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Review

Data-driven decision support in livestock farming for improved animal health, welfare and greenhouse gas emissions: Overview and challenges

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A R T I C L E I N F O

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A B S T R A C T

Precision Livestock Farming (PLF) is a concept that allows real-time monitoring of animals, by equipping them with sensors that surge livestock-related data to be further utilized by farmers. PLF comes with many benefits and ensures maximum use of farm resources, thus, enabling control of health status of animals, while potentially mitigating Greenhouse Gas (GHG) emissions. Due to the complexity of the decision making processes in the livestock industries, data-driven decision support systems based on not only real-time data but also expert knowledge, help farmers to take actions in support of animal health and better product yield. These decision support systems are typically based on machine learning, statistical analysis, and modeling and simulation tools. Combining expert knowledge with data obtained from sensors minimizes the risk of making poor decisions and helps to assess the impact of different strategies before applying them in reality. In this paper, we highlight the role of data-driven decision support tools in PLF, and provide an extensive overview and categorization of the different data-driven approaches with respect to the relevant livestock farming goals. We, furthermore, discuss the challenges associated with reduction of GHG emissions using PLF.

1. Introduction

As population and incomes increase, there will also be a growth in the demand for greater food variety. Studies on human nutrition have shown that a nutrition transition is taking place worldwide, in which people shift towards more affluent food consumption patterns (Bruinsma, 2003; Hadjikakou and Wiedmann, 2017; Popkin, 2002; Wiedmann et al., 2020). Depending on factors like geographical location and health policies, this change of demand patterns from food of plant origin to livestock products, such as meat, eggs and milk, together with the sizeable population growth, needs to be addressed in a sustainable manner without causing irreparable environmental damage or exceeding global resources.

Sustainability in livestock production processes is the vision of the Precision Livestock Farming (PLF) approach (Banhazi et al., 2012; Wathes et al., 2008). PLF is one of the most powerful developments amongst livestock farming industry, offering real-time monitoring and management tools for farmers. PLF includes a wide span of technologies which are being applied along with advanced technologies like microfluidics, sound analyzers, image-detection techniques, sweat and salivary sensing, serodiagnosis, and others (Neethirajan, 2017). However, the growing amount and complexity of data generated by fully automated, high-throughput data recording or phenotyping platforms, and information obtained from real-time noninvasive computer vision, pose challenges to the successful implementation of PLF (Morota et al., 2018). Modelling of complex dynamic processes in livestock production is one of the critical components of the PLF approach (Wathes et al., 2008). Advanced statistical and mathematical modelling techniques, machine learning (ML) and data mining have great potential for describing these complex processes. Hence, they are being widely applied in novel

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algorithms for predictive analytics in animal health and welfare. (Berckmans, 2006; Vázquez-Diosdado et al., 2019)

Modelling and Simulation (M&S) approaches, also help decision makers and farmers in their decisional problems by providing insights into their managerial practices. M&S formalize the real world into a computer-understandable environment and then imitate the processes and the operations of the real world. Traditionally, simulation modeling uses expert knowledge to develop the dynamic models, which are afterwards applied in the simulation process to provide understanding of the systems of interest. Most recent M&S approaches utilize observational datasets or real-time data to extract models and parameters needed to perform simulation.

The goal of this paper is to provide an overview of the existing data-driven approaches in PLF and categorize them according to the different goals they aim for. We split all data-driven approaches in two categories: 1) machine learning and data analytics algorithms; and 2) modeling and simulation based approaches. Each of these approaches can be combined with optimization techniques to enhance the decision support functionality. We consider two major goals in applications of decision support tools in livestock farming as we found them most prominent throughout literature: 1) improving animal health, welfare and production; and 2) reducing GHG emissions. Ultimately, we aim to address the problem of finding a suitable approach, given a goal and the amount/type of data that is available.

The paper is structured as follows: Section 2 provides a background on Precision Livestock Farming as enabler for sophisticated decision support approaches. In Section 3, we review machine learning and data analytics approaches in livestock farming. Existing M&S methodologies are reviewed in Section 4. In Section 5, we discuss about the optimization approaches in PLF, and Discussion in Section 6 is dedicated to the challenges related to the data pathway and key takeaways. Finally, in Section 7, we conclude the paper.

2. Decision support in livestock farming

Increased demand for animal products, reductions in the number of farms together with an increase in the average herd size have been already reported in most of the main dairy regions across the world (Gargiulo et al., 2018). This strongly reduces the available time and attention span for livestock farmers to monitor all of their animals in a reliable way. Managing large numbers of livestock, ensuring that production demands are met and environmental concerns are not discounted, are factors that have caused a shift from traditional to information and communication technology-driven (ICT-driven) farming (Giovannucci et al., 2012; Norton et al., 2019). It is, therefore, important to briefly describe the two associated concepts: Precision Livestock Farming and existing approaches for decision support in PLF systems.

2.1. Precision livestock farming

One of the definitions of PLF, provided in Tullo et al. (2019), describes PLF as "the application of process engineering principles and techniques to livestock farming to automatically monitor, model and manage animal production". Berckmans (2017) defines PLF as a way to manage individual animals through continuous real-time monitoring of health, welfare, production/reproduction, and environmental impact. Wathes (2010) describes PLF as an integrated systems approach that includes automatic monitoring, modelling and management that will direct the processes along specific paths in order to meet the required goals. As such, PLF encompasses various aspects of continuous livestock monitoring, such as data collection and analysis, as well as reporting of relevant events.

Conditions of animals (physical and mental) are continuously changing due to external stimuli. These changes can be continuously recorded, stored and transmitted using sensors that measure bio-signals. Typical sensors used in PLF include accelerometers, gyroscopes, temperature sensors and biosensors (Berckmans, 2006; Karthick et al., 2020; Knight, 2020; Muhammad Sayem et al., 2020; Wathes et al., 2008). The type of data collected by these sensors include animal gait, speed, position, temperature, sounds, heart rate etc. In addition to the sensor data, modelling, simulation and decision support using machine learning models are also being successfully used in PLF. Furthermore, innovative video monitoring and facial expression recognition can be adapted from humans to animals, such as NOLDUS Ethovision (van Eerdenburg et al., 2017), which is used to track and analyze the behavior, movement, and activity of animals (Subea and Suciu, 2019).

In summary, PLF consists of the following components:

- **Continuous or real-time collection of sensor data**: Real-time data, such as temperature, movement, breath emissions of animals are collected using sensors. Collected data can be internal (within the farm) or external (from outside the farm). The use of accurate and low-cost sensor technology is desired (Norton et al., 2019), i.e. long battery life, ease of use, reduced in numbers, lower environmental impact and being noninvasive for animals.
- **Integration and storage of data**: Collected data is integrated, stored, and, subsequently, used in the following steps. Integration is crucial because data is derived from heterogeneous sources with different formats and modalities.
- **Data analysis, machine learning, simulation and modelling**: Obtained data is used for further analysis that aims at providing insights into the current situation of the farm. Simulation of a livestock farm in a lab is the first step towards building a real-world model for the problem. However, simulation alone does not suffice since real livestock farms are much too complex to simulate (Norton and Berckmans, 2017), and other data analytics approaches like machine learning can fill the gaps. Decision Support (DS) and M&S are two key terms that incorporate data and farm specific information to help Decision Makers (DMs) to make key decisions regarding their farming practices.
- **Event detection and signaling**: Occurrences of relevant events are detected and made known to stakeholders. Various statistical and machine learning approaches are usually adopted for event detection (Adrion et al., 2018; Chung et al., 2013).

These PLF components help farmers in their decision-making process by enhancing both the management of their daily tasks and the supervision of their herd. Overall, the benefits reaped by adopting PLF in the livestock industry have been tremendous (Hostiou et al., 2017). If properly implemented, PLF could (1) improve or, at least, objectively document animal welfare on farms; (2) reduce GHG emissions and improve environmental performance of farms; (3) facilitate product segmentation and improve marketing of livestock products; (4) reduce illegal trading of livestock products; and (5) improve economic stability of rural areas (Banhazi et al., 2012). Hence, the implicit benefits mainly include increase in productivity, real-time supply chain management and better marketing, as well as improved working and economic conditions of farmers in rural areas. Some authors have also proposed that via PLF technologies, reduction of environmental impact of livestock farming could be achieved, although there is no PLF application designed specifically to meet this goal up to now (Tullo et al., 2019). The most prominent PLF technology for reducing emissions of GHG and ammonia seems to be the precision feeding (Gerber et al., 2013). Precision livestock feeding aims to match nutrient supply precisely with the nutrient requirements of individual animals, based on real-time feedback from sensor (Zuidhof, 2020).

It is worth noting that although PLF has a positive impact on industrial farming and can be attractive for young people, PLF can also lead to negative impacts on farmers and animals if the tools are not adapted to farmers' needs and skills. It is, therefore, critical to consider the different dimensions of farmers' work to facilitate their adoption of these new technologies (Hostiou et al., 2017). From farmers' point of view, PLF technologies affect the nature and frequency of their daily tasks, specifically in relation to animals. And some farmers fear that with PLF they will lose their observation skills and get dependent on the tools (Kling-Eveillard et al., 2020). Furthermore, many farmers perceive that adopting high productive management systems involves increased financial risk (Bartzanas et al., 2017).

