Autonomic Computing in a Beef-Production Process for Precision Livestock Farming

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Abstract

Precision livestock farming (PLF) offers farmers real-time monitoring and management system. PLF provides a real-time warning when something goes wrong so that the farmer can take immediate action to solve the problem. PLF introduces many new challenges and questions that must be resolved. Some of these challenges are related to the integration of grazing and animal health into the beef-production process. This article introduces an architecture for the self-managing of a beef-production farm. In particular, the architecture includes three autonomous cycles of data analysis tasks (ACODAT) that allow beef producers to have adequate coordination, optimization and planning of the productive process, which are: (i) circuit preparation, (ii) animal purchase, and (iii) animal fattening. This article also instantiates, in a farm, the autonomous animal-fattening cycle, as the first step towards efficient and effective beef-production processes. The main contributions of this architecture are (i) the ability to use everything mining to improve the knowledge of the system and decision-making processes, and (ii) three ACODAT for real-time analysis for sustainable and environmentally-friendly livestock production. The results are encouraging since the ACODAT allows smart management of the beef-production process, naturally introducing artificial-intelligence techniques to develop these tasks. Particularly, modeling using ACODAT allows an adequate description of a precision livestock process. Likewise, the preliminary results of some of the tasks of ACODAT are stimulating because they allow evaluating the feasibility of the proposal. For example, a first task for the identification of cattle fattening has a Mean Absolute Error (MAE) of 5.4 kg, which will be used by ACODAT to identify anomalies in the fattening pro-

cess. The instantiation of the animal-fattening cycle shows the viability and robustness of this proposal.

keywords: Precision Livestock Farming, Autonomic Computing, Industry 4.0, Artificial Intelligence, Beef Production, Data Analytics

1 Introduction

The *Food and Agriculture Organization* (FAO) states that sustainable development is the management and conservation of natural resources, and the orientation of technological and institutional change to ensure the continuous satisfaction of human needs for present and future generations [1]. In parallel to the growing world-population, the demand for animal protein is also increasing. Countries are reviewing the growth of animal production to meet the growing demand for animal protein [2]. On the other hand, animal-care is critical to design sustainable systems, given the loss of forest lands associated with a growing demand for meat. Particularly, environmental-sustainability issues are acute. In the context of beef cattle, (i) water use, (ii) land use, (iii) biomass appropriation (for example, the animal biomass as the feces and urine are natural fertilizers) and (iv) greenhouse-gas emissions are, for example, typically higher per unit of edible product, in beef systems, than in any other livestock systems [3].

In particular, this work considers the relationship between pasture quality and animal feed in the *Precision livestock farming* (PLF) framework [4]. Thus, this work focuses on PLF but using existing technologies in precision agriculture farming (PAF) to improve forage quality. In this way, it is necessary to consider specialized machinery for seeding and fertilizing, the use of different sensors to obtain accurate information about the terrain and weather, accurate soil analysis, among other aspects, to improve animal production, harvest forage more efficiently, and reduce environmental impact [5].

Specifically, knowing the conditions of the farm helps to define an adequate feeding for the animal [6]. A good combination of forage and soil guarantees optimal results in cattle and dairy farms. The relationship between the soils of cattle farms, the types of fodder that are planted on them, and the cattle on the ranch, has recently been used to define strategies to improve the productivity and sustainability of the cattle sector [7]. In this sense, decisions are necessary on the quality of the seed, the fertilization plan, the irrigation system, phytosanitary management, weed control, and grazing programming, among other aspects, as important factors to increase yield forage and nutritional value to improve livestock productivity.

An initiative that aims to improve sustainability is PLF through the monitoring of animals in a herd. Examples of PLF are the following works. Qiao *et al.* [8] identified livestock by video, using artificial intelligence techniques such as Neural Networks. In addition, Denis *et al.* [9] used regularized change-point-estimation and the k-means algorithm for a better understanding of the lactation process. Likewise, Achour *et al.* [10] applied unsupervised automated-monitoring of dairy cows' conduct based on an inertial magnitude unit attached to their reverses. Finally, Guo *et al.* [11] identified the animal poses based on bilateral symmetry applied to the measurement of cattle body in point clouds. All these works have been focused on improving production by means of PLF. In this sense, PLF is a new approach –based on the use and development of information and communication technologies– to achieve automatic, accurate, real-time monitoring and analysis of animal behavior, which helps the producer to make decisions [12].

Previous works on PLF have not taken into account *soil variables*, which, together with *animal activity*, could lead to create robust models to improve grazing methods, and, as a consequence, to a higher production [12]. The objective of this work is to combine grazing with animal health using the paradigm of *autonomous cycles* [13]. This paradigm defines a set of data-analysis tasks for the self-management of a system. *Autonomous cycles of data analysis tasks* (ACODAT) provide cattle ranchers with tools for decision-making. Examples of the benefits of the use of ACODAT, in PLF, could be: (i) to maintain a high production of good-quality forage for the longest period of time, (ii) to maintain a favorable balance among forage species, (iii) to obtain efficient use of the forage produced, (iv) to achieve a profitable livestock production, and (v) to prevent diseases.

