Precision Livestock Farming Technologies: Status and Challenges

*Nwoke Oji Achuka and Ugwu Chinyere Nneoma
Department of Agricultural and Bioresources Engineering, Faculty of Engineering, University of Nigeria, Nsukka, Enugu State, Nigeria,
*Corresponding Author: Email: nwoke.oji@unn.edu.ng, Phone No.:+2348038299006

Abstract- 'Precision Livestock Farming' (PLF) technologies are described as usually hi-tech management tools aimed at continuously and automatically monitoring different aspects of animal production, including production efficiency, environmental sustainability of the farming operation and the health and welfare of animals. Quite a few PLF technologies have been developed by diverse research organizations in recent years, but large-scale field trials of these technologies have never been attempted before. Precision livestock farming (PLF) enables the utilization of technology within livestock systems to provide opportunities for improved farm management and sustainable development. There have been numerous new technologies available to aid farm workers with daily tasks, such as livestock feeding and general health monitoring with the aim to enhance animal productivity, improve animal health and welfare whilst reducing environmental impact. PLF integrates the use of 'smart' sensors into livestock farming, which links production processes into a complex network. These new technologies may be useful in terms of economic benefit and reducing manual workload. However, there may be tradeoffs concerning the adoption of new technologies and the impact this may have on human-animal relationships. This work will examine the recent status of precision livestock farming and the challenges usually encountered by farmers for adopting such technologies. It examines the technological principles upon which PLF is hinged on, highlights some existing applications of PLF, considers suitability of different livestock Processes for the implementation PLF approach, addresses whether PLF represents technology push or market pull, and stresses the need for a future bioethical analysis of PLF. Finally, this work gives a flavour of what could be the next generation of PLF technology, to demonstrate the interdisciplinary collaboration and engineering advances required to realize PLF solutions, and to obviously reveal that PLF research is essential at both laboratory and farm levels.

***Keywords**: Precision; Livestock Farming; image analysis; Sound analysis; Sensor analysis; Data analysis and Algorithms*

1. INTRODUCTION

As the worldwide meat consumption may increase to 73% by 2050, food production and more specifically the animal production sector must become more sustainable (FAO, 2011) Antimicrobial Resistance (AMR) is becoming increasingly important and farmers need to reduce the use of antibiotics to limit the impact of animal farming on human health (Lhermie, Grohn,& Raboisson, 2017). There is also pressure to reduce emissions of greenhouse gases and other environmental pollutants from livestock farms (Poore & Nemecek, 2018). Moreover, the public is more concerned than ever about animal welfare, including both its monitoring and management (Butterworth, 2018). The safe-guarding of animal welfare has an important link to the efficient use of feed energy, and we need more animal product with less feed, less manure and emissions. Therefore, by giving farms animals a life worth living (Wathes, 2010), we can improve the sustainability of the production process (Broom, 2017).

Precision Livestock Farming' (PLF) technologies are described as usually hi-tech management tools aimed at continuously and automatically monitoring different aspects of animal production, including production efficiency, environmental sustainability of the farming operation and the health and welfare of animals. PLF integrates the use of 'smart' sensors into livestock farming, which links production processes into a complex network.

Precision Livestock Farming (PLF) emerged from the need to inform farmers more regularly and in more detail on the health, welfare and productivity of their animals and to help them make quick and evidence-based decisions on the animals needs. It has the power to focus on the individual animal, even within large herds, and to use the behaviour of a body of animals to identify problems with their management.