Shaping a sustainable future will depend on understanding the diversity and complexity of livestock systems and the particular motivations and challenges that stakeholders face in periods of transformative change (FAO, 2019). What works for a farmer in a capital-intensive system can be very different from what works for a pastoralist or a mixed crop-livestock smallholder (FAO, 2019). For all livestock production systems, opportunities to improve the efficiency of production and decrease emissions per unit of animal product exist and are being developed. Some of these options require novel technological interventions, whereas others are 'simple' principles that can be applied already in most production systems (Bartzanas et al., 2017). However, becoming equipped with sensors and, therefore, technologically ready, not only depends on the farm size but also shows interest in using automation to increase productivity and efficiency (Allain et al., 2016; Gargiulo et al., 2018). Adoption of PLF technologies by livestock farmers is currently at a very early stage, and although there are several PLF technologies available, very few of them are used in practice. In order to increase the adoption of these technologies, their advantages need to be disseminated to livestock farmers by stakeholders which have proven themselves trustworthy (e.g. practitioners and consultants), and issues, such as business relationships between sensors owners and farmers, as well as sensor data ownership, need to be clarified and resolved (Benjamin and Yik, 2019). Moreover, further investigation of whether PLF technologies can be successfully implemented (from a technical point of view) in commercial environments would be a prerequisite for their wider adoption (Norton et al., 2019).

Examples of PLF projects that helped to increase the adoption of PLF technologies and to raise awareness among farmers include: BrightAnimal (Lehr, 2011) and EU-PLF (2016). BrightAnimal had the following mission: "To produce a framework for European and non-European small and medium enterprises on effective and acceptable PLF and to create an international, interdisciplinary network for further development and dissemination". EU-PLF's main objective was to deliver a PLF-Blueprint for farmers on how to install and use PLF technologies in their farms.

2.2. Decision support approaches

The need for decision support in livestock farming is vital due to its inherent challenges, like systems' complexity and the need of fulfilling multiple goals. There are a number of decision makers, e.g., livestock farmers (owners) and farmers' consultants, who can benefit from the use of decision support in making crucial decisions regarding the management of livestock. Benefits of decision support systems (DSS) can be quantified by the attainment of two ultimate goals, along with the economic aspects: (a) improving animal health and welfare and (b) GHG emissions reduction. It is worth mentioning that GHG emissions mitigation might not be a goal straight away for the farmer. However, some of the practical actions towards low-carbon livestock are in developing policy measures to drive change and to boost efficiency of livestock production and resource use (FAO, 2019). These policy measures often incentivize farmers that take measures towards GHG emissions reduction (Baker, 2021). Furthermore, "Pull incentives" can help to generate market demand and raise consumer awareness in support of shifts towards best climate change practices (FAO, 2019). Improving animal health and welfare is closely related to the livestock production (meat, milk, eggs, etc.) because for a fixed farm size, products from healthy and well-treated animals are superior, both in terms of quality and quantity (Gonzalez-Rivas et al., 2020; Wang et al., 2017). Aside from the fact that animals health and welfare affect farmers' incomes, optimizing animal welfare also reduces the emissions intensity of producing livestock products (i.e. emissions per unit of product) (Herrero, 2016). Possible interventions to reduce emissions are, therefore, to a large extent based on technologies and practices that improve production efficiency at animal and herd levels. For ruminants, cows mainly, using better feeds and feeding techniques, can reduce CH_4 generated during digestion as well as the amount of CH_4 and N_2O released by decomposing manure. In general, improved breeding and animal health interventions to allow herd sizes to shrink (meaning fewer, more productive animals) will also help (FAO, 2020). This means that it is necessary to ensure that the costs of reducing emissions are balanced with the benefits of livestock welfare and production.

Animal health and welfare: Detection and prevention of animal health issues, and compliance with medical regulations are some of the factors that are considered for improved production or yield. Research in animal welfare using sensor data generally falls in the categories of modelling-based, simulation-based and optimization-based methods. In the modelling-based methods, risk assessment modelling, ML and/or statistics based methods are commonly found. ML algorithms have been widely facilitated within modeling and simulation modules as data analytics steps, mostly to analyze data collected from sensors attached to livestock. The need for ML algorithms for decision support has risen due to the significant increase in the amount of data being collected through livestock farms. Such large amounts of data are ideal for automatically learning useful patterns and performing predictions using ML.

GHG emissions: Improving production is often done in combination with other factors, such as reducing energy consumption, profit maximization and reducing GHG emissions. Compliance with environmental regulations and optimized energy usage are some of the factors in reducing GHG emissions. The Intergovernmental Panel on Climate Change (IPCC) proposed "tiers" for classifying various approaches for coping with climate change due to GHG emissions (Eggleston et al., 2006). A tier represents a level of methodological complexity and three tiers are provided. Tier 1 is the basic method, Tier 2 intermediate and Tier 3 the most demanding in terms of complexity and data requirements. For instance, the enteric fermentation emission factor for a 300 kg buffalo, using relevant tables for Tier 1, equals 55 kg CH_4 $head^{-1}year^{-1}$. But according to Tier 2, the same emission factor equals:

$$\text{EmissionFactor} = \frac{GE\left(\frac{Y_m}{100}\right)365}{55.65}$$

where GE is gross energy intake in MJ $head^{-1}$ day^{-1}, and Y_m is the methane conversion factor. To obtain these values we need even more information about the animal's feeding quality, milk production etc. Tiers 2 and 3 are sometimes referred to as higher tier methods and generally, to develop, evaluate and apply a higher tier method is considered to be more accurate if adequate data is available (Kaneko and Kawanishi, 2016). Depending on the amount of available data, a decision maker can decide about which Tier to apply.

Table 1 lists some of the decision support models which are based on Tier 1 and Tier 2 methodologies for estimating GHG emissions from livestock. Majority of these models are based on cattle (beef and/or

Table 1
Decision support models for GHG emission estimation.

Model	Farm Type	Work
AgRE Calc	Cattle	(Scotland's Rural College, 2014)
COMET-Farm	Cattle	(Paustian et al., 2017)
Cool Farm Tool	Cattle	(Hillier, 2012)
Carbon Navigator	Cattle	(Murphy et al., 2013)
ValorE	Cattle, Pigs	(Acutis et al., 2014)
IPCC inventory software	Not limited	(SPIRIT Inc., 2020)
ALU software	Not limited	(Colorado State University, 2010)

dairy) farms, while some of them also consider pig farms. The subtleties and fine-grained details of a typical farm are generally not incorporated within Tier 1 and 2 methodologies.

In summary, there are a number of studies focused on decision support for increasing production yield, improving animal welfare and reducing GHG emissions of livestock farms. Incorporating ML and deep learning algorithms in the PLF approach can assist in improving of the decisions made by the DMs. Some of the areas that need more research are described below.

- **Reusable DS models**: Most of the works in decision support for PLF perform (run) well for the individual farms under study, but there is no evidence of the utility of these methods in other comparable farms. There is a need for developing generalizable machine learning strategies for performing various tasks in similar kind of farms.
- **Integration and storage of multi-farm data**: There is a need for integrating data from different sources and from various farms. This helps in building a *knowledge base* that is instrumental in achieving the goal of the previous point. An example of such a system is the work by Schuetz et al. (2018) in which a data warehouse and semantic technologies were used to provide effective management of multi-farm data.
- **Balancing GHG emissions, animal welfare and production yield**: Models incorporating these multiple criteria need to be developed. Most of the models developed so far only consider one of these aspects. It would be a challenging yet interesting study that can potentially improve DS in PLF.

3. Machine learning and data analytics for decision support in livestock farming

The field of AI involves development of theory and computer systems capable of performing tasks that normally require human intelligence, such as sensory perception and decision making. Kaplan and Haenlein (2019) defined AI as "the ability of a system to correctly interpret external data, to learn from it, and to use that learning to achieve specific goals and tasks through flexible adaptation". Thus, AI acts on external information from Internet of Things (IoT) and other large data sources, uses knowledge-based rules (provided by developers) or identifies the rules and patterns that underlie the use of machine learning to drive systems to set goals (Fig. 1).

IoT is a technological paradigm seen as a vast network of digitally connected devices and machines (Ashton, 2018). Here, the digital connection of machines or "things" takes place on the "internet". The influence of IoT comes from its ability to allow communication between the physical and digital worlds, a concept often called the fourth industrial revolution (Morrar et al., 2017). IoT platforms serve as a bridge between device sensors and data networks, where connected IoT devices exchange information using Internet transfer protocols. The sensors or devices in an IoT network produce large volumes of data that are continuously transmitted to a "data lake", which could be a local physical server or a cloud-based storage space (i.e. distributed over internet) to enable the necessary data processing through appropriate ML algorithms or techniques to generate actionable knowledge. Thus, we note that IoT is essentially the means to generate and transmit large volumes of data with embedded practical information.

It should be noted that the complexity of agri-food systems is very high due to the involvement of many unpredictable variables in agriculture, the heterogeneity of food materials and the eating habits of consumers. This makes it almost impossible to translate the knowledge of farmers, industry experts and consumers into clearly expressed, well-defined rules (software) that can be implemented in Artificial Intelligence (AI) -based expertise systems (Goyache et al., 2001).

