

**MODELING AND SIMULATION FOR DECISION SUPPORT
IN PRECISION LIVESTOCK FARMING**

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ABSTRACT

Precision Livestock Farming (PLF) is a system that allows real-time monitoring of animals, which comes with many benefits and ensures maximum use of farm resources, thus controlling the health status of animals. Decision support systems in livestock sector help farmers to take actions in support of animal health and better product yield. Due to the complexity of decision making processes, modeling and simulation tools are being extensively used to support farmers and decision makers in livestock industries. Modeling and simulation approaches minimize the risk of making wrong decisions and helps to assess the impact of different strategies before applying them in reality. In this paper, we highlight the role of modeling and simulation in enhancing decision-making processes in precision livestock farming, and provide a comprehensive overview and categorization with respect to the relevant goals and simulation paradigms. We, further, discuss the associated optimization approaches and data collection challenges.

1 INTRODUCTION

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

Precision Livestock Farming (PLF) is one of the most powerful developments amongst livestock farming industry, offering real-time monitoring and management tools for farmers. Modelling and Simulation (M&S) approaches help decision makers and farmers in their decisional problems by providing insights into their managerial practices. Indeed, M&S formalize the real world into a computer-based environment and then imitate the processes and the operations of the real world. Traditionally, simulation

modeling converts expert knowledge into dynamic models and simulates them to understand more about systems. Most recent M&S approaches utilize observational datasets or real-time data to extract models, as well as the parameters needed to perform the simulation.

The contribution of the paper is to provide an overview and categorize the existing simulation and modeling studies on PLF according to different simulation paradigms and the goals they aim for. There are three main M&S paradigms: discrete-event simulation, continuous simulation (also known as system dynamics) and agent-based simulation; and we consider two major goals in Livestock Farming: improving animal welfare/production and reducing GHG (Greenhouse Gas) emission. Aside from simulation modeling, we also discuss other simpler decision support tools in PLF that use calculators to analyze data.

The paper is structured as follows. We begin by providing a background on decision support in livestock farming, including Precision Livestock Farming, as enabler for the sophisticated decision support approaches, in Section 2. We then provide overview of the different decision support approaches that can be of interest in livestock farming. We review the existing modeling, simulation, and data analytics approaches in Section 3. In Section 4, we discuss the challenges related to the data collection for the M&S. Finally, in Section 5 we conclude the paper.

2 DECISION SUPPORT IN LIVESTOCK FARMING

In this section we introduce the basic concepts of precision livestock farming and the use of decision support approaches in PLF. Modelling and Simulation and its application as a decision support approach in PLF is discussed later in Section 3.

2.1 Precision Livestock Farming

Increased demand for animal products has led to increase in the sizes of farms. Managing large number of livestock, ensuring that production demands are met and environmental concerns are not discounted are factors that have caused a shift from traditional to technology-driven farming. Technology can be used to measure the behavior and welfare of the animals. PLF encompasses various aspects of continuous livestock monitoring, such as collection and analysis of data and reporting of certain notable events. The condition (physical and mental) of the animal is continuously changing due to external stimuli. These changes are continuously recorded, stored and transmitted using sensors that measure bio-signals. Typical sensors used in PLF include accelerometer, gyroscope, temperature sensors and biosensors. The type of data collected by these sensors include animal gait, speed, position, temperature, sounds, heart rate etc. In addition to the sensors, modelling, simulation and decision support using machine learning models are also being successfully used in PLF.

The benefits reaped by adopting PLF in the livestock industry has been tremendous (Hostiou et al. 2017). They include increase in productivity, real-time supply chain management, better marketing and reduction in GHG. Examples of successful PLF projects include: BrightAnimal (Lehr 2011), BioBusiness (Romanini et al. 2011) and EU-PLF (Guarino et al. 2017).

PLF consists of the following components: Continuous or real-time processing of sensor data; integration and storage of data; data analysis, simulation and modelling; event detection and signaling. These components help farmers in their decision-making process by enhancing both the management of their daily tasks and the supervision of their herd.

2.2 Decision Support Approaches

The need for decision support is vital in PLF due to its inherent challenges like large heterogeneous data, monitoring of complex systems involving animals and the need for fulfilling multiple goals. Benefits of such a system are manifested in the form of attainment of two ultimate goals: (a) improving animal welfare and (b) GHG reduction. Improving animal welfare is closely related to the livestock production (meat, milk, eggs, etc.), because for a fixed farm size, products from healthy animals surpass those of less healthy ones,

both in quality and quantity. Aside from the fact that this affects the farmers income, optimizing animal welfare also reduces the emissions intensity of producing livestock products (i.e. emissions per unit of product) (Herrero 2016).