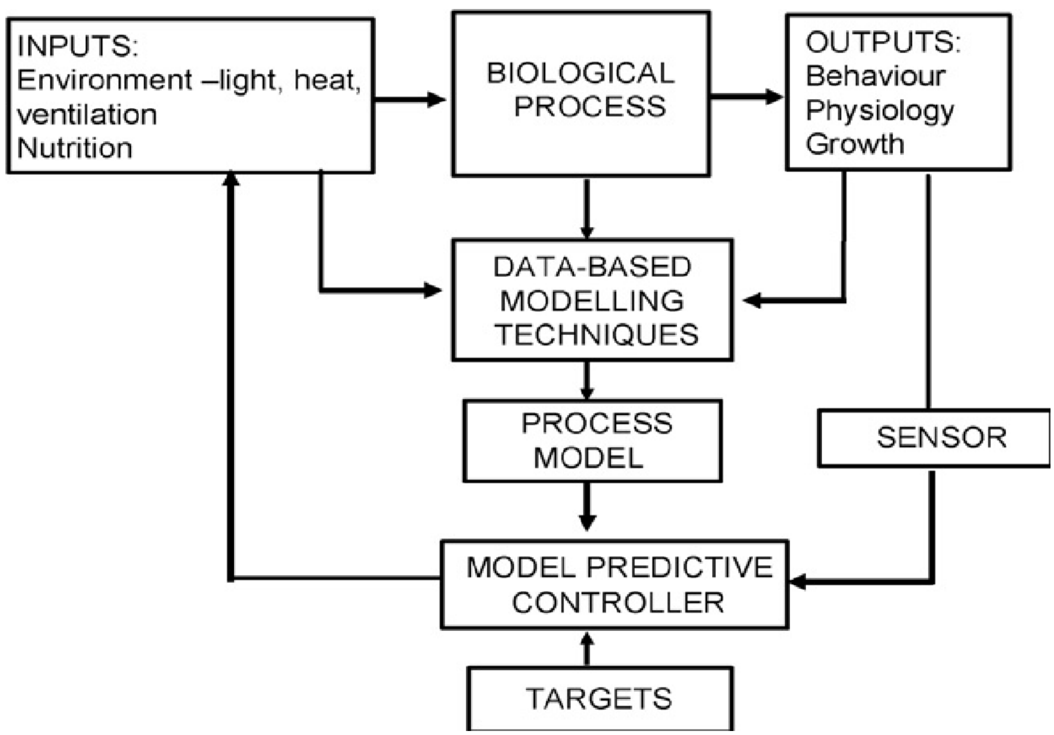

Fig. 1: Schematic overview of the key components of PLF to control biological processes, such as animal behaviour, physiology and growth (after Aerts et al., 1998a, 2003c).

2. PRINCIPLES OF PRECISION LIVESTOCK FARMING (PLF)

One way to realize the PLF scheme shown in Fig. 1 is by using model predictive control. This does not prescribe a specific control strategy, but rather a range of control methods, which use continuous feedback of the process output (as in other control strategies), make an explicit use of a dynamic model of the process to predict the process response, and use this model to calculate the control signal by minimizing an objective function (Clarke, 1988; Soeterboek, 1992; Camacho and Bordons, 1999).

3. DEVELOPMENT OF PRECISION LIVESTOCK FARMING (PLF)

Fig. 2 show a simplified control diagram for the application of the precision farming concept to livestock production.

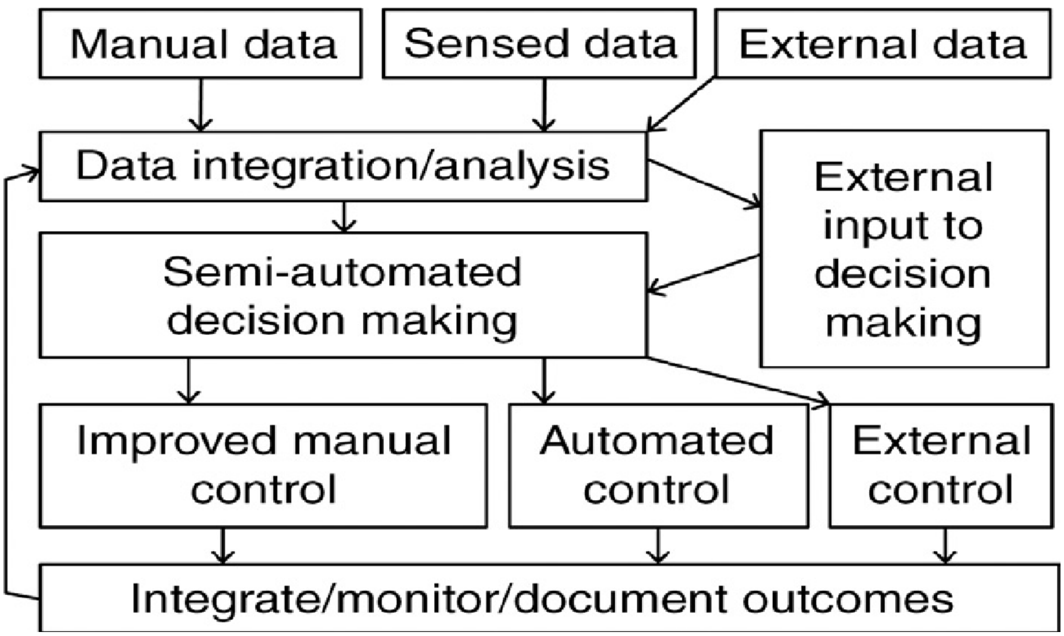

Fig. 2: A simplified control diagram for a precision farming approach to livestock management and production.