ML based AI is suitable for systems where frequent system training is not a constraint and greater accuracy is desired, which is true for agri-food systems. ML is one of the central topics of AI, because a characteristic usually attached to intelligence is the ability to learn from the environment. ML is an AI development technique that offers the possibility of a computer system to learn without being explicitly programmed (Mitchell et al., 2013). ML is also known as statistical learning,

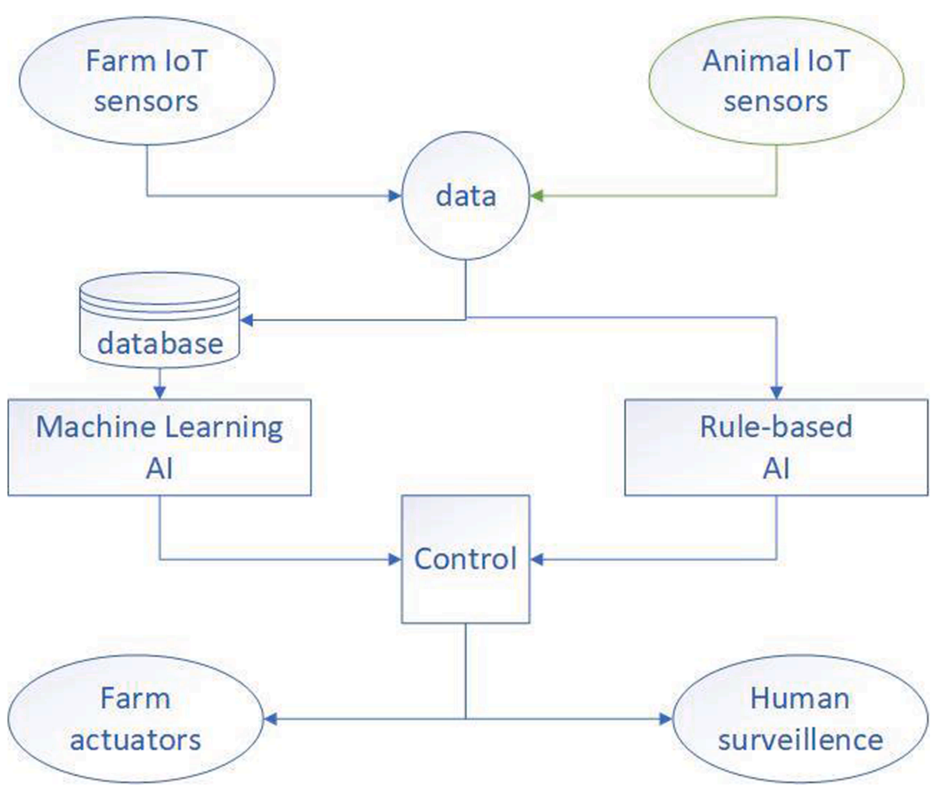

Fig. 1. General AI-based PLF system data workflow.

a subfield of AI dedicated to the study of algorithms for prediction and inference. Learning from data is at the core of ML, and data mining shares a similar spirit with ML and is often discussed in the same context (Morota et al., 2018).

3.1. Overview of existing machine learning approaches in livestock farming

In most practical cases, the ultimate aim of machine learning is to predict the animals response(s) to its process input(s). For instance, predicting the growth trajectory of broiler chickens or cattle, using the food supply or the past evolution of the flock or herd, as a control input (Aerts et al., 2003; Alonso et al., 2015). However, not every mathematical model can be used for complex dynamic processes such as livestock production, which often require an adaptive approach: farm animals constitute complex, individual, time-varying dynamic systems (Berckmans, 2006).

The complexity of the modelling approach chosen by a decision maker depends on the PLF target and the amount of available data to achieve this target. Considering animal welfare, algorithms are mostly very complex with too many restrictions to control the process input(s). To better explain a case where there is a need to control the inputs to a process, suppose we are interested in assessing the effects of environmental factors such as temperature on the average daily gain, feed intake, heat production or physiological status of swine (Bridges et al., 1995). Different levels of changes in the environmental condition as a controller (input parameter) can be assessed on i.e. the average daily gain as the response variable. The simpler empirical models applied for control purposes, are static and they cannot cope with the dynamic nature of the process response (Wathes et al., 2008). As for GHG emissions, there are fewer studies in PLF context (Hosseinzadeh-Bandbafha et al., 2016; Pérez-Miñana et al., 2012; Zheng et al., 2016). The reason for this is the fact that GHG emissions are mostly estimated under IPCC approaches. The lack of recorded or historical data on GHG emissions, that is discussed more in Section 6, is also another factor influencing the lack of ML-based research in coping with GHG emission mitigation. There is a lack of methods to accurately calculate GHG emissions on livestock farms to support a ML based approach, but there are several studies to empirically measure some of the factors that contribute to the total GHG emissions such as CH_4, CO_2, N_2O levels in farms. Such data and analysis are in our opinion a starting point for accurately estimating the amount of GHG emissions in livestock farms, which is a very important factor related to the sustainability of such farms. As more relevant data becomes available, the ML models can become more effective. Morota et al. (2018) outline a framework for machine learning and data mining and offer a glimpse into how they can be applied to solve pressing problems in animal sciences.

In the simplest case, where less data is needed, a PLF process may only have one system input and one system output (SISO). However, in most practical applications, PLF systems have several process inputs and outputs that interact, resulting in complex multiple-input, multiple-output systems where the component processes may act in series, in parallel or with feedback (Wathes et al., 2008). Many black box models reproduce highly complex nonlinear phenomena, including those for which theories have not been proposed yet, and they are defined as models where no understanding of the model structure and its parameters is required. However, black box models are not well accepted in PLF applications because they lack explainability which is crucial for building trust (Table 2). Grey box models combine a partial theoretical structure with data to complete the model (Bohlin, 2006). Hence, they can remedy the lack of explainability in black box models, since the parameters in grey box models can be interpreted on the basis of the underlying biological or physical processes (Kristensen et al., 2006). Wathes et al. (2008) discuss that the challenge is to develop tools to determine the biological meaning of a model's structure, order and parameters.

Table 2 outlines some of the tasks considering PLF goals: Welfare and GHG emission, that have been done successfully using ML algorithms.

The majority of the previous works have delved into animal welfare studies including activity recognition, behavioral pattern assessments, and disease detection. There were also a few studies into estimating emissions arising from livestock farms. In the following, we discuss the different efforts, based on the type of study, as well as the ML approaches that were used.

Table 2
ML based data-driven decision support considering PLF goals: Welfare and GHG emission.*

Goal	Task	Work	Method used	Data source
Welfare	Activity identification	(Godsk and Kjærgaard, 2011)	END	GPS
		(Vázquez-Diosdado et al., 2019)	Offline k-NN, online k-means	Accelerometer, Gyroscope sensors
	Anomaly detection	(Adrion et al., 2018)	z-score thresholding	RFID
	Estimation of cattle weight trajectories	(Alonso et al., 2015)	SVM	Bovine weights
	Predicting growth trajectory of broiler chickens in real time	(Aerts et al., 2003)	Recursive linear modelling	broiler chickens
	Rumen fermentation pattern detection	(Craninx et al., 2008)	ANN	Milk samples
	Pig wasting diseases detection	(Chung et al., 2013)	SVDD, SRC	Cough sounds
	Study relation between feed intakes and vocal recordings	(Aydin et al., 2015)	Threshold based	Livestock audio recordings
	Cattle behavioral classification	(Dutta et al., 2015)	Bagging ensemble with tree learner	3-axis accelerometer and magnetometer
	Identification and classification of chewing patterns in calves	(Pegorini et al., 2015)	Decision Tree C4.5	Optical fiber Bragg grating sensors
	Early detection of problems in egg production curves	(Morales et al., 2016)	SVM	Egg production database
	Animal tracking and behavior annotation	(Matthews et al., 2017)	GMM	Video camera data
	Face recognition	(Hansen et al., 2018)	CNN	Webcam images
	Livestock vocalization detection	(Bishop et al., 2019)	SVM	Livestock audio recordings
	Grazing and ruminating behavior, lameness detection in sheep	(Kaler et al., 2020)	RF, NN, SVM, KNN	Triaxial gyroscope and accelerometer
GHG emissions	Estimating GHG emissions	(Pérez-Miñana et al., 2012)	BN	Dairy farm data
	Modelling GHG emissions	(Hosseinzadeh-Bandbafha et al., 2016)	ANFIS	Dairy farm data questionnaire
	Modelling methane emissions	(Zheng et al., 2016)	BN	Dairy farm data

* Abbreviations: END (Ensembles of Nested Dichotomies) (Frank and Kramer, 2004), k-NN: k-nearest neighbors, SVM: Support Vector Machines, SVDD: Support Vector Data Description, NN: Neural Networks, ANN: Artificial Neural Network, SRC: Sparse Representation Classifier, SVR: Support vector regression, GMM: Gaussian Mixture Models, CNN: Convolutional Neural Network, ANFIS: Adaptive Neural Fuzzy Inference System, BN: Bayesian Network, RF: random forest, KNN: AdaBoost and k-nearest neighbor.

