilk test, some of the residuals of the regression models were found to be unsatisfactory as a prerequisite for normal distribution. Therefore, log transformation was carried out for the dependent variable of the models.
The linear regression equations for occupational dust at broiler height are presented below.

$$\mathbf{C_{Inhalable}\ in\ MV = -62.304 + 0.960 \cdot Age - 3.565 \cdot VR - 561.317 \cdot AH_o + 2.437 \cdot T_i - 851.148 \cdot AH_i + 10.760 \cdot Ac} \quad (1)$$

$$\mathbf{C_{Respirable}\ in\ MV = -3.812 + 0.061 \cdot Age - 0.362 \cdot VR - 75.671 \cdot AH_o + 0.131 \cdot T_i + 0.008 \cdot WC + 0.628 \cdot Ac} \quad (2)$$

$$\mathbf{C_{Inhalable}\ in\ NV = 12.552 + 0.219 \cdot Age - 986.194 \cdot AH_i + 0.091 \cdot WC + 11.096 \cdot Ac} \quad (3)$$

$$\mathbf{\log(C_{Respirable})\ in\ NV = 4.706 - 63.707 \cdot AH_o - 0.126 \cdot T_i - 72.217 \cdot AH_i} \quad (4)$$

The linear regression equations for occupational dust at worker respiration height are presented below.

$$\mathbf{\log(C_{Inhalable})\ in\ MV = 0.595 + 0.047 \cdot Age - 1.021 \cdot VR + 0.069 \cdot T_i - 156.645 \cdot AH_i + 0.873 \cdot Ac} \quad (5)$$

$$\mathbf{\log(C_{Respirable})\ in\ MV = -5.597 + 0.083 \cdot Age - 0.972 \cdot VR - 117.939 \cdot AH_o + 0.154 \cdot T_i + 0.668 \cdot Ac} \quad (6)$$

$$\mathbf{C_{Inhalable}\ in\ NV = 6.568 + 0.318 \cdot Age - 5.216 \cdot VR - 598.522 \cdot AH_i + 0.082 \cdot WC + 3.348 \cdot Ac} \quad (7)$$

$$\mathbf{\log(C_{Respirable})\ in\ NV = 4.585 - 67.609 \cdot AH_o - 0.174 \cdot T_i} \quad (8)$$

Age and activity status of the broilers, ventilation rate and indoor absolute humidity level were significant variables in several regression models. Considering that the broiler's age and activity status as the farmer enters are uncontrollable factors, temporal management of the ventilation rate and humidity level of the facility can be helpful to reduce the dust concentration in broiler houses. The ventilation rate range that can be applied in livestock production

facilities is limited, and an inappropriate increase in the ventilation rate could cause unfavourable thermal and humidity conditions in the animal zone. In terms of applicability, control of the humidity level can be a significant factor in reducing occupational dust in broiler houses. However, increased humidity could cause proliferation of micro-organisms and loss of productivity. Therefore, additional research to derive optimal indoor humidity levels, taking account of both biological safety and dust environment, is needed.

Conclusions

In this study the concentration of TSP, PM10, inhalable dust, and respirable dust in different environmental condition was regularly monitored in mechanically and naturally ventilated broiler houses. Relatively high dust concentrations were measured in the naturally ventilated broiler house. It was found that dehumidification and increased broiler activity due to sunlight entering through the winch curtain, and a relatively high rearing density were the cause of this phenomenon. Multiple linear regression analysis was conducted to derive the relationship between occupational dust concentration and environmental factors including ventilation rate calculated using CFD simulation. As a result, it was found that the activity status of broilers, ventilation rate and the humidity level of the facility were major factors in occupational dust generation. In terms of practical applicability, the humidity level can be the key factor for dust control in broiler houses. However, humidity inside the facility should be carefully controlled with a view to ensuring biological safety.

References

Banhazi, T. M., Seedorf, J., Rutley, D. L., & Pitchford, W. S. 2008. Identification of risk factors for sub-optimal housing conditions in Australian piggeries: Part 2. Airborne pollutants. *Journal of Agricultural Safety and Health*, 14(1), 21.

Hartung, J., & Saleh, M. 2007. Composition of dust and effects on animals. *Landbauforsch. Völk*, 308, 111-116.

Hessel, E. F., & Van den Weghe, H. F. 2007. Airborne Dust (PM 10) concentration in broiler houses as a function of fattening day, time of the day, and indoor light. In: *DustConf International Conference in Maastricht*, The Netherlands (pp. 23-24).

Hugh-Jones, M., Allan, W. H., Dark, F. A., & Harper, G. J. (1973). The evidence for the airborne spread of Newcastle disease. *Journal of hygiene*, 71(02), 325-339.

Pedersen, S., & Robertson, J. 1994. Aerial environment in animal housing-concentrations in and emissions from farm buildings. *CIGR*, 1.

Power, C. A. (2005). An investigation into the potential role of aerosol dispersion of dust from poultry barns as a mode of disease transmission during an outbreak of avian influenza (H7: N3) in Abbotsford, BC in 2004. *BULLETIN-AQUACULTURE ASSOCIATION OF CANADA*, 105(1), 7.

Rosentrater, K. A. (2004). Laboratory analysis of an electrostatic dust collection system. *CICR Journal of Scientific Research and Development*.

Tucker, W. G. (2000). An overview of PM 2.5 sources and control strategies. *Fuel Processing Technology*, 65, 379-392.

PLF technologies: model development for solving heat stress problems on dairy farms

B. Ji[1], T. Banhazi[1], C. Wang[2] , B. Li[2]
[1]*Department of Civil Engineering and Surveying, University of Southern Queensland, West Street, Toowoomba, QLD 4350, Australia*
[2]*Department of Agricultural Structure and Bioenvironmental Engineering, China Agricultural University, Beijing 100083, China*
Thomas.Banhazi@usq.edu.au

Abstract

Regular occurrence of heat stress conditions is a significant challenge in dairy farming. Dairy cattle under heat stress will encounter sub-optimal welfare that can ultimately results in production loss for farmers. In precision livestock farming (PLF), studies aimed at modelling the influence of heat stress have been undertaken for several decades. Mitigation solutions including optimal shed structure, ventilation systems, targeted feeding regimes, improved farm management and genetic selection have also been used widely on farms. However, under different on-farm conditions, the heat tolerance and coping ability of cattle can vary significantly. Until now, the results from different developed models can only provide generalized heat stress thresholds for on-farm use. Similar problems exist in relation to mitigation solutions. This review will summarize current developments and analyse the differences in current on-farm research. The results related to thermal indices, animal responses, production loss and mitigation approaches will be compared and analysed. Instead of conducting large international studies to identify and overcome inconsistencies between different study results, alternative solution may be developed via more robust modelling or programming for specific farm and building systems. The developed model or program should be self-recalibrated based on the real-time collection of information on key parameters. The feasibility of the proposed system will be supported by innovative PLF and information technologies.

Keywords: modelling, mitigation, animal welfare, thermal comfort.

Introduction

The welfare and comfort of dairy cows are increasingly seen as moral and practical concerns, especially in developed countries (Silanikove, 2000). Under heat stress conditions, the optimal welfare of the dairy cow can be compromised by decreased feed intake, resting and rumination time (Grant, 2012). The sub-optimal animal comfort due to heat stress is the primary cause of production losses in the global dairy industry, especially for high-producing cows (Biby, 2010). The general mitigation technique to combat heat stress on-farms is to control the thermal environment around animals (Mader *et al.*, 2007). However, the high cost associated with climate control systems cannot be economically justified in many cases (Zimbelman, 2007). The adjustment of diet (to reduce the negative effects of heat stress) have also been studied as a potential on-farm mitigation procedure (Kanjanapruthipong *et al.*, 2015). At the same time, the genetic selection of heat tolerant breeds has also been progressed with various level of success (Roland *et al.*, 2016).

At present, various precision livestock farming (PLF) techniques are being developed for the benefit of modern livestock industries. A number of authors reported using innovative PLF technologies to better detect heat stress, the quality of environments surrounding the animals and their physiological conditions (Pollard *et al.*, 2004; Schmidt *et al.*, 2004; Eigenberg *et al.*, 2008). Several mathematical models were also developed from these studies to assess and predict the effects of heat stress on animals (Mader *et al.*, 2010; Gaughan *et al.*, 2008). Based on the developed models, mitigation approaches such as auto-controlled sprinkling was also evaluated (Mader *et al.*, 2007). However, the outcomes from current studies can only provide generalized heat-stress evaluations for on-farm use. Further development is still necessary to enable commercial farm application, and to overcome the variance between different on-farm studies. This review aims to summarise the current research in relation to heat stress in dairy cattle. The primary focus of this review will be on the published thermal comfort indices, on-farm measurement and the developed climate mitigation techniques. The potential of using PLF techniques to provide accurate modelling output on heat stress will be highlighted. It is widely accepted that PLF technologies do include model or software based developments, not only hardware type developments (Black *et al.*, 2016; Willis *et al.*, 2016).