Each of the above benefits could use the specification of an ACODAT. In addition, to achieve these benefits, the beef-production farms must have the technology to capture and process the necessary data to build the knowledge models defined in an ACODAT. The main contributions of this research are the following.

- The use of the autonomous-computing paradigm to define an architecture for the self-managing of beef-production farms.
- The ability to integrate various mining techniques (e.g., data mining and process mining) to generate knowledge models of the farm.
- The definition of several ACODAT –with different goals about the beef-production process– to allow real-time analysis and to help decision-making for sustainable and environmentally-friendly livestock production.
- The integration of multiple variables about soil, animal welfare, pasture, and climate for the analyses.

This is a theoretical proposal that aims to show the feasibility of using the ACODAT concept to model PLF. The preliminary results of some of the analysis tasks that compose the ACODATs are encouraging. For example: the ACODAT that supervises the animal fattening process is composed of a task that defines a cattle weight identification model using machine learning techniques for the detection of anomalies [14], and a system to diagnose the anomaly in the cattle fattening process in rotational grazing using a fuzzy classification system [15]

This article is organized as follows. Section 2 presents related work. Section 3 introduces ACODAT and shows the methodology used in this work. Section 4 shows the proposed architecture for beef production in the context of PLF and, briefly, describes the three *autonomic cycles* (AC) for the self-management of a beef-production process. After, Section 5 describes the specification of an AC for self-planning of paddock rotation and its instantiation in a case study. Finally, Section 6 shows a comparison with previous work, and the article ends with conclusions in Section 7.

2 Related Works

With PLF and data-mining tasks, considerable progress has been made in the use of tools to –routinely– cover and collect information from animals and farmsteads in a lower laborious manner than before, generating large volumes of data [16]. In what follows, this section presents related works on PLF and grazing with animal health.

For the problem of grazing automation and animal health, Segerkvist *et al.* [17] proposed a method, based on an unmanned automatic precision-weighing system –that can be used in pastures–, which alert farmers when animals show abnormal weight-gain curves. This work is -primarily- focused on detecting pasture-borne nematode-parasite infections that reduce calf weight-gain.

For the problem of weighing, Feng *et al.* [18] proposed a dynamic-weighing algorithm, for cows, based on support vector machines and empirical wavelet transforms for classification. The dynamic-weight curve is obtained using a weighing device placed along a cow travel corridor, and data is preprocessed using signal acquisition, feature extraction and normalization techniques. The results are divided into three levels during the movement: low, medium and high. Finally, recently, a model of normal weight identification in cattle was designed [14].

In addition to automatic weighing, monitoring is also important –as many operations are performed manually in livestock farms. Jung *et al.* [19] proposed a livestock-tracking system based on *Wireless Sensor Networks*. The livestock-tracking system can monitor farm animals using the *Internet of Things* (IoT) and cloud platforms. Through a collar on the neck of an animal, using IoT equipment, the system monitors the activity of the livestock. Fuentes *et al.* [20] proposed an artificial-intelligence system to increase milk quality by reducing heat stress. Particularly, rising global temperatures and climatic anomalies, such as heat waves, are affecting heat-stress levels of farm animals. These impacts have detrimental effects on the milk quality and productivity of dairy cows. Fuentes *et al.* argued that their system allows to –automatically– assess animal welfare, productivity and milk quality.

A task in monitoring is tracking. To solve this problem, Vayssade *et al.* [21] proposed a method to process images, taken by a commercial drone, to automate the tracking of animal activities. Their method, automatically, detects goats from images and tracks their activity using a combination of thresholding and supervised-classification methods. In another work, using drones, Li *et al.* [22] deployed a cluster of Unmanned Aerial Vehicles (UAV) to -autonomously- track and monitor livestock –such as cattle and sheep– in a pasture. Li *et al.*'s goal was to find the optimal deployment of UAV to minimize the average UAV-Animal distance, using a standard k-means clustering algorithm.

In another work using images, Benze *et al.* [23] designed and implemented a computer-vision system for cow individual food-intake measurement, based on deep Convolutional Neural Networks, and a low-cost RGB-D (Red, Green, Blue, Depth) camera. Timmerman *et al.* [24] designed a multi-layer monitoring support system to help the poultry farmer. The multi-layer support system consists of a static system for flock observation (an existing PLF technology), and robot(s) to observe bird health and behavior, in order to perform daily routine tasks.

Finally, Germani *et al.* [25] designed and implemented an IoT architecture to continuously monitor livestock, in barns, during grazing. Germani *et al.* adopted the *LOng RAnge* (LoRa) *low-power wide-area network* (LPWAN) technology to cover diverse environments, and a suitable configuration of web services to perform data storage, analysis and visualization.