Type of study: Research works on welfare of animals can be categorized into the following two categories: first, animal behavior monitoring and second animal product monitoring. The first category delves into various aspects of animal behavior such as their movements, chewing and vocal patterns, while the second category consists of methods that monitor the quantity and quality of animal products. We first detail both categories of animal welfare and then we discuss the research on GHG emission as follows:

(1) Considering animal welfare:
- In animal behavior monitoring, Aydin et al. (2015) performed a study of the relation between feed intake and vocal (pecking sounds) recordings of broiler chickens. Their results indicate that there is a strong correlation between the two variables, indicating the applicability of sound analysis for monitoring feeding behaviors of chickens. Chung et al. (2013) used pig coughing sounds to detect respiratory diseases. Bishop et al. (2019) used live audio recordings of three different kinds of animals, namely, sheep, pigs and cattle for vocalization classification. While using audio recordings, preprocessing of the data is often done in order to obtain the actual audio signal prior to applying ML.
- In animal product monitoring, Alonso et al. (2015) have used various bovine measurements and characteristics such as length, age, sex, while Morales et al. (2016) used egg production data and Craninx et al. (2008) used milk samples. Kaler et al. (2020) showed for the first time that features extracted from triaxial accelerometer and gyroscope sensors signals can detect grazing and ruminating behavior, and also differentiate between lame and non-lame sheep while standing, walking and lying.

(2) Existing research on GHG emissions in livestock farms deals with the whole livestock farm data in contrast to data taken from animals alone. Whole farm studies have been more frequently used for GHG emission estimation because there are also other sources of emissions at the farm level apart from animals, such as storage of manure, feeding situation, crop and pasture land (Rotz, 2018). Whole farm models are not aligned with the PLF approach, as important components of the PLF approach (such continuous and real-time measurements with low-cost sensor equipment) are not a prerequisite for their development or use. Recent studies have employed ML algorithms for estimating GHG emissions from farm data. Pérez-Miñana et al. (2012) included dairy farms, crop farms, mixed (dairy and crop) farms and low grazing farms in their GHG modelling. Profiles of such farms, which include attributes, such as size of farms (in hectares), herd size, fertilizers applied, solid wastes, electricity used, gas used etc., are given as input to their model. Hosseinzadeh-Bandbafha et al. (2016) collected data using a face to face questionnaire, while others used animal, diet and production data from dairy farms (Zhang et al., 2016; Zheng et al., 2016).

Type of approach: The Ensembles of Nested Dichotomies (END) algorithm was used by Godsk and Kjærgaard (2011) to identify four activities, namely, eating/seeking, walking, lying and standing of 14 cows. They performed a comparison of their approach with other methods such as Support Vector Machines (SVMs), decision trees and Random Forest and found that END algorithm obtained the best accuracy of 86.2%. This value is the average accuracy of the classifier over all the activities: lying, standing, walking, eating seeking while using 10 ensembles of the classifier. The individual activities accuracies were as follows: lying 76.5%, standing 75.8%, walking 100% and eating seeking 90%. The input parameters relating to the features were varied and it was found that the classifier performance was not affected to any large extend by such changes. In a different approach by Vázquez-Diosdado et al. (2019), clustering by k-means algorithm and classification using k-Nearest Neighbor (k-NN) were applied for three types of activities of 17 sheep, namely, walking, standing and laying. The combination of online k-means and offline k-NN algorithm achieved an average accuracy of 85.2% over all activities. The use of online k-means is justified by its effectiveness in dealing with the effects of concept-drift (distribution changes) in the data. Audio based disease detection was done by Chung et al. (2013) using audio preprocessing followed by ML techniques. Detection of disease in pigs was cast as an anomaly detection task, and by using Support Vector Data Description (SVDD) average accuracy of 94% was obtained. Furthermore, three main types of diseases, namely, Postweaning Multisystemic Wasting Syndrome (PMWS), Porcine Reproductive and Respiratory Syndrome (PRRS) virus and Mycoplasma Hyopneumoniae (MH) were identified with average accuracy of 91% using Sparse Representation Classifier (SRC). Simple thresholding based classification were done by Aydin et al. (2015) and Adrion et al. (2018) for the tasks of feed intake-vocal measurement and anomaly detection respectively. When prediction of some event or phenomena such as animal activity is the goal, then SVM has been demonstrated to be successful in various kinds of farms and tasks. If the data recorded are videos, then Convolutional Neural Networks (CNNs) tend to be more successful than traditional ML algorithms. Other approaches such as Artificial Neural Networks (ANN) and Gaussian Mixture Models (GMMs) have been used for rumen fermentation pattern detection and animal tracking by Craninx et al. (2008) and Matthews et al. (2017), respectively. Regression tasks, such as animal weight prediction, have been done successfully with SVM (Alonso et al., 2015). For the task of modelling GHG emissions, Bayesian Networks (BNs) have been found to be useful in modelling causal relationships between the factors affecting methane emissions (Pérez-Miñana et al., 2012; Zheng et al., 2016). In the work of Zheng et al. (2016), a comparison was made between BNs, SVMs, Decision Trees (J48) and instance-based classifiers (KStar) on the task of predicting GHG emissions. The results revealed that BN achieved the best accuracy.

3.2. Risks and challenges

Due to the nature of tasks in PLF, there are various associated risks and challenges. We categorize the current problems in ML for PLF into two main categories: (1) Model related and (2) Data related.

(1) **Model related**: Selecting the appropriate ML model for a given task is a key step that determines how well we make sense of the data. Among the common issues encountered in applying ML to life sciences, besides *model selection* is the issue of *interpretability*. Depending on the type of model, clarity on the behavior of the model varies. In PLF, one would be interested to know why a certain model gives a certain prediction. As observed from Table 2, most of the studies include interpretable ML models as opposed to black box models. On the other hand, the upside of black box models, such as deep learning methods, is that they have been shown to be extremely successful in various difficult tasks such as speech recognition (Dahl et al., 2011), image captioning (Johnson et al., 2016), machine translation (Sutskever et al., 2014), protein structure prediction (Senior et al., 2020) etc. This fact indicates that in areas such as livestock management, which is considered a complex scenario involving humans, animals and environment, deep learning models could be used to provide deep undiscovered insights.

(2) **Data related**: the data collected from livestock farms are of *varied types* (modality) and often contain *missing* and/or *noisy* values. The success of applying ML on data depends to a high degree on the correctness of data. There are two distinct tasks here: the first has to do with validating the data that has been acquired, and the second has to do with validating the ML model that has been learned from the data. The varied nature of data, ranging from images, video, audio and logs and the presence of noise and other artefacts must be handled prior to learning as part of data validation. The second task of model validation must be done to

ensure that the obtained models agree with the data that has been observed so far. The degree to which stakeholders trust the ML model is tied to the second task.

4. Modelling and simulation for decision support in livestock farming

Decision management is becoming increasingly important in today's livestock farming, and decision support systems play a vital role in management and making the right decision at the right moment. DSS integrate optimization, modeling and simulation in a computer-based environment, in order to provide the required level of insight in the decisional problem. An important step in the development of effective real-world DSS is to formalize the decisional problem into a model (modelling phase) and then to simulate possible scenarios in order to evaluate their performance, to screen alternatives and finally focus only on the promising ones. Therefore, simulation refers to imitating the operations and processes of a system in the real world; while modeling is the process of understanding and describing the behavior of a system (Banks et al., 2010).

To assist farm managers in their decision processes, M&S delivers valuable insights on the potential impact of various decisions farmers make before actually implementing them in the real-world. Obviously, this contributes towards a large reduction in costs, risks, and unnecessary human efforts. The downside of M&S is that it is a very expensive and resource-consuming process, both in terms of human effort to build models, but also in terms of computation time (Banks et al., 2010). Therefore, M&S is not an approach that is easily accessible to small farms, and it is more of a luxury that only large farms or cooperation of farms can afford. Finally, the validation processes for the built simulation models can be very challenging, depending on the complexity of the system. Most of the studies concerning M&S approaches in PLF, are process-oriented simulation methods. On a farm, various objects or subroutines represent processes. Some examples of major processes in a farm are: feed availability, the herd, manure handling, and gas emissions. In this section, we first describe different M&S paradigms, and we describe the use of the processes in M&S more in detail. We then categorize the studies on M&S in PLF with respect to the different M&S paradigms.

4.1. Modelling and simulation paradigms

Traditional M&S Paradigms: Simulation modeling is a process that generally involves converting expert knowledge into dynamic models and simulating them to understand more about the system. This traditional simulation modeling has the advantage that a modeler can use existing knowledge to create meaningful simulation models representing the system. These handcrafted models are also useful for testing theories about how a system works. If a model faithfully represents a system, then it will produce the same behavior as the real system. In this scenario the model can be thought of as a hypothesis for how the real system works. The most popular simulation paradigms are: discrete-event simulation, continuous simulation (also known as system dynamics) and agent-based simulation. As illustrated in Fig. 2, at the bottom are the physical-level approaches that use highly-detailed representations of real-world objects. The models at the top are highly abstract, and they typically use aggregates such as consumer populations rather than individual objects (Grigoryev, 2012). Other models have an intermediate abstraction level. We elaborate more on these simulation paradigms in the following.

Discrete-Event Simulation: A discrete-event simulation (DES) models the operation of a system as a (discrete) sequence of events in time. Each event occurs at a particular instant in time and marks a change of state in the system (Robinson, 2004). Traditionally, DES models are based on data extracted from a physically existing system or a system that has been developed and tested before (i.e. historical data). This data can be enhanced with a set of experimental rules and mathematical algorithms to enable prediction of system behaviors well in advance. To improve animal health and welfare, modeling the spread of disease in a large farm can help to simulate the disease behavior and make the best decision to prevent it from spreading more. Considering finite number of infectious stages (i.e. Susceptible, Intermittent and Persistent), transiting from one stage to another with a given rate, is an event which makes changes to the herd system (Bruijnis et al., 2010; Sørensen et al., 2017). DES approaches have not been used up to this moment for GHG emission estimation. Nevertheless, DES approaches for simulation of animal diseases could be used in combination with the Life Cycle Assessment (LCA) methodology to quantify the impact of the disease on GHG emissions (Mostert et al., 2018).