Indicators and Measurements in Field Studies

The indicators or parameters selected to evaluate the severity of heat stress on-farms are usually dependent on available devices, farm management procedures and the status of animals. Indicators and devices that provide information on the thermal environment, physiological condition and production efficiency of the animals are typically selected, as reviewed in Table 1. Supported by such devices, the mathematical model was executed to provide estimation or prediction functions for on-farm applications, such as understanding the shading effect during heat stress (Brown-Brandl *et al.*, 2005).

Table 1 Automatic devices applied in field studies to evaluate the severity of heat stress

Type of parameters	Devices	Manufacture	References
Temperature & humidity	Tinytag Plus 2 logger	Gemini loggers Ltd, Chichester, UK	Schuller *et al.* (2014); Banhazi *et al.* (2008a); Banhazi *et al.* (2008c); Banhazi *et al.* (2008b)
	HMP45 dataloggers	Vaisala, Helsinki, Finland	Tucker *et al.* (2008)
	HOBO Pro dataloggers	Onset Computer Corporation, Pocasset, MA	Ortiz *et al.* (2015)
Wind speed	Hall effect anemometer	NRG Systems, Hinesburg, VT, USA	Tucker *et al.* (2008)
	Hot-wire anemometers	Alnor Instruments (Shoreview, Minn)	Banhazi *et al.* (2008c)
Solar radiation	Pyranometers Licor Li200x	Campbell Scientific Inc. Logan, UT, USA	Tucker *et al.* (2008)
Integrated measurement	Automated weather stations, Vantage PRO weather recorder	Davis Instruments, Hayward, CA., USA	Eigenberg *et al.* (2005a)
Sweating rate	Evapo-meter	Delfin Technologies Ltd., Kuopio, Finland	Rungruang *et al.* (2014)
Respiration rate	Automatic dataloggers	U.S. Meat Animal Research Central	Eigenberg *et al.* (2005a)
Lying patterns	HOBO Pendant G	Onset Computer Corporation, Pocasset, MA	Wang *et al.* (2016)
Rectal temperature	Digital thermometer, GLA-M500	Agricultural Electronics, San Luis Obispo, CA	Church *et al.* (2014)
	Stainless steel probe YSI	1700 Brannum Lane, Yellow Springs, OH	Brown-Brandl *et al.* (2003)
Vaginal temperature	Vaginal controlled drug	CIDR™, InterAg, Hamilton, New Zealand	Schütz *et al.* (2009)
Skin temperature	Infrared thermometer Model RAYST80XB	Raytek Corporation, Santa Curz, CA, USA	Scharf *et al.* (2012)
Production data	Variables including the body weight, feed intake, milk yield, and conception rate are frequently recorded on-farms using a number of PLF devices in dairy and other livestock industries.		Porto *et al.* (2015); Halachmi *et al.* (1998); Banhazi and Banhazi (2015); Banhazi *et al.* (2015); Banhazi *et al.* (2011)

Modelling on Heat Stress – the Thermal Indices

The modelling of heat stress is the first step to provide precise control of heat stress. Initially, a simple temperature and humidity index (THI), was established as discomfort index (THI-1) using Tdb and Twb based on evaluating human

comfort (Thom, 1959). The adapted THI equation (THI-2) used the rectal temperature of bull calves and different combination of Tdb and Twb (Bianca, 1962). The equations of THI-3 and 4 (Berry *et al.*, 1964; Yousef, 1985) were based on information obtained on Heifer cattle (MY: 15.5 kg/d) kept in climate chambers. The equation of THI-5 was used to report a strong correlation between thermal condition, milk production and animal comfort (Johnson, 1965). The disadvantage of THI equations is insufficient consideration of convection and radiation heat transfer, as they only contain temperature and humidity parameters. To improve the previous THI equations, Tbg was used to replace dry bulb temperature in the general THI equation which resulted in the development of the black globe humidity index (BGHI) (Buffington *et al.*, 1981). The equivalent temperature index (ETI) was built by analysing the relationship between milk production, temperature, humidity, wind speed and heat-loss rates (Baeta *et al.*, 1987). An upgraded version (THI-6) was also published which adjusted the equation of THI-4 by adding the effect of wind speed and solar radiation (Mader *et al.*, 2006). The respiration rate index (RR) was developed by modelling environmental parameters with respiration rate (Brown-Brandl *et al.*, 2005). Gaughan *et al.* (2002); (2008) developed the heat load index (HLI-1 and 2) for feedlot beef cattle. This model was based on panting observations in four Australian commercial feedlots. The management factor, shaded or unshaded, was also taken into consideration. Tbg, RH, and WS were used as parameters in the model describing the environment. Based on the HLI equation, the comprehensive climate index (CCI) was developed to assess both cold and heat stress (Mader *et al.*, 2010). The CCI index was aimed at developing an apparent temperature that represented ambient temperature. CCI included varied equations to focus on different thermal factors such as wind speed. Although, the thermal indices provided acceptable performance to evaluate the heat stress under conditions that were similar to where they were developed. Unfortunately, there is always some level of inconsistency between different thermal indices (different thresholds) when evaluating the same environmental conditions (Table 2). The weight of different thermal parameters and animal responses in different equation significantly affect their performance under different conditions (Bohmanova *et al.*, 2007). Several studies compared the published indices and provided different recommendations (Hammami *et al.*, 2013; Li *et al.*, 2009). Furthermore, to apply thermal indices, the time duration (short-term vs. long-term) and delay effect of heat stress can also result in varied performance of the indices (Morton *et al.*, 2007; Zimbelman, 2007). With the improvement of devices and equipment, researchers are now able to monitor more

animals and for longer time periods. Animal variables such as breed, coat colour, body condition and production status are also being considered in current development of models. These considerations result in more complex equations that are more applicable to practical conditions. However, the latest indices (HLI and RR) were focused on feedlot cattle kept in open area. Making efforts to understand the differences between beef and dairy cattle as well as the variance between intensive and extensive farming systems is still necessary.

Table 2 Threshold values based on thermal indices equations

Tdb[a]	RH	WS	SR	THI-2[b,g]	THI-3[g]	THI-4[g]	THI-5[g]	THI-6[g]	BGHI[c,g]	ETI[d,g]	HLI-2[e,g]	RR[f,g]
20	52	7.0	475	61	65	65	74	59	72	18	67	28
21	54	6.5	517	63	67	67	76	62	74	20	70	37
22	57	6.0	560	65	68	68	77	65	75	21	72	46
23	59	5.5	602	67	70	70	79	68	77	23	75	55
24	61	5.0	645	69	71	72	80	70	79	25	78	64
25	63	4.5	687	71	73	73	81	73	80	27	81	73
26	66	4.0	730	73	74	75	83	76	82	29	84	82
27	68	3.5	772	75[g]	76	77	84	79	84	31	87	91
28	70	3.0	815	77	77	78	86	82	86	34	90	99
29	72	2.5	857	80	79	80	87	86	87	36	94	108
30	75	2.0	900	82	81	82	89	89	89	39	97	117
31	77	1.5	942	84	82	84	90	92	91	42	101	126
32	79	1.0	985	86	84	86	92	95	92	44	105	135
33	81	0.5	1027	88	85	88	93	99	94	47	111	144
34	84	0.0	1070	90	87	90	95	102	96	50	118	153
35	86	0.0	1112	93	88	92	96	104	97	53	121	161

a: Assumed environmental condition with varied Tdb [20-35] C^{o}, RH [52-86]%, WS [0-7] m/s and SR [475-1112] W/m^2

b: Thresholds for THI and BGHI: Normal:<74; Alert: 74-79; Danger: 79-84; Emergency:>84; (Eigenberg *et al.*, 2005b)

c: Thresholds for ETI: Normal:<30; Alert: 30-34; Danger: 34-38; Emergency:>38; (Silva *et al.*, 2007)

d: Thresholds for HLI-2: Normal:<80; Alert: 80-88; Danger: 88-92; Emergency:>92; (Hammami *et al.*, 2013)

e: Thresholds for RR: Normal:<90; Alert: 90-110; Danger: 110-130; Emergency:>130;(Eigenberg *et al.*, 2005b)

f: The legend of colour and levels: Normal, Alert, Danger, Emergency

g:References for the equations: THI-2: Bianca (1962); THI-3: Berry *et al.* (1964); THI-4: Yousef (1985); THI-5: Johnson (1965); THI-6: Mader *et al.* (2006); BGHI: Buffington *et al.* (1981); ETI: Baeta *et al.* (1987); HLI-2: Gaughan *et al.* (2008); RR: Eigenberg *et al.* (2005a).