4. USES OF PRECISION LIVESTOCK FARMING (PLF) TECHNOLOGIES

It has been shown that this technology can provide several solutions already such as (Berckmans, 2016):

i. Early warnings for infections in fattening pigs through real-time sound analysis;
ii. Monitor the first sign of lameness in milking cows and give a list of cows to be inspected due to potential lameness problems;
iii. Give an alarm for more than 95% of all experienced problems (light, climate, feeder line, drinking line, etc.) in broiler houses;
iv. Detect unacceptable aggression in fattening pigs through real-time image analysis;

v. Monitor real feed intake of broilers, being the most costly process input to be optimized with precision feeding;
vi. Monitor accurately the water intake of pigs as an indicator for health problems.

5. CURRENT SHEEP PRECISION LIVESTOCK FARMING TECHNOLOGIES

5.1 Electronic Identification (EID)

Although image recognition systems have the potential to identify individuals of some breeds of farm animals that is those with individually different coat patterns, the development of low cost radio-frequency identification (RFID) technology [now more widely known as electronic identification (EID)] has revolutionized automated animal identification.

5.2 Automatic weighing systems

Live weight is a useful indicator of nutritional status, and regular automated measures of liveweight are a potentially useful management tool. By linking an EID reader to an electronic weigh platform, it is possible to record a liveweight estimate for each animal as it walks over the platform, known as walk-over-weighing (WOW).

5.3 Automatic shedding gates

Automatic shedding gates (also known as automatic sorting or drafting gates) allow animals to be automatically segregated as they move down a raceway. Typically, pneumatically driven gates direct the sheep into two or three groups as they exit a crate. A gate at the entrance to the crate prevents the next sheep from ‘rushing’ through the segregation gate. The shedding gate can be linked to an EID system allowing farmers to select specific sheep based on their EID number (Berckmans, 2004)

5.4 Predator Alert Systems

Domestic sheep suffer attacks from wild, feral and domestic carnivores, usually canids, in most parts of the world, although the Australian sheep industry has a particular problem with predation by wild dogs (Berckmans,2004).

6. STATUS OF PRECISION LIVESTOCK FARMING

Europe has been the birthplace of PLF research, and it continues strongly with over three decades of research and innovation through at least 4 major EU-funded (EU-PLF, BioBusiness, AllSmartPigs, BrightAnimal) and many other national projects (Mottram, 2016; Wathes, Kristensen, Aerts, & Berckmans, 2008). Interesting solutions have emerged from this research, some of which have found their way to the market as successful technologies (Berckmans, 2016). Now, the importance of PLF is growing globally, as evi-denced by current agricultural research agendas in the EU (European Commission, 2018) and US (National Academies o Sciences, Engineering and Medicine, 2018).

Moreover, while the European Conference on Precision Livestock Farming (ECPLF, 2018) was once the only worldwide bi-annual conference in this field now similarly themed conferences have started in the US (ILES, 2018) and China (Zheng, Wang, Liu, Li, & Xin,2016).

Precision Livestock Farming is unique among research domains in that its success hinges on tight interdisciplinary research, and the translation of good scientific and engineering principles into impactful technology. It unites many complementary fields such as the farm animal sciences in health, nutrition and ethology with bio-engineering, computer science and socio-economics. This complementarity is absolutely essential to realize technologies that can monitor and help manage individual animals for their benefit (health and welfare) as well as that of the farmer, the community and the environment. By promoting such scientific collaborations we can provide trustworthy systems to farmers and their animals.

We can thus avoid problems of mistrust like those faced in the human wearable sensor market, where it was reported that only 5% of that technology is formally scientifically validated (Peake, Kerr, & Sullivan, 2018).

7. ENGINEERING ADVANCES IN PRECISION LIVESTOCK FARMING

This section discusses the latest findings in the PLF research domain, by demonstrating how the combination of engineering principles with other disciplines, forms the basis of interesting findings at the fundamental and applied level. It is organized into 4 focus areas, namely:

i. image analysis,
ii. sound analysis,
iii. sensor analysis, and
iv. data analysis & algorithms.