Continuous Simulation: Continuous simulation (CS), also known as

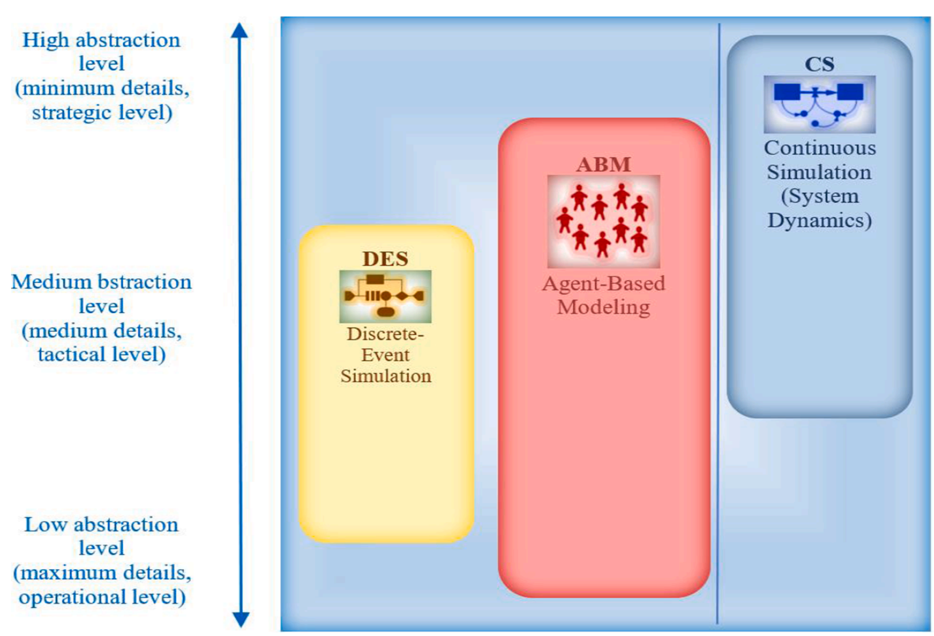

Fig. 2. Different simulation paradigms.

System Dynamics, is a methodology to recognize and solve problems by analyzing the information feedback, dealing with the dynamic structure and feedback mechanism between the qualitative and quantitative factors of the complex procedure, to obtain the overall cognition and problem solving of the system (Bayer, 2004). In the CS methodology, a problem or a system (e.g., ecosystem, farming system or mechanical system) may be represented as a causal loop diagram (Bayer, 2004). Causal loop diagrams aid in visualizing a system's structure and behavior, and analyzing the system qualitatively (Fig. 3). To perform a more detailed quantitative analysis, a causal loop diagram is transformed to a stock and flow diagram. A stock is the term for any entity that accumulates or depletes over time (i.e. milk production, feed intake, manure production or GHG emission). A flow is the rate of change in a stock, in terms of formulas or equations with stocks as the variables in the formula. Depending on the problem at hand, modeling the equations can be done in continuous or discrete time.

In Rotz et al. (2011) the major components or processes of the model include available feeds, animal intake and manure production, and manure handling. The feeds available and their nutrient contents are provided through user input. Balanced rations are prepared for each animal group on the farm and their feed intake is determined to meet their energy and protein requirements. Based upon feed intake, growth and milk production, the nutrient output in manure is predicted. From this nutrient excretion, emissions are predicted as a function of weather conditions and management practices. Regarding animal welfare, stocks in CS can be defined as bacteria concentration which are transported via surface water or air (Widgren et al., 2019). Other studies of use of CS in modelling the dynamics of GHG emissions or animal welfare can be found in Table 3.

Agent-Based Modeling: Agent-based modeling (ABM) is commonly used to study the dynamic movement behaviors of various types of systems, such as flocks of birds, pools of fish, pedestrian crowds, road traffic and livestock. A system can be simulated using a mobile agent-based model if it contains many similar agents, such as people who move around in a shared environment, act autonomously, and only have local knowledge (and possibly global knowledge about the environment: like a familiar building's layout). On a dairy herd, agents can be defined as individual cows. Al-Mamun and Grohn (2017) developed a multiscale agent based simulation model of a dairy herd. In their model each cow was tracked from birth to death, residing at different management operations: adult/milking, calf and heifer. Their model was successfully applied to estimate critical parameters (i.e. insemination time) for management decisions.

Data-Driven M&S: Data-Driven Simulation (DDS) is an approach where the simulation models are parameterized by data, allowing users to create and run a simulation model without the need to do explicit modelling. The goal of DDS is to generate simulation models directly from external data sources using data structuring and analysis algorithms for creating and configuring the model. The degree of parameterization within data-driven simulation in research varies, affecting the flexibility of scenarios which can be modelled. Some DDS approaches

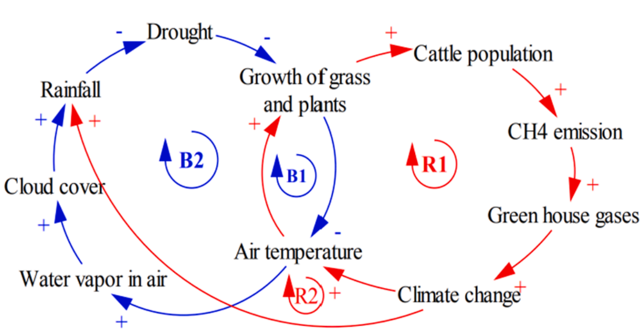

Fig. 3. Example of causal loop diagrams for the interrelationships between cattle population and air temperature (Van Nguyen and Nguyen, 2013).

use data only to estimate the model parameters (Al-Mamun et al., 2018), but other studies also drive the model structure from observational data (Widgren et al., 2019). Dynamic Data-Driven Simulation (DDDS) is a type of data-driven simulation which uses real-time data to detect the system model and feeds the simulation results back into the model continuously to gain more accurate and on time results.

4.2. *Overview of modelling and simulation approaches pertaining to livestock farming goals*

M&S approaches in livestock are applied to either improve animal health, productivity/profit and welfare, or reduce GHG emissions. IPCC-based M&S approaches are mostly process-based, and are primarily developed by scientists to better understand the relevant processes and predict how they interact. Some CS models in livestock farming consider manure management processes in their modules (Holzworth et al., 2014), whereas other models consider processes for enteric fermentation (Bannink et al., 2010), and some processes consider more than that (Schils et al., 2007), which is the main difference between CS approaches. The addition of new processes to an existing model structure, requires much time and effort to develop or to adapt, and that is a weakness compared to the simpler and more flexible DS models of Table 1. Table 3 illustrates M&S studies of livestock farming according to the PLF goals of interest: animal health/welfare, and estimation/mitigation of GHG emissions, and the three simulation paradigms: DES, CS and ABM. These M&S examples do not address the farmer directly but rather the farmer's consultant for provision of advice. However, livestock farmer's input is needed in this respect.

We observe that most of the M&S research in livestock is process-based, typically categorized as continuous simulation. The reason is that there are variables for which a continuous description is more natural, e.g., GHG emissions, feed intake, milk production, temperature, concentration of bacteria in an infectious environment. For these variables, discrete counting would clearly not be feasible. Data-driven and dynamic data-driven simulation approaches have received much less attention since data availability has been a challenge in livestock sector. Furthermore, considerable additional efforts are needed for both transition sensor technology and the models that exploit sensor readings into decision support systems (Tomic et al., 2015), as elaborated in Section 6. We anticipate an increase in studies in these fields since animal and transition sensors are being used and developed more widely.

5. Optimization in precision livestock farming

Advanced technologies in PLF are utilized to optimize the contribution of each animal towards predefined goals. Goals, such as profit maximization and GHG emission reduction are driving factors behind any ethical farming practice. Casting these goals as an optimization problem is natural and widely accepted. Methods focused on animal welfare are more concentrated on optimal feed formulation and diet strategies (Babić and Perić, 2011; Moraes and Fadel, 2013). These models are often formulated as multi-objective problems.

Other main issues that have been addressed by various optimization algorithms include: optimal design of animal housing to ensure good ventilation for animals while trying to reduce aerodynamic drag, optimization of transportation structures (Gilkeson et al., 2013), energy consumption optimization (Awan et al., 2019) and reproductive performance optimization (Herskin et al., 2018). Optimizing feed formulation has also gained more attention in the literature, because of its effects, mainly, on farm costs and feed production and with significant environmental impact on GHG emissions from enteric fermentation and manure management. Namely, GHG emissions from enteric fermentation, as one of its main sources, represent 39 percent of total emissions from livestock (FAO, 2020).

Table 3
M&S approaches regarding different simulation paradigms and PLF goals.