Animal welfare: Detection and prevention of animal health issues, and compliance with medical regulations are some of the factors that are considered while aiming towards improved production or yield. Research into animal welfare generally falls into the categories of modelling and simulation-based optimization methods. In the modelling-based methods, Machine Learning (ML) and/or statistics based methods are commonly found: identification and classification of chewing patterns in calves (Pegorini et al. 2015), estimation of cattle weight trajectories (Alonso et al. 2015) and anomalous activity identification (Vázquez-Diosdado et al. 2019). In the simulation-based optimization category, simulation methods are combined with optimization to achieve goals in animal welfare. Discussion about the research in this category is provided in Section 4.5.

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 the various approaches for combating climate change due to GHG emissions (Yan et al. 2009). 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. Tier 1 consists of simple methods that have various underlying assumptions and are, hence, subject to high uncertainties, while Tier 2 methods have more region/country specific data and are less prone to uncertainties. Tier 3 consists of methods that are detailed and data-driven and have, hence, even lower degree of uncertainties. Among the decision support models proposed in the past, there are models that are simple and conform to IPCC Tiers 1 and 2, but, M&S based models along with data-driven ML and/or statistics based methods are categorized as Tier 3 methods. 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.

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)

In summary, there have been many different kinds of studies into improving animal welfare, production yield and reducing GHG emissions of livestock farms. Incorporating ML and deep learning algorithms in decision support for PLF helps achieve several goals.

3 M&S FOR DECISION SUPPORT IN LIVESTOCK FARMING

Decision management is becoming increasingly important in today’s livestock farming, and decision support systems (DSS) 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. 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 they make before actually implementing them in the real-world. M&S can be

combined with optimization techniques and shape other methodologies, also known as Hybrid Modelling. 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, then we categorize M&S studies in PLF regarding two goals: animal welfare and GHG emission and the simulation paradigms. Finally, applications of simulation-based optimization or hybrid models in PLF are discussed in section 3.4.

3.1 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, which we elaborate in the following.

3.1.1 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 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 (Sørensen et al. 2017; Bruijn et al. 2010). Considering GHG emissions, DES approaches can again be used to simulate diseases and production of an animal over time. Life Cycle Assessment (LCA) methods can then be applied to quantify the GHG impact of the disease (Mostert et al. 2018).

3.1.2 Continuous Simulation

Continuous simulation (CS), also known as System Dynamics, is a methodology to recognize and solve the system problems by analyzing the information feedback, dealing with the dynamic structure and feedback mechanism between the qualitative and quantitative factors of the complex system, 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. 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 2.

3.1.3 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.

3.2 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 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.

3.3 Simulation Approaches with Respect to Goals in Livestock Farming

M&S approaches in livestock are applied to either improve animal welfare or reduce GHG emissions. The bulk of GHG emissions by livestock originate from four main categories of activities: enteric fermentation, manure management, feed production and energy consumption (FAO 2020). M&S approaches applied to estimate GHG emissions, are mostly CS, and each emission source is considered as a process to be modelled. Some CS models in PLF, consider manure management processes in their modules (Holzworth et al. 2014), some have processes for enteric fermentation (Bannink et al. 2010), and some also consider the emissions in the farm level (i.e. energy consumption) (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 2 illustrates M&S studies on livestock according to three simulation paradigms: DES, CS and ABM; and the most relevant PLF goals: welfare and GHG reduction.

Table 2: M&S approaches regarding different simulation paradigms and PLF goals.

Literature	Goal	M&S type	Description
(Bruijnjs et al. 2010)	welfare	DES	Use dynamic stochastic Monte Carlo simulation model to assess the effect of disease on income.
(Sørensen et al. 2017)	welfare	DES	Use dynamic mechanistic Monte Carlo simulation model for disease in pigs using R software.
(Bannink et al. 2008)	welfare	CS	Use mechanistic simulation model on rumen fermentation.