Mitigations of Thermal Environments

Thermodynamic principles (i.e. conduction, convection, radiation and evaporation) must be followed when adjusting thermal environments. Basically shading, bed cooling, ventilation and evaporative cooling are the practical solutions. Shading constructions are typically used to minimize radiation load and maximize the efficiency of ventilation as the most basic heat stress reduction method in dairy farming (Sparke *et al.*, 2001). An integrated index, the radiation heat balance was developed by Berman and Horovitz (2012). By accounting radiation heat transfer from sources around animals, the index indicated the increased height of shading construction can cause indirect radiation, and the increased shaded area per animal can only provide limited cooling. Shoshani and Hetzroni (2013) reported some new barn construction designs, such as sliding roof, shuttered roof, open ridge roof and pagoda (capped-gable) roof. The orientation, width, height and slope of the new designed shading can be adjusted according to the wind and sunshine direction. To improve the cooling when animal lying down, high conductive cooling efficiency of the bedding material is preferred. Recently, a conductive cooling system applying waterbed was developed and evaluated by Perano *et al.* (2015). The system used water circulation to supply chilled water to the waterbed and in addition, an approximately one cm sawdust bedding was sprinkled on the top of the waterbed. The study reported nearly 5% increase in milk yield. The effect of materials on the water bedding (dried manure and sand) and seasonal variation (hot, dry, thermo neutral and hot humid climate) was further studied by Ortiz *et al.* (2015). For normal bedding material, Seyfi (2013) found the cattle preferred to use the courtyard for resting during all seasons instead of the high-cost stalls. The ventilation cooling is the most direct way of cooling the cattle. In natural ventilation systems, the construction of the barn (flat roof or ridge roof) can have a significant influence on the efficiency of ventilation system (Marciniak, 2014). Mechanical ventilation and air mixers are required under severe heat stress. Development and evaluation of different fans and sprinkling systems were conducted by several studies (Hillman *et al.*, 2005; Smith *et al.*, 2007). Mader *et al.* (2007) also studied the performance of auto-controlled sprinklings and their relationship with the predicted value of THI. The use of automatically controlled sprinkling systems resulted in a significant reduction on the animal panting score compared with the once per day sprinkling. Some studies focused on improving the automatic control strategies, such as Qi and Deng (2009), Daskalov *et al.* (2006) and Soldatos *et al.* (2005). These improved control strategies (liner or nonlinear robust control) can control multiple thermal variables simultaneously

without affecting each other. However, these strategies rely only on thermal variables and do not consider animal responses in the calculation. The potential improvement for the future mitigations may be obtained by considering sensitive animal responses (e.g. respiration rate) instead of exclusively the environmental and production data. Grant (2012) reported the benefit of cooling facilities in several studies and the summary of these results are presented in Table 2. A significant improvement in milk production was identified in buildings with fans and sprinkler cooling systems (1.4 - 7.7 kg/d/cow). In contrast, conductive cooling and shading can only provide limited reduction in heat stress (0.5 – 2.1 kg/d/cow). However, animal physiological status such as the days in milk need to be also accounted for the variance.

Table 2 Efficiency of environmental mitigations (adapted from Grant (2012))

DIM (days)	Cooling method	MY* (control) (kg/d/cow)	MY increase (kg/d/cow)	Reference
56	Fans + Misting	25.2	7	Avendano-Reyes *et al.* (2006)
60	Fans + Shades + Sprinklers	38.2	1.4	Urdaz *et al.* (2006)
42	Fans + Sprinklers	25.2	7.7	Do Amaral *et al.* (2008)
140	Fans + Sprinklers	30.5	4.7	Do Amaral *et al.* (2009)
90	Fans + Foggers	38.8	2.1	Adin *et al.* (2009)
147	Fans + Sprinklers	28.9	5	Tao *et al.* (2011)
166	Waterbed cooling	30.3	2.1	Perano *et al.* (2015)
315	Waterbed cooling + sands	29.6	1.4	Ortiz *et al.* (2015)
145	Fans + Misting	29	0.6	Frazzi *et al.* (2000)
	Fans	29	0.4	
178	Shading	17.2	0.5	Kendall *et al.* (2006)

*: daily milk yield of lactation cow

The Attitude towards Inconsistency – PLF Potentials

Inconsistent results and conclusions are always the major problem in relation to heat stress studies of dairy cattle. For example, inaccurate estimations can be generated by choosing an unsuitable model. In practical terms, cattle breeds, location of the study (i.e. field vs. laboratory studies), physiological conditions of the animals, time-lag effects and the system error of measurement devices can all contribute to the inconsistency. Researchers are currently trying to develop measurement and modelling systems in relation to minimize inconsistency covering large geographical area (national and global range) and using widely

agreed standards (Gaughan *et al.*, 2008). For exmaple, web-based early warning systems were developed based on the previously mentioned study. The forecast systems obtained weather data from the nearest weather station around the farm and predicted heat stress levels for the coming 1-5 days. Such studies and practical outcomes are necessary for providing regional threshold standards and early warning alerts. However, the economic and labour cost associated with running these systems could be significant. The data of these projects need to be updated periodically (2-5 years) as the climate (Segnalini *et al.*, 2013) and genetic background of the animals change (West, 2003). Moreover, for practical usage of the website, Gaughan *et al.* (2012) concluded the forecasting from the website could not specify the effect of building structure, such as wind speed in the building. It was also reported that different ventilation systems and floor types can cause varied heat transmission between internal and external environment (Seedorf *et al.*, 1998). These variances will still cause inconsistency in forecasting of heat stress for specific farm conditions.

A number of possible new solutions may be developed depending on the (1) current progress achieved by PLF techniques and by information technology (IT) in the future. These solutions (hardware or software systems) may be compiled and automated to: 1) collect information from integrated monitoring systems; 2) model the collected data as prediction function (such as THI); 3) determine the key factors (such as RR and MY); 4) assess the performance of prediction functions; 5) self- recalibrate the function periodically based on self-assessment of performance and 6) control the mitigation facilities based on the prediction function (such as THI to control sprinkler). Research needs to focus on building construction, management specifications and individual animal management on farms. A historical database needs to be established for tracing the varied conditions and animal responses on the farm. Moreover, some improved control strategies need to be applied to work together with the prediction functions (Daskalov *et al.*, 2006). Once all this achieved, dairy facilities might be operated more cost effectively by farmers.

Conclusions

Solving heat stress is the primary challenge facing currently dairy farming. Although much progress has been made in this research area, such as the development of advanced sensors and measurement devices, livestock producers still enjoy only limited practical improvements on farms. In this case, precise

heat-stress modelling together with the financial consequences of heat stress may provide more practical results. This review focused on summarizing the progress achieved in current heat stress studies. The published models (thermal comfort indices) were compared, as well as the practicality of mitigation techniques. The outputs of current indices varies significantly due to several factors, such as the difference between laboratory and field studies. Similar variance also exists in mitigation solutions. Fans and sprinklers are reported as the most effective cooling tools for heat stress. Nevertheless, the energy cost and reduced performance under hot-humid condition are still a major concern in field applications. To overcome such inconsistent results, recent studies tended to use large number of farms in one study. The collected information is typically stored in large databases for further analysis. However, the periodical upgrading of these databases with huge labor and finanical cost is always necessary to correspond to changes in climate and genetic selection of livestock. Instead of focusing on the general solutions, it may be more effective to develop solutions that are applicable on specific farms. By taking advantage of PLF developments in this specific area, such systems could provide optimized models, such as dynamical calibrated algorithms (such as THI). The calibration could be automatically conducted based on the continuals on-farm monitoring. Robotic sensors and cooling facilities might be connected to this envisaged control system. A historical database of the specific farm can then be built to provide accurate mitigation strategies for either individual animal or for the whole herd.

Acknowledgements

The author would like to appreciate the funding provided by University of Southern Queensland for the PhD. research project.

References

Adin, G., Gelman, A., Solomon, R., Flamenbaum, I., Nikbachat, M., Yosef, E., Zenou, A., Shamay, A., Feuermann, Y. & Mabjeesh, S. (2009). Effects of cooling dry cows under heat load conditions on mammary gland enzymatic activity, intake of food and water, and performance during the dry period and after parturition. *Livestock Science* 124(1): 189-195.