Goal	M&S type	Literature	Description
welfare	DES	(Bruijnis et al., 2010)	Use dynamic stochastic Monte Carlo simulation model to assess the effect of disease on income.
		(Sørensen et al., 2017)	Use dynamic mechanistic Monte Carlo simulation model for disease in pigs using R software.
	CS	(Kahn and Lehrer, 1984)	Reproductive performance of beef cows.
		(Conrad, 2004)	For cattle and crop production.
		(Bannink et al., 2008)	Use mechanistic simulation model on rumen fermentation.
		(Guimarães et al., 2009)	For goats.
		(Parsons et al., 2011)	APSIM and System dynamic.
		(Tedeschi et al., 2011)	Applied for small ruminants.
		(Widgren et al., 2016)	SimInf: R package.
		(Widgren et al., 2019)	SimInf extended: to support data-driven spatio-temporal simulations of disease transmission in wildlife.
	ABM	(Pomar et al., 2011)	
		(Al-Mamun and Grohn, 2017)	MABSDairy: a multiscale agent based simulation of a dairy herd.
		(Al-Mamun et al., 2018)	Data-driven (only parameters) individual-based model of infectious disease.
GHG reduction	DES	(Mostert et al., 2018)	The impact of foot lesions in dairy cows on GHG emissions of milk production: Using LCA method and mechanistic simulation model (developed in R).
	CS	(Berntsen et al., 2003)	FASSET: Process simulation used to evaluate consequences of changes in regulations, management, prices and subsidies on farm production, profitability, nitrogen losses, energy consumption and GHG emission.
		(Holzworth et al., 2014; Keating et al., 2003)	APSIM: Applications, including support for on-farm decision making, development of waste management guidelines.
		(Schils et al., 2007)	DairyWise: Combines already existing simulation models of specific subsystems into a whole farm model for use in interdisciplinary studies.
		(Johnson et al., 2008)	DairyMod and EcoMod: Biophysical process simulation of the dairy pasture system.
		(Bannink et al., 2010)	A dynamic, mechanistic model of enteric fermentation in dairy cows based on the model of (Mills et al., 2001).
		(Little et al., 2010)	Holos: Process-based emission factors estimate all important direct and indirect sources of GHG emissions of livestock operations.
		(Del Prado et al., 2011)	SIMS(Dairy): Process simulation of the effects of management, climate and soil properties on nitrogen, phosphorus, and carbon losses along with profitability, biodiversity, soil quality, and animal welfare.
		(Rotz et al., 2011)	DairyGEM: a software tool for whole farm assessment of emission mitigation strategies from manure.
		(Chardon et al., 2012)	MELODIE: Dynamic simulation of the flows of carbon, nitrogen, phosphorus, copper, zinc and water within animal, pasture, crop and manure components.
		(Li et al., 2012)	Manure-DNDC: A biogeochemical process model for quantifying greenhouse gas and ammonia emissions from livestock manure systems.
		(Rotz, 2012)	IFSM: Process simulation of all important farm components representing the performance, economics, and environmental impacts including direct and indirect GHG emissions and carbon footprint.
		(EU AnimalChange, 2015)	FarmAC: Process-related emission factors represent carbon and nitrogen flows on arable and livestock farms quantifying GHG, soil C sequestration, and N losses to the environment.
	ABM,CS	(Matthews and Bakam, 2007)	A combined agent-based and biophysical modelling approach to address GHG mitigation policy issues

5.1. Simulation-based optimization

M&S combined with optimization can be a powerful decision support approach (Ólafsson and Kim, 2002). The potential solutions, subjected to the objective function, and the constraints of the optimization problem, are evaluated solely via simulations. The advantages of adopting simulation-based optimization include ability to solve optimization problems without being affected to a large extent by the complexity of the system and the power to change the objective function and constraints dynamically as the system changes (Azadivar, 1999; Hüllen et al., 2020).

In the domain of livestock farming, we discovered use of optimization approaches, both in combination with M&S and without, which is summarized in Table 4.

Welfare: There are a few works that combine optimization and simulation for ensuring the health and welfare of livestock. They include the works of Bajardi et al. (2012) and Michalak (2019), which deal with epidemic control in livestock farms. Bajardi et al. (2012) performed spatial simulations of cattle movements to detect epidemic spreading paths. Although sustainable feed formulation is the main goal of some studies, the nutritional welfare of pigs and broilers is also considered (Alqaisi et al., 2017; Garcia-Launay et al., 2018; Morel and Hill, 2011; Uyeh et al., 2018). Providing adequate ventilation is necessary to ensure the welfare of livestock. In the absence of proper ventilation, dust concentrations inside the shelter increase and cause health issues to the animals. Ecim-Djuric and Topisirovic (2010) provided a study into optimal design of ventilation in livestock shelters and Fawaz et al. (2014) considered a simulation based optimization of heat and ventilation within chicken shelters. Diez-Olivan et al. (2019) proposed a data-driven modelling process performed by a quantile regression forests approach that allows estimating growth, welfare and mortality parameters on the basis of environmental deviations from optimal farm conditions.

Production, Costs and Sustainability: The work of Halachmi (2015) provided a simulation-based optimization of fish farms with the aim of maximizing production. Their model incorporated fish growing phases, with discrete-event and continuous-time variables and ideas from queuing theory. Zhang et al. (2016) studied prediction of milk production of dairy farms in Ireland by combining simulation of herd and milk production, while optimizing the production quantities.

Optimizing the costs associated with livestock farming is also important from a sustainability viewpoint. A study into the most effective routes from milk transportation was done by Caria et al. (2018). The problem that was studied falls under the category of profit maximization, where profit is maximized by minimizing the cost of milk collection. Their solution to this problem, which is a case of the Travelling Salesman Problem (TSP), consisted of the Ant Colony Optimization (ACO) algorithm. Similarly, Zhang et al. (2020) proposed a genetic algorithm based optimization of sheep transportation paths. Some researchers use optimized feed formulations for diet optimization as another way of reducing the costs associated with livestock farms (Alqaisi et al., 2017; Garcia-Launay et al., 2018; Morel and Hill, 2011; Uyeh et al., 2018). Energy consumption within farms is also another aspect that contributes to the costs of maintaining such farms. In fact, good design of livestock shelters which permit good ventilation reduces the need for using artificial ventilation and thus improves energy

Table 4
Previous research in simulation-based optimization for livestock farming.

General reference	Optimization objective	Optimization model	Farm type
(Lopes et al., 2016)	Reproductive performance optimization: survey		Cattle
(Babić and Perić, 2011)	Formulating optimal feed blend	multi-criteria based goal programming model	pigs
(Moraes and Fadel, 2013)	Diet optimization	linear, dynamic and stochastic programming	
(Gilkeson et al., 2013)	Designing optimal trailers for transporting livestock	Computational Fluid Dynamics (CFD) based optimization	
(Singh and Saxena, 2015)	Diet optimization	Linear programming and self-organizing migrating genetic algorithm (SOMGA)	Dairy cattle
(Awan et al., 2019)	Optimizing the energy consumption in wireless sensor networks	Grey Wolf Optimization (GWO) algorithm	
(Xu et al., 2016)	Optimal feed formulation	Particle Swarm Optimization (PSO) algorithm	Poultry
(Wijayaningrum et al., 2017)	Optimal feed formulation	Hybrid adaptive genetic algorithm and simulated annealing	Poultry
(Nasseri and Darvishi, 2018)	Optimal feed formulation	Fuzzy linear programming	Dairy cattle
(Diez-Olivan et al., 2019)	Growth, welfare and mortality parameters	quantile regression forests	broiler meat chickens

Simulation-based reference	Optimization objective	Constraints	Farm type	Simulation done with respect to:
(Morel and Hill, 2011)	Profit and GHG emissions	Feeding cost	Pigs	Growth
(Ecim-Djuric and Topisirovic, 2010)	Ventilation (energy)	Wind velocity and direction	Pigs	Ventilation and fluid dynamics
(Bajardi et al., 2012)	Reduction in epidemic spread	Animal movements	Cattle	Bovine movements
(Soufi et al., 2013)	Energy	Livestock shelter parameters	Cattle	Stand-alone photovoltaic systems for livestock shelters
(Fawaz et al., 2014)	Temperature and air quality	CO2, NH3 concentrations	Chicken	Thermal flow, CO2, NH3 concentrations
(Halachmi, 2015)	Yearly turnover (production)	Space/culture volumes	Fish	Fish growth phases
(Mančić et al., 2016)	Polygeneration system configuration	Temperature, GHG emissions	Pig	Energy demand, polygeneration system
(Zhang et al., 2016)	Milk production forecast	Climate, Physical aspects of cows	Cattle	Yield production model, herd
(Alqaisi et al., 2017)	Nutritional and economic feed formulation	Feed requirements, Dietary nutrients	Broiler	Feed formulations for broiler life cycle
(Garcia-Launay et al., 2018)	Feed formulation cost	Nutritional, GHG emissions	Pig, broiler, young bulls	Life cycle assessment
(Uyeh et al., 2018)	Feed formulation cost	Nutritional	Cattle	Feed formulations
(López-Andrés et al., 2018)	Environmental impact, profit, resources	Production limits, raw materials and energy requirements	Chicken	Raw material, energy requirements
(Michalak, 2019)	Epidemic control	Time, Control strategy parameters	General livestock	Livestock population
(Zhang et al., 2020)	Logistics cost, GHG emission, energy consumption	Vehicle and sheep cost parameters	Sheep	Delivery path
(Paul et al., 2020)	Annual income, Annual farm balance, GHG emissions	Farm size, Feed balance, organic matter balance	Cattle	Bio-economic model, FarmDESIGN based simulation

efficiency. Ecim-Djuric and Topisirovic (2010) provide a simulation based study into finding optimal ventilation in livestock shelters. Soufi et al. (2013) provided a simulation-based optimization study into the energy consumption in livestock farms. A similar study by Fawaz et al. (2014) provided a simulation-based optimization of heat and ventilation in chicken shelters. Mančić et al. (2016) proposed a simulation-based study involving the optimization of configurations of an energy system in order to meet the energy demands of a pig farm. Identifying and controlling epidemic spread among livestock is another area which influences the cost. Bajardi et al. (2012) and Michalak (2019) provided simulation based optimization of epidemic spread.