(Widgren et al. 2016)	welfare	CS	SimInf: R package.
(Widgren et al. 2019)	welfare	CS	SimInf extended: to support data-driven spatio-temporal simulations of disease transmission in wildlife.
(Tedeschi et al. 2011)	welfare	CS	Applied for small ruminants.
(Conrad 2004)	welfare	CS	For cattle and crop production.
(Guimarães et al. 2009)	welfare	CS	For goats.
(Kahn and Lehrer 1984)	welfare	CS	Reproductive performance of beef cows.
(Parsons et al. 2011)	welfare	CS	APSIM and System dynamic.
(Pomar et al. 2011)	welfare	ABM	
(Al-Mamun and Grohn 2017)	welfare	ABM	MABSDairy: a multiscale agent based simulation of a dairy herd.
(Al-Mamun et al. 2018)	welfare	ABM	Data-driven (only parameters) individual-based model of infectious disease.
(Mostert et al. 2018)	GHG reduction	DES	The impact of foot lesions in dairy cows on GHG emissions of milk production: Using LCA method and mechanistic simulation model (developed in R).
(Bannink et al. 2010)	GHG reduction	CS	A dynamic, mechanistic model of enteric fermentation in dairy cows based on the model of (Mills et al. 2001).
(Holzworth et al. 2014)	GHG reduction	CS	APSIM: Applications, including support for on-farm decision making, development of waste management guidelines.
(Johnson et al. 2008)	GHG reduction	CS	DairyMod and EcoMod: Biophysical process simulation of the dairy pasture system.
(Chardon et al. 2012)	GHG reduction	CS	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)	GHG reduction	CS	Manure-DNDC: A biogeochemical process model for quantifying greenhouse gas and ammonia emissions from livestock manure systems.
(Berntsen et al. 2003)	GHG reduction	CS	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.
(Little et al. 2010)	GHG reduction	CS	Holos: Process-based emission factors estimate all important direct and indirect sources of GHG emissions of livestock operations.
(Rotz et al. 2011)	GHG reduction	CS	DairyGEM: a software tool for whole farm assessment of emission mitigation strategies from manure.
(Schils et al. 2007)	GHG reduction	CS	DairyWise: Combines already existing simulation models of specific subsystems into a whole farm model for use in interdisciplinary studies.
(van den Pol-van Dasselaar et al. 2014)	GHG reduction	CS	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 (EU AnimalChange project).
(Rotz 2012)	GHG reduction	CS	IFSM: Process simulation of all important farm components representing the performance, economics, and environmental impacts including direct and indirect GHG emissions and carbon footprint.
(Del Prado et al. 2011)	GHG reduction	CS	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.
(Matthews and Bakam 2007)	GHG reduction	ABM, CS	A combined agent-based and biophysical modelling approach to address GHG mitigation policy issues

We observe that most of the M&S research in livestock, are process-based which are mostly categorized as continuous simulation. The reason is that there are typically variables for which a continuous description is more natural: GHG emission, feed intake, milk production, temperature, concentration of bacteria in an infectious environment. For these variables individual counting would clearly not be feasible. Also, DES are mostly applied for improving animal welfare, rather than GHG emissions, due to the fact that most diseases have finite number of stages. Data-driven and dynamic data-driven simulation approaches has received much less attention since data availability has been a challenge in livestock sector, as elaborated in Section 4. We expect the studies in these fields to be highly rising since animal sensors are being used more widely.

3.4 Simulation-Based Optimization

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. M&S, combined with optimization can be a powerful decision support approach (Ólafsson and Kim 2002). The

objective and the constraints of the optimization problem are evaluated solely via simulations. 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). In the domain of livestock farming, we have found the following optimization approaches that have been used in combination with M&S, as shown in Table 3.

Table 3: Previous research in simulation-based optimization for livestock farming.

Work	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	CO ₂ , NH ₃ concentrations	Chicken	Thermal flow, CO ₂ , NH ₃ 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
(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

In summary, there are many works that try to optimize costs associated with livestock farms. This is because, costs can easily be formulated as an optimization objective. However, this is not the case with welfare because the overall health of livestock is harder to quantify. 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.

4 DATA COLLECTION AND ASSOCIATED CHALLENGES

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. Tomic et al. (2015) defines this problem as a 4-Level functional model, that integrates the measurement level (Level 1); the interpretation level (Level 2); the integration level (Level 3); 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. Therefore, there is a need to automatically integrate available data within a decision support 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. Figure 1 illustrates the envisioned PLF platform.