Avendano-Reyes, L., Alvarez-Valenzuela, F., Correa-Calderón, A., Saucedo-Quintero, J., Robinson, P. & Fadel, J. (2006). Effect of cooling Holstein cows during the dry period on postpartum performance under heat stress conditions. *Livestock Science* 105(1): 198-206.

Baeta, F., Meador, N., Shanklin, M. & Johnson, H. (1987). Equivalent temperature index at temperatures above the thermoneutral for lactating dairy cows. *American Society of Agricultural Engineers (USA)*.

Banhazi, T., Seedorf, J., Rutley, D. L. & Pitchford, W. S. (2008a). Identification of risk factors for sub-optimal housing conditions in Australian piggeries: Part 1. Study justification and design. *Journal of Agricultural Safety and Health* 14(1): 5-20.

Banhazi, T., Seedorf, J., Rutley, D. L. & Pitchford, W. S. (2008b). Identification of risk factors for sub-optimal housing conditions in Australian piggeries: Part 2. Airborne pollutants. *Journal of Agricultural Safety and Health* 14(1): 21-39.

Banhazi, T., Seedorf, J., Rutley, D. L. & Pitchford, W. S. (2008c). Identification of risk factors for sub-optimal housing conditions in Australian piggeries: Part 3. Environmental parameters. *Journal of Agricultural Safety and Health* 14(1): 41-52.

Banhazi, T., Vranken, E., Berckmans, D., Rooijakkers, L. & Berckmans, D. (2015).Word of caution for technology providers: Practical problems associated with large scale deployment of PLF technologies on commercial farms. In *7th European Conference on Precision Livestock Farming*, Vol. 1, 105-111 (Ed I. Halachmi). Leuven, Belgium: Wageningen Academic Publishers

Banhazi, T. M. & Banhazi, A. (2015).Long term monitoring of growth rates and environmental parameters on selected European pig farms. In *8th European Conference on Precision Livestock Farming*(Eds D. Berckmans and M. Guarino). Milan, Italy: University of Milan.

Banhazi, T. M., Tscharke, M., Ferdous, W. M., Saunders, C. & Lee, S.-H. (2011). Improved image analysis based system to reliably predict the live weight of pigs on farm: Preliminary results. *Australian Journal of Multi-disciplinary Engineering* 8 (2): 107-119

Berman, A. & Horovitz, T. (2012). Radiant heat loss, an unexploited path for heat stress reduction in shaded cattle. *J Dairy Sci* 95(6): 3021-3031.

Berry, I., Shanklin, M. & Johnson, H. (1964). Dairy shelter design based on milk production decline as affected by temperature and humidity. *Transactions of the ASAE* 7(3): 329-0331.

Bianca, W. (1962). Relative importance of dry-and wet-bulb temperatures in causing heat stress in cattle. *Nature* 195: 251.

Biby, W. W. T. I. F. J. B. T. R. (2010).Interrelationships of Heat Stress and Reproduction in Lactating Dairy Cows. In *High Plains Dairy Conference*.

Black, J., Sara Willis, S. & Banhazi, T. M. (2016).Estimation of Accuracy Needed for Live Weight and Feed Intake Measurements in Precision Livestock Farming Systems Using Auspig Simulation Software In *First Asian Precision Livestock farming conference* in-print (Ed C. Wang). Beijing, China China Agricultural University

Bohmanova, J., Misztal, I. & Cole, J. B. (2007). Temperature-humidity indices as indicators of milk production losses due to heat stress. *J Dairy Sci* 90(4): 1947-1956.

Brown-Brandl, T., Eigenberg, R., Nienaber, J. & Hahn, G. L. (2005). Dynamic response indicators of heat stress in shaded and non-shaded feedlot cattle, Part 1: Analyses of indicators. *Biosystems Engineering* 90(4): 451-462.

Brown-Brandl, T., Nienaber, J., Eigenberg, R., Hahn, G. & Freetly, H. (2003). Thermoregulatory responses of feeder cattle. *Journal of Thermal Biology* 28(2): 149-157.

Buffington, D., Collazo-Arocho, A., Canton, G., Pitt, D., Thatcher, W. & Collier, R. (1981). Black globe-humidity index (BGHI) as comfort equation for dairy cows. *Transactions of the ASAE* 24(3): 711-0714.

Church, J. S., Hegadoren, P. R., Paetkau, M. J., Miller, C. C., Regev-Shoshani, G., Schaefer, A. L. & Schwartzkopf-Genswein, K. S. (2014). Influence of environmental factors on infrared eye temperature measurements in cattle. *Res Vet Sci* 96(1): 220-226.

Daskalov, P. I., Arvanitis, K. G., Pasgianos, G. D. & Sigrimis, N. A. (2006). Non-linear Adaptive Temperature and Humidity Control in Animal Buildings. *Biosystems Engineering* 93(1): 1-24.

Do Amaral, B., Connor, E., Tao, S., Hayen, J., Bubolz, J. & Dahl, G. (2009). Heat-stress abatement during the dry period: Does cooling improve transition into lactation? *Journal of Dairy Science* 92(12): 5988-5999.

Do Amaral, B., Hayen, J., Connor, E., Tao, S. & Dahl, G. (2008). Heat stress abatement for dry cows: Does cooling improve transition into lactation? *Journal of Dairy Science* 91: 379.

Eigenberg, R., Brown-Brandl, T., Nienaber, J. A. & Hahn, G. L. (2005a). Dynamic response indicators of heat stress in shaded and non-shaded feedlot cattle, Part 2: Predictive relationships. *Biosystems Engineering* 91(1): 111-118.

Eigenberg, R. A., Brown-Brandl, T. M. & Nienaber, J. A. (2008). Sensors for dynamic physiological measurements. *Computers and Electronics in Agriculture* 62(1): 41-47.

Eigenberg, R. A., Brown-Brandl, T. M., Nienaber, J. A. & Hahn, G. L. (2005b). Dynamic Response Indicators of Heat Stress in Shaded and Non-shaded Feedlot Cattle, Part 2: Predictive Relationships. *Biosystems Engineering* 91(1): 111-118.

Frazzi, E., Calamari, L., Calegari, F. & Stefanini, L. (2000). Behavior of dairy cows in response to different barn cooling systems. *Transactions of the ASAE* 43(2): 387.

Gaughan, J., Goopy, J. & Spark, J. (2002). Excessive heat load index for feedlot cattle. *Sydney: MLA*.

Gaughan, J., Mader, T. & Gebremedhin, K. (2012).Rethinking heat index tools for livestock. In *Environmental physiology of Livestock*, 243-265: Wiley-Blackwell Chichester.

Gaughan, J., Mader, T. L., Holt, S. & Lisle, A. (2008). A new heat load index for feedlot cattle. *Faculty Papers and Publications in Animal Science*: 613.

Grant, R. (2012). Economic Benefits of Improved Cow Comfort. *Novus Int. St. Charles, MO*.

Halachmi, I., Edan, Y., Maltz, E., Peiper, U. M., Moallem, U. & Brukental, I. (1998). A real-time control system for individual dairy cow food intake. *Computers and Electronics in Agriculture* 20(2): 131-144.

Hammami, H., Bormann, J., M'Hamdi, N., Montaldo, H. H. & Gengler, N. (2013). Evaluation of heat stress effects on production traits and somatic cell score of Holsteins in a temperate environment. *J Dairy Sci* 96(3): 1844-1855.

Hillman, P., Lee, C. & Willard, S. (2005). Body temperature versus microclimate selection in heat stressed dairy cows. *Trans. Am. Soc. Agric. Eng., 2003b* 48(2): 795.

Johnson, H. D. (1965). Environmental temperature and lactation (with special reference to cattle). *International Journal of Biometeorology* 9(2): 103-116.

Kanjanapruthipong, J., Junlapho, W. & Karnjanasirm, K. (2015). Feeding and lying behavior of heat-stressed early lactation cows fed low fiber diets containing roughage and nonforage fiber sources. *Journal of Dairy Science* 98(2): 1110-1118.

Kendall, P. E., Nielsen, P. P., Webster, J. R., Verkerk, G. A., Littlejohn, R. P. & Matthews, L. R. (2006). The effects of providing shade to lactating dairy cows in a temperate climate. *Livestock Science* 103(1-2): 148-157.

Li, S., Gebremedhin, K. G., Lee, C. N. & Collier, R. J. (2009).Evaluation of thermal stress indices for cattle. In *2009 Reno, Nevada, June 21-June 24, 2009*, 1: American Society of Agricultural and Biological Engineers.