GHG emissions' estimation and mitigation has been mostly achieved as an indirect consequence of the optimization goals in the majority of the studies in the scientific literature. By optimizing costs of milk or in fact any kind of animal product transportation, the energy consumption and emissions can be reduced significantly (Caria et al., 2018; Chokanat et al., 2019; Pretty et al., 2005; Sethanan and Pitakaso, 2016; Zhang et al., 2020). Another area that impacts the sustainability of a livestock farm is the feed formulation. In fact, formulating feeds of the livestock by including agricultural by-products would lead to reduced GHG emissions (Alqaisi et al., 2017; Guo and Zhang, 2020; Sihananto et al., 2019; Wijayaningrum et al., 2017). Uyeh et al. (2018) used a differential evolution algorithm combined with feed formulation simulations to find the optimal feed formulation for cattle farms. Unlike aspects such as transportation in the context of a livestock farm, feed formulation is animal specific. Each type of animal requires special feed formulations. Pig farms can be large source of methane emissions if their feed formulations do not match their growth requirements. In this context, Morel and Hill (2011) performed a simulation based study to optimize feed formulations. The consequences of optimal feed formulations include reduction in nitrous oxide and methane emissions, which in turn imply reduced GHG emissions. The work of Garcia-Launay et al. (2018) considered a multi-objective optimization of feed formulation consisting of sustainability and cost factors. Optimizing the energy consumption of livestock farms also contribute to lowering of GHG emissions (Mančić et al., 2016). A study made by Paul et al. (2020) performed simulation-based optimization of GHG emissions and other sustainability factors while increasing the annual farm income. Similarly, López-Andrés et al. (2018) provided a combination of process simulation, Monte-Carlo simulation and artificial intelligence techniques to maximize profits while minimizing environmental impacts.

Single-farm* vs. *multi-farm studies: It is interesting to see how much research has been done on individual farms alone and on multiple farms because the scale of the study determines how well the models generalize. Most of the works discussed above were single farm studies. The works of Bajardi et al. (2012) and Zhang et al. (2016) were multi-farm studies. The milk transportation route optimization solution of Caria et al. (2018) involves multiple farms (milk suppliers) of a particular region. Their ideas can be extended to other regions and even different kinds of farms. The work of Caria et al. (2018) uses an ACO algorithm to solve their particular milk transportation problem by incorporating problem-specific parameters such as number of suppliers, total milk produced per day, distance between farm and cheese factory etc. Their idea of finding the optimal routes using ACO can be adapted to other regions with different terrains and constraints by changing the parameters of the optimization problem, and then using ACO to solve the new problem. The peculiarities of regions and farms can then be incorporated within the optimization problem in the form of parameters or constraints.

5.2. Summary and challenges

In summary, there are many works that try to optimize costs associated with livestock farms. This is because, costs can be easily formulated as an optimization objective. However, this is not the case with welfare because the overall health of livestock is harder to quantify. Yet, there are optimization studies for epidemic transmission paths and living conditions of livestock (Alqaisi et al., 2017; Bajardi et al., 2012; Ecim-Djuric and Topisirovic, 2010; Fawaz et al., 2014; Garcia-Launay et al., 2018; Michalak, 2019; Morel and Hill, 2011; Uyeh et al., 2018). Some of the open challenges in ensuring animal welfare include the following:

- modelling risk associated with animal welfare such as muscle, skeletal disorders and diseases,
- development of welfare assessment models using multiple perspectives such as economic, food security and health, and
- selection and validation of the best simulation model (Collins and Part, 2013).

Sustainability of livestock farms is also another widely studied topic in the context of simulation-based optimization. It includes aspects such as optimizing energy consumption and reducing GHG emissions. This topic still has many open challenges, such as the following:

- incorporation of a region/state/nation-wide study,
- reducing emissions from the viewpoint of multiple farms, and
- improving optimization through validation of models and data.

6. Discussion

Throughout the paper we discussed how different modelling techniques like M&S approaches in livestock are applied to either improve animal health, productivity/profit and welfare, or reduce GHG emissions. However, data coming from different sources, i.e., sensor data or farmer's input and the models that exploit sensor readings into decision support systems are needed in this respect. In this section we delve more into the challenges regarding data pathway and the key takeaways.

6.1. Data pathway and associated challenges

Precision Livestock Farming deeply changes farmers working processes (Hostiou et al., 2017) by providing new information – often in large quantities – on the health status of the animals, their welfare, and their food requirements to preserve and improve the technical, economic and environmental performances of farms (Pannell, 1999). One of the central problems in the management of information for PLF is integration and interpretation of heterogeneous data coming from different equipment and data sources. Semantic annotation and publishing of metadata is a common approach for discovering data across numerous heterogeneous sources, and it enables users to search in a standard and transparent way. To support the semantic annotation of metadata, standard vocabularies have been proposed such as the Data Catalog Vocabulary (DCAT) (Zeginis et al., 2019).

Through PLF, valuable data is generated by modern farm equipment, such as automated milking and feeding systems, milking robots and parlors, feed mixers, concentrate feeders, animal health monitoring systems such as pedometers, active ear-tags or rumination collars, weather monitoring systems or specialized environment sensors, and not the least, farmers (Tomic et al., 2015). The initial filtering and processing of raw data helps to better understand the state of the (agri-food) system. Furthermore, by using advanced algorithms and monitoring the performance of the system with respect to desired output, a system can become capable of taking appropriate decisions and performing independent localized actions. Therefore, a "smart" agri-food system would contain capabilities such as parameter sensing, decision making and output control (Misra et al., 2020).

There are already commercial systems in use that can perform simple actions such as automatically start irrigation processes, open/close windows for temperature controlling, robotic milking or automatic feeding. The purpose of all these DSSs, in-line with the PLF approach, is not to replace the farmer but to facilitate the sustainable management of the farm (Wathes et al., 2008). The farmer's perception of a potential solution will always play the major role in the decision-making process.

Tomic et al. (2015) mention that mostly a 4-Level functional model (Fig. 4) has been used to integrate the measurement level (Level 1), where the individual parameters are assessed, e.g., activity measurement; the interpretation level (Level 2) , where sensor data is translated into status information, e.g., estrus; the integration level (Level 3), at which sensor information is to be integrated with other systems' information to produce advice, e.g., whether to inseminate a cow or not; and the automation / the decision support level (Level 4) where farmers make decisions based on the system output or the system makes the decision autonomously, e.g., to call the inseminator. They also indicate that considerable additional efforts are needed for both transition sensor technology and the models that exploit sensor readings into decision support systems (Level 3 and Level 4 systems) that can be used on commercial farms. Moreover, Tomic et al. (2015) discuss about the information overload for farmers, that makes them spend a lot of time in inserting, accessing and interpreting information, i.e., in interacting with their systems over many different interfaces. There is therefore a pressing need to automatically integrate available data within a decision support (Level 4) system that can then provide holistic advices to farmers leading to more efficient herd management (Tomic et al., 2015).

As such, we argue for an integrated use of wireless sensor networks, data analytics and modelling that enable an efficient decision support system that can enable farmers to concentrate on their daily farm activities and use the data for their advantage. Fig. 5 illustrates our envisioned PLF platform, which is a hybrid approach that uses advanced data analytics and modelling and simulation.

Specifically, IoT devices can be installed in the farm for monitoring key parameters of:

- the stable environment (temperature, humidity, gas sensors (NOx, COx, CH4, NH3, etc.),
- the animal (accelerometer, motion sensor, weight sensor, etc.), and
- the feed (flow sensor, weight sensor, humidity sensor etc.).

A cloud based platform could collect and analyze all the aforementioned data for providing recommendations to the livestock farming stakeholders (farmers, consultants, etc.) in order to take management decisions for reducing GHG emissions. In addition, blockchain technology can be used in the platform for developing different features such as data protection, data privacy, data sharing, traceability and smart contracts among the livestock farming stakeholders. Specifically, the smart contracts feature of the platform can help livestock farming stakeholders to have contracts with better prices due to decreased GHG emissions.

There are several other schemes proposed in the literature tackling precision livestock farming. Arrowhead (Marcu et al., 2020) is an open source local cloud framework, which enables integration of real-time IoT protocols such as Message Queuing Telemetry Transport (MQTT) and local cloud edge processing used in agriculture. However, it is not targeted yet for livestock farming and lacks the blockchain component. Another proposal is a swine management system (Piñeiro et al., 2019) for improving GHG emissions that also lacks the blockchain component.

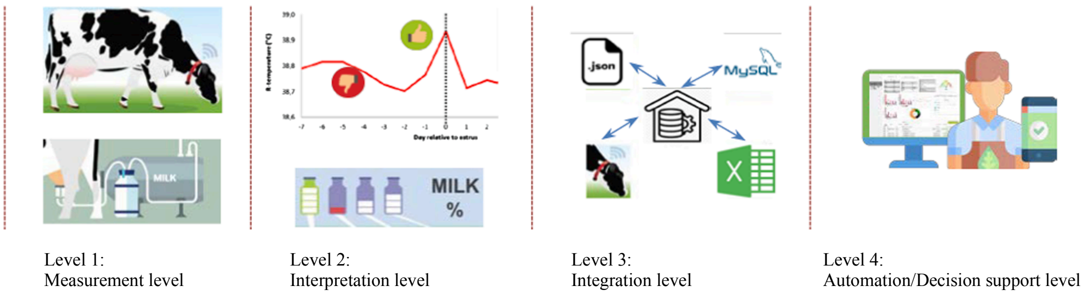

Fig. 4. A 4-level functional model.