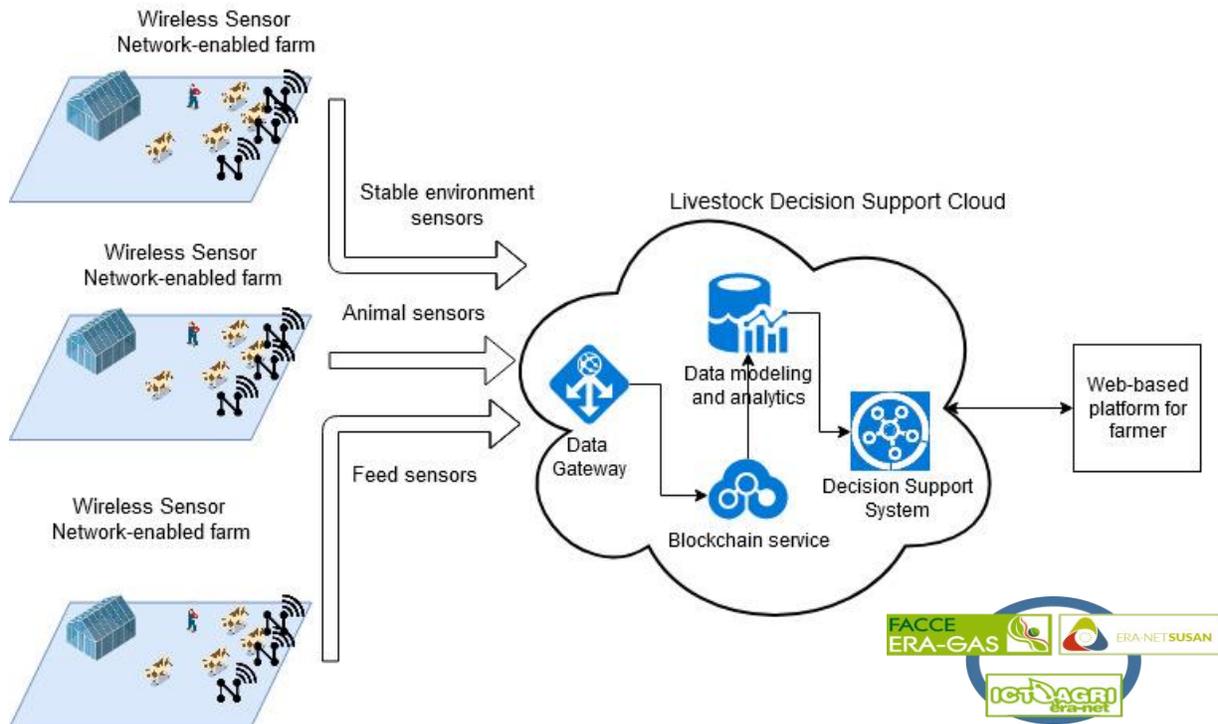


Figure 1: Proposed precision livestock farming platform.

Specifically, IoT devices can be installed in the farm for monitoring key parameters of: 1) stable environment (temperature, humidity, gas sensors (NO_x, CO_x, CH₄, NH₃, etc.), 2) animals (accelerometer, motion sensor, weight sensor, etc.), and 3) feeds (flow sensor, weight sensor, humidity sensor etc.).

A cloud-based platform can collect and analyze all the aforementioned data for providing recommendations to the livestock farming stakeholders (farmers, consultants, etc.) 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, smart contracts can help livestock farming stakeholders to have contracts with better prices due to decreased GHG emissions.

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

- **GHG estimation.** It is currently not possible to correctly measure GHG emission, rather estimate them as accurately as possible using the different Tiers of IPCC methodology.
- **Data sharing and interoperability.** The key challenge of integrating different livestock agricultural systems is how to deal with the heterogeneity of multiple information resources.
- **Visualization for farming stakeholders.** Many initiatives have been developed presently that boast user-friendly UIs for non-IT skilled agriculture stakeholders. However, for an end-user it is highly important to be offered already insight and decision support based on data analytics. This is an end-goal of implementing the platform presented in Figure 1.

5 CONCLUSIONS

We have provided an overview of the need and use of Modelling and Simulation to support the main goals of Precision Livestock Farming. We have identified the main goals as enhancement of animal welfare and reduction of GHG emissions. 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 by simulation paradigm and goals, 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. 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.

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