Mader, T. L., Davis, M. & Brown-Brandl, T. (2006). Environmental factors influencing heat stress in feedlot cattle. *Journal of Animal Science* 84(3): 712-719.

Mader, T. L., Davis, M. S. & Gaughan, J. B. (2007). Effect of sprinkling on feedlot microclimate and cattle behavior. *Int J Biometeorol* 51(6): 541-551.

Mader, T. L., Johnson, L. J. & Gaughan, J. B. (2010). A comprehensive index for assessing environmental stress in animals. *J Anim Sci* 88(6): 2153-2165.

Marciniak, A. (2014). The use of temperature-humidity index (thi) to evaluate temperature-humidity conditions in freestall barns. *Journal of Central European Agriculture* 15(2): 73-83.

Morton, J., Tranter, W., Mayer, D. & Jonsson, N. (2007). Effects of environmental heat on conception rates in lactating dairy cows: Critical periods of exposure. *Journal of Dairy Science* 90(5): 2271-2278.

Ortiz, X., Smith, J., Rojano, F., Choi, C., Bruer, J., Steele, T., Schuring, N., Allen, J. & Collier, R. J. (2015). Evaluation of conductive cooling of lactating dairy cows under controlled environmental conditions. *Journal of Dairy Science* 98(3): 1759-1771.

Perano, K. M., Usack, J. G., Angenent, L. T. & Gebremedhin, K. G. (2015). Production and physiological responses of heat-stressed lactating dairy cattle to conductive cooling. *Journal of Dairy Science* 98(8): 5252-5261.

Pollard, B., Dwyer, M., Fitzgerald, A., Gentry, P., Henderson, D. & Collier, R. (2004).Effects of ambient temperature and solar radiation on skin evaporative water loss in dairy cattle. In *Journal of Dairy Science*, Vol. 87, 198-198: AMER DAIRY SCIENCE ASSOC 1111 N DUNLAP AVE, SAVOY, IL 61874 USA.

Porto, S. M. C., Arcidiacono, C., Anguzza, U. & Cascone, G. (2015). The automatic detection of dairy cow feeding and standing behaviours in free-stall barns by a computer vision-based system. *Biosystems Engineering* 133(0): 46-55.

Qi, Q. & Deng, S. (2009). Multivariable control of indoor air temperature and humidity in a direct expansion (DX) air conditioning (A/C) system. *Building and Environment* 44(8): 1659-1667.

Roland, L., Drillich, M., Klein-Jobstl, D. & Iwersen, M. (2016). Invited review: Influence of climatic conditions on the development, performance, and health of calves. *J Dairy Sci* 99(4): 2438-2452.

Rungruang, S., Collier, J., Rhoads, R., Baumgard, L., de Veth, M. & Collier, R. J. (2014). A dose-response evaluation of rumen-protected niacin in thermoneutral or heat-stressed lactating Holstein cows. *Journal of Dairy Science* 97(8): 5023-5034.

Scharf, B., Johnson, J., Weaber, R. & Spiers, D. (2012). Utilizing laboratory and field studies to determine physiological responses of cattle to multiple environmental stressors. *Journal of Thermal Biology* 37(4): 330-338.

Schmidt, S., Bowers, S., Dickerson, T., Graves, K. & Willard, S. (2004).Assessments of udder temperature gradients pre-and post-milking relative to milk production in Holstein cows as determined by digital infrared thermography. In *Journal of Dairy Science*, Vol. 87, 460-461: ELSEVIER SCIENCE INC 360 PARK AVE SOUTH, NEW YORK, NY 10010-1710 USA.

Schuller, L. K., Burfeind, O. & Heuwieser, W. (2014). Impact of heat stress on conception rate of dairy cows in the moderate climate considering different temperature-humidity index thresholds, periods relative to breeding, and heat load indices. *Theriogenology* 81(8): 1050-1057.

Schütz, K. E., Rogers, A. R., Cox, N. R. & Tucker, C. B. (2009). Dairy cows prefer shade that offers greater protection against solar radiation in summer: Shade use, behaviour, and body temperature. *Applied Animal Behaviour Science* 116(1): 28-34.

Seedorf, J., Hartung, J., Schröder, M., Linkert, K., Pedersen, S., Takai, H., Johnsen, J. O., Metz, J., Koerkamp, P. G. & Uenk, G. (1998). Temperature and moisture conditions in livestock buildings in Northern Europe. *Journal of Agricultural Engineering Research* 70(1): 49-57.

Segnalini, M., Bernabucci, U., Vitali, A., Nardone, A. & Lacetera, N. (2013). Temperature humidity index scenarios in the Mediterranean basin. *Int J Biometeorol* 57(3): 451-458.

Seyfi, S. U. (2013). Hourly and seasonal variations in the area preferences of dairy cows in freestall housing. *J Dairy Sci* 96(2): 906-917.

Shoshani, E. & Hetzroni, A. (2013). Optimal barn characteristics for high-yielding Holstein cows as derived by a new heat-stress model. *animal* 7(01): 176-182.

Silanikove, N. (2000). Effects of heat stress on the welfare of extensively managed domestic ruminants. *Livestock Production Science* 67: 1-18.

Silva, R. G. d., Morais, D. A. E. F. & Guilhermino, M. M. (2007). Evaluation of thermal stress indexes for dairy cows in tropical regions. *Revista Brasileira de Zootecnia* 36(4): 1192-1198.

Smith, J., Harner, J., de Haro Marti, M., Sheffield, R., Zulovich, J., Pohl, S., Fulhage, C., Nicoli, D., Hetchler, B. & Jacobson, L. (2007).Comprehensive evaluation of a low-profile cross-ventilated freestall barn. In *Proceedings of the 8th Western Dairy Management Conference, America*, 127-147.

Soldatos, A. G., Arvanitis, K. G., Daskalov, P. I., Pasgianos, G. D. & Sigrimis, N. A. (2005). Nonlinear robust temperature–humidity control in livestock buildings. *Computers and Electronics in Agriculture* 49(3): 357-376.

Sparke, E., Young, B., Gaughan, J., Holt, S. & Goodwin, P. (2001). Heat load in feedlot cattle.

Tao, S., Bubolz, J., Do Amaral, B., Thompson, I., Hayen, M., Johnson, S. & Dahl, G. (2011). Effect of heat stress during the dry period on mammary gland development. *Journal of Dairy Science* 94(12): 5976-5986.

Thom, E. C. (1959). The discomfort index. *Weatherwise* 12(2): 57-61.

Tucker, C. B., Rogers, A. R. & Schütz, K. E. (2008). Effect of solar radiation on dairy cattle behaviour, use of shade and body temperature in a pasture-based system. *Applied Animal Behaviour Science* 109(2-4): 141-154.

Urdaz, J., Overton, M., Moore, D. & Santos, J. (2006). Technical note: Effects of adding shade and fans to a feedbunk sprinkler system for preparturient cows on health and performance. *Journal of Dairy Science* 89(6): 2000-2006.

Wang, F. X., Shao, D. F., Li, S. L., Wang, Y. J., Azarfar, A. & Cao, Z. J. (2016). Effects of stocking density on behavior, productivity, and comfort indices of lactating dairy cows. *J Dairy Sci* 99(5): 3709-3717.

West, J. (2003). Effects of heat-stress on production in dairy cattle. *Journal of Dairy Science* 86(6): 2131-2144.

Willis, S., Black, J. & Banhazi, T. (2016).Estimation of Production Losses associated with Short Term Growth Rate Reduction and Sub-Optimal Thermal Conditions on Pig Farms Using Auspig Simulation Software. In *Asian Conference on Precision Livestock Farming (PLF-Asia 2016)*, Vol. 1, 45-52 (Eds G. Zhang, L. Zhao, C. Wang, W. Zheng, Q. Tong, D. Berckmans and K. Wang). Beijing, China: China Agricultural University.

Yousef, M. K. (1985). *Stress physiology in livestock. Volume III. Poultry.* CRC Press Inc.

Zimbelman, R. J. C. R. B. (2007).Heat Stress Effects on Cattle: What We Know and What We Don’t Know. In *22nd Annual Southwest Nutrition & Management Conference*.