7.1 Image Analysis

Four articles fall under the image analysis focus of this discourse. In two of these articles, the researchers have demonstrated the feasibility of modern 3D camera technology in estimating of animal weight (Condotta et al., 2018; and; Nir et al., 2018). The feasibility of image analysis to detect physical wearing of the knees of cows has been evaluated by Guo et al. (2018), while Meunner et al. (2018) have demonstrated how image analysis can be used to refine measurements of cow location determined by real-time location systems.

7.2 Sound Analysis

Two articles fall under the Sound Analysis focus: The first of these addresses the challenge of cough detection in calf rearing houses, and demonstrates how it is now possible to monitor in commercial rearing environments with good precision (Carpentier et al., 2018). The second focuses on a novel application of determining sex, age and distress automatically from sound signal characteristics (Cordeiro et al., 2018).

7.3 Sensor Analysis

Four articles fall under the Sensor Analysis focus. The first considers the feasibility of a newly patented electronic nose technology to detect coccidiosis from the aerial environment of a broiler house (Grilli et al., 2018). Then the paper of Han et al. (2018) defines and evaluates ocular features from spectral analysis to determine vitamin deficiency of Japanese black cattle. In the third paper, Krieger et al. (2018) demonstrate that it is technically possible to predict calving in dairy cows using a tail-mounted tri-axial accelerometer. And finally Besteiro et al. (2018) show that the activity of piglets can be effectively monitored using passive infrared detectors, with the analysis showing key moments of peak activity.

7.4 Data Analysis and Algorithm Focus

Nine articles fall under the Data Analysis and Algorithms focus: Van Hertem et al. (2018a) show that gait score correlated significantly with flock activity and with flock distribution, as measured by the camera system eYeNamic®, proving the possibility of carrying out the automated measurement of broiler flock behaviour. In the next paper Pena Fernandez et al. (2018) model data from the same device to demonstrate that deviations in broiler activity patterns are correlated to hock burns, while deviations in broiler occupation patterns are correlated to foot pad lesions. The following paper of Naaset al. (2018) evaluate a novel algorithm based on paraconsistent logic to determine gait score from broiler velocity and acceleration data.

Then the paper by Cross et al. (2018) evaluates a feed-forward artificial neural network approach for predicting feeding behaviour of pigs, whereas in the next article Demmers et al. (2018) evaluate a novel method neural network model for pig and broiler growth and their incorporation into a model-based predictive controller.Then Maselyne et al. (2018) define and evaluate different warning systems based on individual pig feeding patterns and demonstrate the value of implementing time-varying individual limits. Arcidiacono et al. (2018) focus their work on dairy farms, and specifically on the development of a software tool for the automatic and real-time analysis of cow velocity data in free-stall barns. This software tool can be used to acquire useful information related to the occurrence of oestrus. Continuing on the theme of dairy farming,

Van Hertem et al. (2018b) evaluate the performance of automated lameness detection and show that cow traffic and farm design are key factors in automatic detection performance. Finally a thorough review of technology in aquaculture is carried out by Fore et al. (2018), who also introduce the Precision Fish Farming (PFF) concept and elucidate its main goal, which is to stimulate transition from experience-to knowledge-based production.

8. CHALLENGES OF PLF

According to ((Bartzanas Thomas et al., 2017) The increased complexity of the systems inhibits easy adoption and makes calculations as to the financial benefits uncertain. As indicated by many PLF experts, the main problem of commercialization and fast implementation of PLF systems in livestock production chain is the:

i. lack of support mechanisms,
ii. lack of knowledge transfer and
iii. A consistent service offering for farmers.
iv. Experts highlight the need for a service sector that will be able to (Banhazi et al. 2012).
   a. take care of technology components,
   b. interpret data captured by sensors,
   c. formulate and send simple, relevant advice to farmers on a regular basis,
   d. Involve users in technology developments.

9. CONCLUSIONS

In conclusion, our intention for this presentation was : to share our actual insights and give a flavour of what might be the next generation of PLF technology, to demonstrate the interdisciplinary collaboration and engineering advances needed to realise PLF solutions, and to clearly demonstrate that PLF research is important at both laboratory and farm levels

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