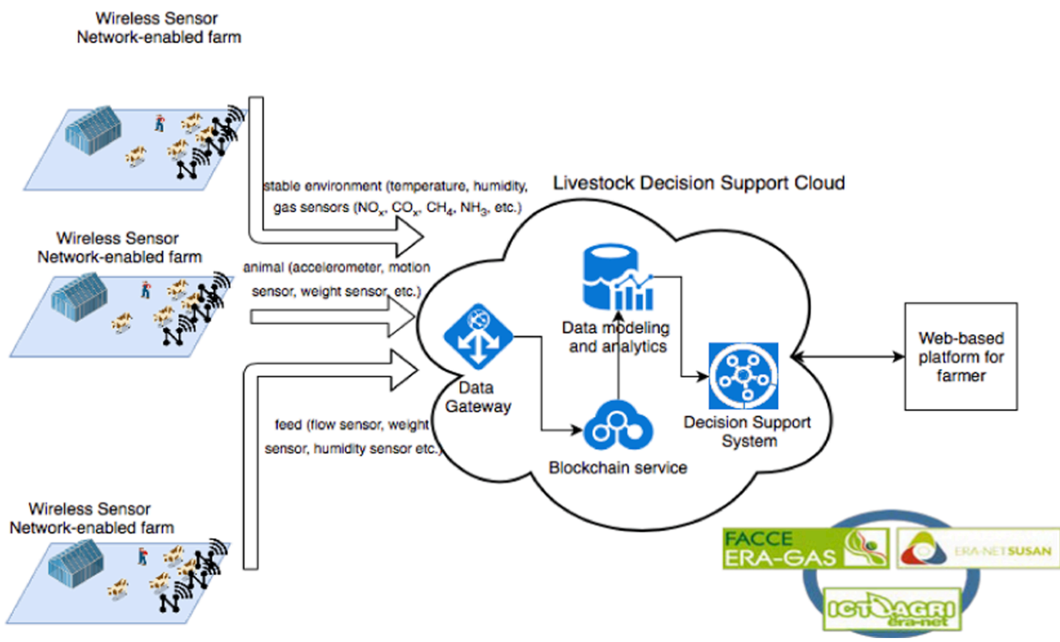

Fig. 5. Proposed Precision Livestock Farming platform.

There are numerous companies offering either AI-based analytics or blockchain for livestock farming. Vence (2018) is offering Artificial Intelligence and Sensor based big data for controlling animal movement, monitor wellbeing and creating virtual fence lines during grazing. However it lacks both blockchain and GHG emission reduction components. BeefChain (2018) is a blockchain-based platform for enhancing traceability and enabling unique animal identification and ensuring origin in cattle farming, but it does not have GHG emission monitoring/reduction capabilities. In summary, there are numerous proposed platforms as well as companies that provide such platforms, but none of them have this combination of GHG monitoring, blockchain and decision support system based on data modelling and analytics. Our platform combines all three elements to provide farmers with a holistic view on the farm and animal status and enable efficient GHG-reducing management.

Finally, a knowledge base in the platform through which ICT processes are shared by farmers can help them to:

- decide about the various inter-related parameters that are required to have optimum use of environmental resources available (i.e. reduced GHG emissions),
- share with experts, any interim or major problems that may crop up during the whole livestock farming process e.g. sowing of seed to delivering milk from cows, and
- market products with reduced GHG to livestock farming stakeholders.

There are several challenges that relate to data collection in this specific scenario as follows:

- **GHG estimation.** As mentioned previously in Section 4, it is currently not possible to correctly measure GHG emission, rather estimate them as accurately as possible using the different Tiers of IPCC methodology. Therefore, the Tier used and the data available on the farm premises, as well as the extent of the measurements will have a significant impact on the design of the model within the cloud platform. This means that the different farm structures (e.g. cattle-only farms, mixed livestock farms) will require the implementation of different models (and with this the overhead in terms of resources needed to implement them).
- **Data sharing and interoperability.** The key challenge of integrating different livestock agricultural systems is how to deal with the heterogeneity of multiple information resources. Therefore, one requirement includes an ontology-based approach to describe and extract the semantics of agriculture IoT objects and a mechanism and data model for sharing and reusing livestock agricultural specific knowledge. While for other disciplines ontologies have already been well established, for agriculture little efforts have been made especially since ICT-enabled agricultural systems are not widespread.
- **Visualization for farming stakeholders.** Many initiatives have been developed presently that boast user-friendly interfaces for non-IT skilled agriculture stakeholders. However, for an end-user it is highly important to not only have relevant data in an at-a-glance,

easy to understand visual format, but also to be offered already insight and decision support based on data analytics. This is an end-goal of implementing the platform presented in Fig. 5. Future PLF systems should be highly adapted to the different way of processing/analyzing data according to who is the end-user. For example, whether it is a farmer (where a more friendly and relatively punctual analysis is needed) or cooperative (where a more complex analysis should be offered) the system should adapt accordingly.

6.2. Key takeaways

Best practices to reduce livestock GHG emissions include improving feed quality and digestibility, improving animal health and welfare using PLF, and manure management, consisting of collection, storage and utilization (Reisinger and Andeweg, 2015). Besides, the goal of reduction in GHG emissions, increasing the productivity or profit of livestock farms is also an important goal of PLF, which is associated with ensuring the welfare of animals. Data with respect to animal welfare has been collected by many studies in the past. It includes data related to animal feed formulation, animal activity, sounds, product monitoring etc. Simulation-based optimization has offered a great help in improving feed quality. We also discussed about the applications of ML and other data analytics approaches in improving animal health and welfare. Manure management is mostly modeled by continuous simulation and as a process interacting with other processes involved in a farm.

Technologies to reduce GHG emissions usually result in low-intensive animal products and that will not necessarily translate into lower total emissions (Reisinger and Andeweg, 2015). The first step to mitigate GHG emission from livestock, is to estimate it under different managerial scenarios. Here, M&S offers holistic techniques to estimate emission intensity of animal products, or the total emission from a farm. Input data volume, indicates the methodology and the precision of our estimates to successfully capture the distinction between different scenarios. ML has been successfully applied to animal welfare and productivity/profit related tasks, which provides a promising starting point for an advanced monitoring and diagnostic system that integrates the best ML models and M&S to exploit the varied amounts of heterogenous data that are collected for the purpose of achieving PLF goals.

Throughout the study, we were able to spot a number of patterns and form conclusions that we present as follows. We noticed that for the goal of improving animal health and welfare, when low resolution information, or small amount of data is available, most of the approaches resorted to classical statistical and M&S methods, whereas the large amounts of data lead to the use of more advanced and sophisticated methods, such as data-driven M&S and ML (Table 5).

On the other hand, existing IPCC guidelines help in estimating GHG emission as a part of a mitigation goal. However, methods to deal with GHG emission lack the optimization part and they merely try to estimate emissions under different circumstances and from different sources. Whereas, optimization approaches are applied mostly for animal health and welfare (feed formulation especially), to increase the efficiency and productivity of the system (i.e. early disease detection, best insemination time). Table 5 indicates four broad categories of methodologies one can apply, depending on the amount of available data and the goal of the research.

Table 5
Available data vs. goal vs. approach.

Data volume	Goal	
	Improving animal health and welfare	Estimating/reducing GHG emission
Small data	Classical Statistical models, and M&S (using data and models from the existing literature and expert knowledge)	IPCC Tier 1 and Tier 2
Big data	Data-driven M&S, data analytics (ML, Advanced Statistical methods)	IPCC Tier 2 and Tier 3 (including data analytics and M&S methods)

7. Conclusions

Livestock Farming is a complex and dynamic problem that involves a high degree of uncertainty. It is apparent that

decisions in the way livestock farming is performed can have far-reaching effects, especially on the environment and the natural resources. In light on the complexity of the livestock farming, the prevalence and ease of collecting data through the new and emerging technologies provides an opportunity to ease the decision making processes that occur daily. We have provided an overview of the need and use of data-driven decision support for the main goals of Precision Livestock Farming. Based on literature, we have identified the main goals as enhancement of animal health and welfare, and reduction of GHG emissions. The latter goal is especially gaining in importance due to the climate change, and there are repeated calls for reducing the environmental footprint of livestock production. Nowadays, with the availability of advanced sensing technologies, data has become more available, and this is also slowly changing the way in which traditional simulation is performed, yielding new and more data-driven approaches. We scoped the existing approaches and categorized them into machine learning and data analytics (more black box model based), and modeling and simulation (more white box model-based) to provide an exhaustive overview and a tool of deciding on a suitable approach with respect to a given problem. We, furthermore, discussed the challenges associated with the data collection processes, and a possible solution. By integrating the fields of IoT, big data, and AI, PLF opens doors for more advanced and sophisticated approaches and fully transforms the traditional livestock farming processes, especially when combined with M&S and advanced data analytics approaches. It could prove to be an important piece of the puzzle yielded by the challenges associated with the climate changes and sustainable food production.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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