Design of a software tool for the analysis of UWB RTLS data: a use case of an application to identify cow oestrus behavioural patterns in a free-stall barn

C. Arcidiacono, S.M.C. Porto, M. Mancino, F. Valenti, G. Cascone
Department of Agriculture, Food and Environment (Di3A), University of Catania
claudia.arcidiacono@unict.it

Abstract

The need to monitor large herds housed in intensive livestock buildings has enhanced the development of automated monitoring systems. Consistent handling of large amounts of data has created a need to improve the data stream analysis process and to use new tools for analysis and visualisation of information. These tools could be a valuable support for farmers in herd management and for researchers in the analysis of animal behavioural activities.
In this context, a software tool for automatic and real-time analysis of cow location data acquired by an ultra-wide band real-time location system (UWB RTLS) in a free-stall barn was designed and developed. The main functionality of this tool was a user-interface feature which provided a visual representation through a colour map of the frequency of two-dimensional cow position data (CowHeatMap). In this functionality, the different colour and colour intensity denoted the difference in sample density at a location. The feasibility of the software tool for visualisation and analysis of UWB data was assessed. A use case of this software tool was carried out to verify its suitability for acquisition of useful information related to the occurrence of cow oestrus. The results showed that a behavioural pattern related to the cow oestrus status could be identified from the CowHeatMap and that the area of the house involved in the motor activity of the cow increased from 16.42% to 45.78% during the cow's feeding time and from 11.33% to 37.30% during the lying time.

Keywords: UWB tag, heat map, livestock buildings, cow localisation, oestrus detection; software tool.

Introduction

In recent years, several real-time monitoring systems based on different ICT technologies have been developed in order to enable farmers to localise and detect cow behavioural activities (Huhtala et al., 2007; Kumar and Hancke, 2015; Wietrzyk and Radenkovic, 2008, Gygax et al., 2007; Ipema et al., 2013;

Porto et al., 2012; Arcidiacono et al., 2017 a and 2017 b; Viazzi et al., 2014). For this reason, a huge amount of data has to be handled, including in real time. Therefore, challenges still exist with data analysis and interpretation.

In previous research studies (Porto et al. 2013, 2014), the assessment of localisation and identification performance of a Real-Time Location System (RTLS) based on Ultra Wide Band (UWB) technology (Ubisense, UK) within a free-stall barn showed that localisation errors based on tags applied to the cow's body were less than 1 m. Moreover, RTLS performance in the environment considered proved to be generally independent of cow behaviour. Therefore, UWB RTLS was considered suitable for determining the occupancy level of the different functional areas of the barn, computing cow behavioural indices, and tracking each animal in the herd.

The possible applications of this UWB RTLS would then include real-time data analysis aimed at the early detection of a specific physiological status, such as cow oestrus, or disease, such as lameness. However, the software tools provided with the system for the analysis of real-time location data were very limited. For this reason, there is a need to develop and implement specific software tools which enable farmers to take advantage of automated analysis of location data for early detection of a specific cow status.

On this basis, the main objectives of this study were to improve the analysis software tools for a data location stream coming from the Ubisense UWB RTLS through the introduction of a new real-time visualisation tool called CowHeatMap. A use case of the CowHeatMap was performed to assess its performance in terms of obtaining useful information on the occurrence of cow oestrus.

Materials and methods

The experiment was carried out in the central box of a dairy house, located in the province of Ragusa (Sicily, Italy). The box included a resting area with 16 head-to-head stalls, a feeding alley, a service alley and two side passages.

A commercial RTLS based on UWB technology (Ubisense, UK) was installed in the box to detect the position of eight dairy cows. Please refer to our previous work (Porto et al., 2014) for further details on the system hardware and data acquisition and selection.

In this paper, specific software was developed by using Microsoft® Visual C# Express (framework .NET) to allow visualisation of cow location data acquired by the UWB RTLS. The flow chart for the data flow process used in this software tool is shown in Figure 1.

CowHeatMap implementation

A heat map is a raster image in which the colour of each pixel is based on the result of an inverse distance weighted function applied to a collection of points. The number of data points located near a pixel helps to rate each pixel of the map (Pro HTML5 Programming, 2011). Since a heat map is useful when there is a large number of observation points spread across space, which was the case for cow location data, a 'CowHeatMap' was implemented for visualisation of the two-dimensional spatial distribution of the data acquired from the UWB RTLS within the study area. In the CowHeatMap, two dimensions were the Cartesian coordinates (x and y values) and the third dimension showed the intensity of a data point in comparison to the absolute maximum of the dataset in a considered time interval. The different colour and colour intensity denoted the difference in data point density at a location, i.e. if only a single data point was added to the dataset it was displayed as the hottest (red) spot, whereas when another point with a higher count was added, CowHeatMap dynamically recalculated the colour intensity. Red (hot) was used for the maximum values and blue (cold) for the minimum values.

As shown in the flow chart in Figure 1, implementation of the CowHeatMap involved two separate modules, i.e. the server side and the client side. After receiving a request from the client, which asked to view the CowHeatMap for a specific

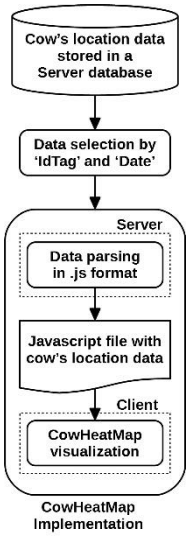


Figure 1: Data flow process of the system implemented in the software tools for visual analysis of the cow location data.

data set (i.e. the selected rows of a particular ‘idTag’ in a defined time interval), the coordinates x and y were converted from metres to pixels. The purpose of this operation was to transform the data into a format that was suitable for mapping onto a panoramic top-view image of the barn, which was produced in a previous study (Porto et al., 2015). Following transformation of the data, the software running on the server produced a Javascript file (dataset.js), which included the pixel dataset for the client. This file was used as input for an open-source JavaScript library called ‘heatmap.js’ (Wied, 2011-2013) to build the CowHeatMap.

Visualisation of the CowHeatMap could not be achieved with the Location Engine Config (LEC) of Ubisense software because it was designed to support only the visualisation of system components (Figure 2). Therefore, the CowHeatMap was visualised in a specially designed User Interface (Figure 3) which included the map of the barn under study and a mosaicked top-view image of the barn, which was acquired by a previously designed multi-camera system (Porto et al., 2015).

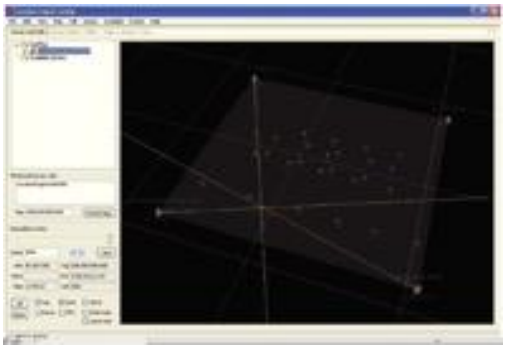


Figure 2: Three-dimensional view of the barn with tags and antennae displayed by the Location Engine Config of Ubisense software.

Figure 3: User Interface of the software for visualisation of the CowHeatMap.

A use case of the software tool: cow oestrus detection from UWB data

A use case of the CowHeatMap tool for automatic and real-time analysis of cow location was performed to assess the accuracy of the results obtained from its use when an oestrus event occurred.

The data analysed in this experiment was acquired by the UWB RTLS during the week from 10 August 2013 to 16 August 2013 and obtained from the tag with ID020. The farmer observed visually that the cow fitted with this tag manifested the state of oestrus on 12 August 2013, at around 9:30 a.m.

For each day, two sets of time intervals, which were characterised by the most frequently studied cow behaviours, i.e. lying and feeding behaviours, were identified:

– CFTime (Cow Feeding Time), i.e. the set time interval when the Cow Feeding Index (CFI) achieved the maximum values on average. CFI was calculated as the ratio between the number of cows that were at the feed rack and the total number of cows in the barn. In this experiment, CFTime was composed of two time intervals: the first between 6:00 a.m. and 9:30 a.m. and the second between 6:00 p.m. and 7:30 p.m.
– CLTime (Cow Lying Time), i.e. the set time interval when the Cow Lying Index (CLI) assumed the maximum values on average. CLI is defined as the ratio between the number of cows in the decubitus (lying) position inside the cubicles and the total number of cows in the barn. In this experiment, CLTime was composed of two time intervals: the first between 0:00 a.m. and 5:00 a.m. and the second between 11:00 a.m. and 2:30 p.m.

For each of the seven days considered and for each set of time intervals, i.e. CFTime and CLTime, a CowHeatMap and a CowVelocityGraph were built and analysed for the cow fitted with the ID020 tag. For the description and outcomes of the CowVelocityGraph used, please refer to another study (Arcidiacono et al., submitted to Biosystems Engineering).

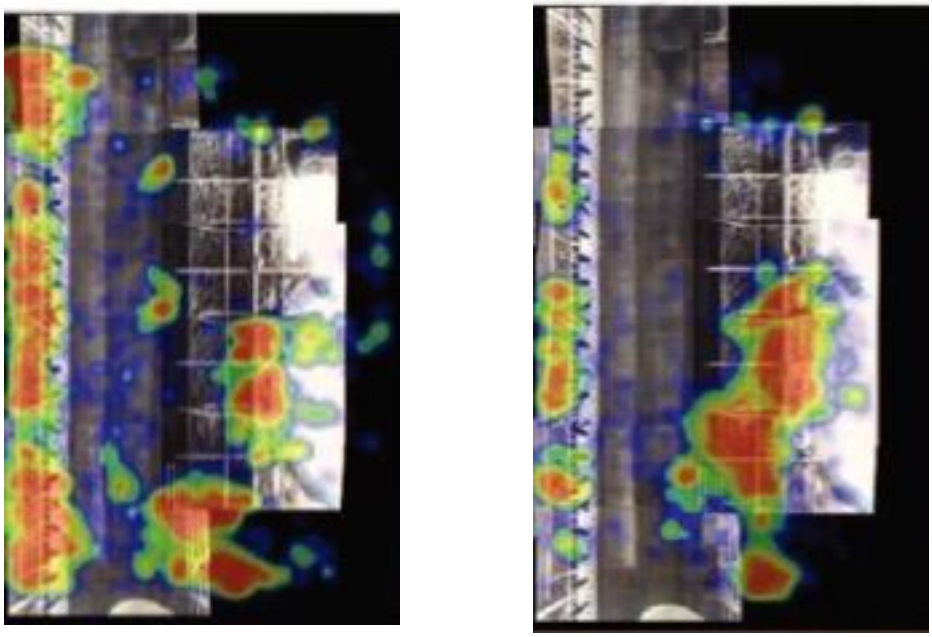
In this study, the aim of assessing the feasibility of the proposed software tool for the visualisation and analysis of UWB RTLS data was pursued by analysing the information contained in the heat maps for the different time intervals. The objective of performing real-time recognition of cow oestrus status was implemented by monitoring whether the cow increased its occupancy levels of the different functional areas of the barn.

Results and discussion

The results of CowHeatMap implementation were reported on the User Interface (UI), which was specially designed to visualise the tags over the map of the barn. The CowHeatMap was capable of providing valuable information on the following:

- Cow behaviour in the two sets of time intervals considered, i.e. the CFTime and CLTime, as well as during the daytime and night-time. This makes it possible to analyse differences in behaviour.
- Residence time in the functional areas of the barn, which makes it possible to analyse cow behaviour.
- Overall area involved in the motor activity of the cow.
- Preference for specific stalls or position at the feed rack.

In the week considered, the CowHeatMap showed that the monitored cow did not prefer to feed in a particular place along the feed rack, mainly used two adjacent cubicles along the service alley, and often stayed in the side passage where the water point was located (Figure 4). The difference in cow behaviour between daytime and night-time could be also observed using the CowHeatMap. Cow behavioural activities which commonly recur in hot climatic conditions can be seen in Figure 5, which shows the CowHeatMap for 11 August 2013. During daylight, the cow preferred to stand still in the feeding alley where a sprinkler system was installed to mitigate the effects of the hot climate, whereas feeding at the feed rack and lying activities were more frequent during the night.



(a) (b)

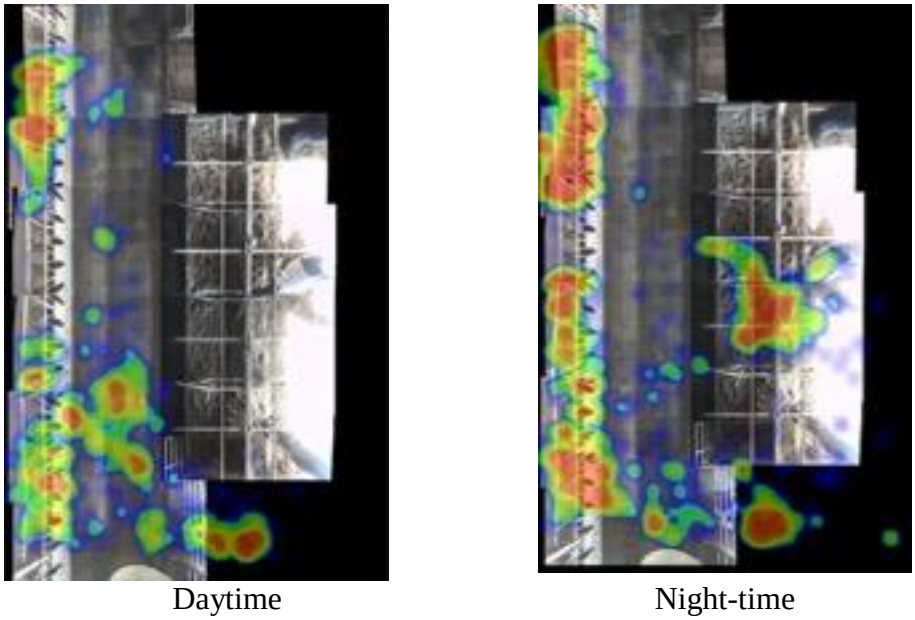
Figure 4: CowHeatMaps for the tag with ID 020 in CFTime (a) and CLITime (b) on 10 August 2013.

Use case for the software tool: feasibility of oestrus detection

The pattern related to the cow behaviour analysed, i.e. when the state of oestrus occurred, can be identified in CowHeatMap as evidenced by the use case carried out in this study. The comparisons between the day when oestrus occurred and other days of the week considered can be derived from Figures 4, 5, and 6 which present the CowHeatMaps for the tag with ID 020 for the CFTime and CLITime on 10, 11 and 12 August 2013.

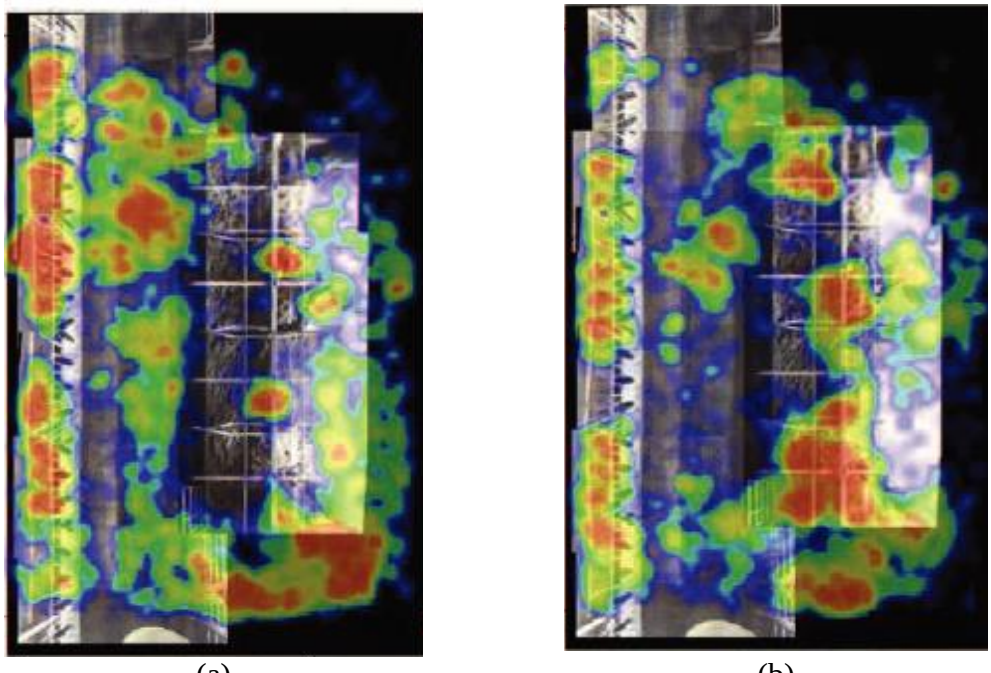
From the information provided by CowHeatMap (Figures. 4, 5 and 6), it was observed that the position of the location points in the analysed area was not spread out and maintained a similar pattern on each of the days selected for

analysis, with the exception of 12 August when a distribution of points over a wider area was observed. In the CFTime interval, the zones of the study area most frequented by the cow in question were mainly located at the feed rack, as expected, in the left passage lane (probably due to the presence of the water point) and in the cubicles, in the middle or south-eastern stalls. On 12 August 2013, by contrast, the spatial distribution of the points was more uneven, mainly involving the feed rack, the service alley, the left and right passage lanes and the feeding alley. It was clear that, on the day when oestrus occurred, the animal exhibited more sustained motor activity than that recorded on the other days. The percentage of the area involved in the motor activity of the cow (Table 1) was about 45.78% of the house on 12 August whereas it ranged between about 16.42% and about 30.30% on the other days, with an average value of 23.56% for CFTime, whereas the area percentage was about 37.30% of the house on 12 August and ranged between 11.33% and 37.20% on the other days with an average value of 19.65% for CLTime. These results highlighted the fact that an increase in motor activity was also observed during the two days preceding the oestrus event. Computation of the values presented in Table 1 could be automated by specifically-designed software which is currently the subject of further research.



Daytime Night-time

Fig. 5: CowHeatMaps for the tag with ID 020 during daytime and night-time on 11 August 2013 in CFTime.



(a) (b)

Figure 6: CowHeatMaps for the tag with ID 020 in CFTime (a) and CLTime (b) on 12 August 2013.

Table 1 - Percentage of the area involved in the motor activity of the cow in the week considered in CFTime and CLTime.

	CFTIME	CLTIME
10 August	30.30%	18.18%
11 August	26.98%	37.20%
12 August	45.78%	37.30%
13 August	21.12%	16.89%
14 August	16.42%	11.33%
15 August	23.04%	15.12%
16 August	23.48%	19.18%

The software tool proposed in this work, which was developed for the visual analysis of dairy cow location data acquired by UWB RTLS in a free-stall barn, achieved good results in this use case of an application for automatic oestrus detection. In other work, the application of UWB technology allowed for accurate detection of 9 out of 10 cows in oestrus (Homer et al., 2013). Moreover, the software tool was capable of providing valuable information on dairy cow behaviour in the two sets of time intervals considered, i.e. the CFTime and

CLTime. Limitations of this work lie in the application of this tool to oestrus detection in just one cow, although this software tool proved to be a promising tool for computation of the occupancy level of the different functional areas of the barn.
The full benefits of application of the software tool proposed for the UWB RTLS used in this paper remain to be verified in different farming systems and for other specific farming objectives.
Further experimental work could include the use of this software tool, in combination with different data obtained from other automated monitoring systems, such as data coming from accelerometers, in order to verify the extent to which the efficacy of cow oestrus status detection and reduction of false alarms could be improved.

Conclusions

In this paper, the objective of designing and developing a software tool for automatic and real-time visualisation and analysis of cow location data acquired by a UWB RTLS, based on the implementation of a CowHeatMap, was achieved. If corroborated by further research focusing on within-cow and between-cow variability of cow oestrus detection, this software would fully exploit the potential of RTLS to provide the farmer with a useful tool for performing specific analyses on the herd.

References

Arcidiacono, C., Porto, S.M.C.., Mancino, M., Cascone, G., 2017 a). A threshold-based algorithm for the development of inertial sensor-based systems to perform real-time cow step counting in free-stall barns. Biosystems and Engineering 153, 99–109.

Arcidiacono, C., Porto, S.M.C.., Mancino, M., Cascone, G., 2017 b). Development of a threshold-based classifier for real-time recognition of cow feeding and standing behavioural activities from accelerometer data. Computers and Electronics in Agriculture 134, 124-134. http://dx.doi.org/10.1016/j.compag.2017.01.021

Arcidiacono, C., Porto, S.M.C.., Mancino, M., Cascone, G. A Software Tool for the Automatic and Real-Time Analysis of Cow Velocity Data in Free-Stall Barns: the Case Study of an Oestrus Detection from UWB Data (submitted to Biosystems Engineering)

Gygax, L., Neisen, G., Bollhalder, H., 2007. Accuracy and validation of a radar-based automatic local position measurement system for tracking dairy cows in free-stall barns. Computers and Electronics in Agriculture 56, 23–33. doi:10.1016/j.compag.2006.12.004

Huhtala, A., Suhonen, K., Mäkelä, P., Hakojärvi, M., Ahokas, J., 2007. Evaluation of Instrumentation for Cow Positioning and Tracking Indoors. Biosystems Engineering 96, 399–405. doi:10.1016/j.biosystemseng.2006.11.013

Ipema, A.H.H., Van De Ven, T., Hogewerf, P.H.H., T.A. Ven, van de, Hogewerf, P.H.H., 2013. Validation and application of an indoor localization system for animals. Precision Livestock Farming 2013 - Papers Presented at the 6th European Conference on Precision Livestock Farming, ECPLF 2013, 135–144.

Kumar, A., Hancke, G.P., 2015. A Zigbee-Based Animal Health Monitoring System. IEEE Sensors Journal 15, 610–617. doi:10.1109/JSEN.2014.2349073

Porto, S.M.C., Arcidiacono, C., Giummarra, A., Anguzza, U., Cascone, G., 2014. Localisation and identification performances of a real-time location system based on ultra wide band technology for monitoring and tracking dairy cow behaviour in a semi-open free-stall barn. Computers and Electronics in Agriculture 108, 221–229. doi:10.1016/j.compag.2014.08.001

Porto, S.M.C.M.C., Arcidiacono, C., Anguzza, U., Giummarra, A., Cascone, G., 2013. Accuracy assessment of localisation of dairy cows housed in free-stall barns using a system based on ultra wide band technology, in: 6th European Conference on Precision Livestock Farming, ECPLF 2013, Leuven, 145–153.

Porto, S.M.C., Arcidiacono, C., Anguzza, U., Cascone, G., 2015. The automatic detection of dairy cow feeding and standing behaviours in free-stall barns by a computer vision-based system. Biosystems and Engineering 133, 46–55. doi:10.1016/j.biosystemseng.2015.02.012

Porto, S.M.C., Arcidiacono, C., Cascone, G., Anguzza, U., Barbari, M., Simonini, S., 2012. Validation of an active RFID-based system to detect pigs housed in pens. Journal of Food, Agriculture and Environment 10, 468–472.

Saumande, J., 2002. Electronic detection of oestrus in postpartum dairy cows: Efficiency and accuracy of the DEC® (showheat) system. Livestock Production Science 77, 265–271. doi:10.1016/S0301-6226(02)00036-2

Viazzi, S., Bahr, C., Van Hertem, T., Schlageter-Tello, A., Romanini, C.E.B., Halachmi, I., Lokhorst, C., Berckmans, D. 2014. Comparison of a three-dimensional and two-dimensional camera system for automated

measurement of back posture in dairy cows. Computers and Electronics in Agriculture, 100, pp. 139-147.

Wietrzyk, B., Radenkovic, M., 2008. Practical MANETs for Pervasive Cattle Monitoring University of Nottingham School of Biosciences 14–23. doi:10.1109/ICN.2008.78

Pro HTML5 Programming, by Peter Lubbers, Frank Salim, Brian Albers, Apress, 29 nov 2011 - 352 p.

Wied, P. 2011-2013. Js heatmaps. Accessed: 08/10/15, from http://www.patrick-wied.at/static/heatmapjs/index.html

Homer, E.M., Gao, Y., Meng, X., Dodson, A., Garnsworthy, P.C.. 2013. Technical note: A novel approach to the detection of estrus in dairy cows using ultra-wideband technology. Journal of Dairy Science, 96 (10), 6529-6534

Author index

Precision Livestock Farming ’17

Development of PLF technologies requires close collaboration between several sectors, including engineers, animal scientists, veterinarians, farm technicians, physiologists, ethologists and farmers. Companies have been established in recent years in order to pursue developments in the field of PLF with the aim of improving livestock wellbeing and increasing farm profitability. However, this requires a new way of working, for both farmers and other stakeholders such as farm technicians, veterinarians, feed manufacturers, slaughterhouses, etc. The objective of PLF technology is to measure and analyse parameters continuously in real-time so that it is not necessary to store large amounts of data originating from the sensors, while at the same time providing farmers with real-time support based upon information from the data.

Depending on the agreements between stakeholders, this data may be transmitted to some stakeholders (for example to slaughterhouses as a means of predicting slaughter date, or to feed manufacturers). It can also be used by technical and health teams to analyse livestock data. Furthermore, it is now becoming common for SMEs to provide a complete monitoring service to help farmers improve farm productivity.

Improving animal health, minimising the environmental impact, and increasing the productivity and competitiveness of the livestock sector in a globalised world are the overriding objectives of PLF. However the sustainability of production systems also depends on improving the working conditions of farmers in order to attract more and more young people. PLF technology must also occupy its full place in this field.
The ultimate goal is to create a win-win situation for the entire livestock sector, in order to achieve socially, environmentally and economically sustainable farming.

Nantes 2017