All the previous works above focused on monitoring or capturing animal behavior; however, in the case of grazing, they did not use soil data. Similarly, they did not combine animal welfare with pasture intake. These limitations were also highlighted in a recent systematic literature review [12]. To overcome such limitations found in previous works, this article focuses on the use of soil variables for optimal decision-making on grazing and autonomous beef production.

3 Autonomous Cycles of Data Analysis Tasks

This section presents a background on data-mining tasks in PLF and ACODAT.

3.1 Definition of ACODAT

Autonomous computing is a paradigm in which the computing system as a whole offers much more capabilities than the sum of its parts, with self-management capabilities to adapt to its environment [26]. *Autonomic cycles of data analysis tasks* (ACODAT) have been defined by Aguilar et al. [27], [28], [29] as a set of data analysis tasks that act autonomously to supervise and/or control a process. These Data Analysis tasks are based on knowledge models (e.g., prediction, description, diagnosis, among others), and they interact and interrelate with each other according to the objectives of the cycle. Each data analysis task has a different function: (i) to observe the process, (ii) to analyze and interpret what is happening in the process, and (iii) to make decisions to improve the process.

ACODAT has been used in different domains; for instance, in smart classrooms [27], [29] and Industry 4.0 [30], [31], [32]. These works based on ACODAT present a different way of introducing the autonomous computing paradigm in smart classrooms and in industry 4.0 to previous works [33], [34], [35], since ACODAT is based on data analysis tasks that can be self-managed.

ACODATs are designed using the *Methodology for the development of data-mining applications based on organizational analysis* (MIDANO) [36]. MIDANO integrates data analysis tasks into a closed-loop that can solve complex problems. In this sense, it is essential to integrate data-analysis tasks in a consistent way to generate strategic knowledge useful to achieve business objectives. A detailed description of the function, of each task category, in ACODAT, is explained in what follows.

- ***Monitoring:*** Tasks responsible to observe the monitored system. These tasks must capture data and information about the behavior of the system. In addition, these tasks are responsible for data preparation (e.g., preprocessing and selection of relevant features) for the following steps.
- ***Analysis:*** These tasks interpret, understand and diagnose what is happening in the monitored system. Particularly, these tasks allow building *knowledge models* from the dynamics observed in the system, oriented to know what is happening in the system.
- ***Decision-making:*** These tasks define and implement the necessary actions, based on previous analysis, to improve or correct the failures of the monitored system. Thus, these tasks affect the dynamics of the monitored system. The effects of the decision-making tasks are evaluated by the monitoring and analysis tasks, restarting a new iteration of the cycle.

The development of these specialized tasks (Monitoring, Analysis, and Decision-Making) depends on the context. For example, if one wishes to develop data-based models for diagnosing or predicting behavior, one can use the "Cross-Industry Standard Process for Data Mining" (CRISP-DM) methodology. On the other hand, if one wishes to develop a decision-making model using expert knowledge, one can use the "Knowledge Discovery in Databases" (KDD) methodology. In section 6.2, we present a discussion about it.

In this work, we will propose a PLF approach based on ACODAT. It is the first time that ACODAT has been applied to PLF, in a deployment environment as broad and complex as farms with cattle rotation. In addition, it is the first time that ACODAT has been proposed in a context with a great diversity of data sources (see section 4.2), which has a large number of sensors to be considered.

3.2 Methodology to develop ACODAT

The methodology used in this work is MIDANO [36]. MIDANO is used to develop data-mining applications based on organizational analysis. MIDANO is designed to develop applications based on ACODAT. MIDANO consists of three phases.

Phase 1. Identification of the sources of knowledge in an organization: The main objective of this phase is to know the organization, its processes and its experts, in order to define the objective of the application of data-analysis techniques in the organization. In addition, in this phase, a specification of the ACODAT to be developed is made.

Phase 2. Data preparation and processing: This process is based on the extraction of data from its sources, transformation of the data, and the load of the data into the AC data warehouse. To carry out this process, a feature engineering process is carried out in order to select the main variables of the studied process. Finally, a mineable view is created, which is composed of the description of all the variables of interest.

Phase 3. Development of the ACODAT: This phase aims to implement the different data analysis tasks of the ACODAT, which generate the required knowledge models (e.g., predictive models and descriptive models). This phase ends with the implementation of a prototype of each AC. During this phase, experiments are performed to validate the knowledge models generated by the data-analysis tasks.

In this research, MIDANO has been used for the definition of ACODAT to improve the production process of a beef farm. The data sources analyzed were animal-weighing history, animal welfare, soil quality of each paddock, climate, temperature, pastures, paddock rotations, and sale and purchase price of animals. Table 1 summarizes the use of MIDANO in this work.

Table 1: Use of MIDANO Phases in this work

Phases	Use
Phase 1	Analysis of grazing and animal-health management process. For that, this research proposes several ACODATs to improve the beef-production process.
Phase 2	Identification of data sources (e.g., pasture, soil, animal weight) and definition of the multi-dimensional data model
Phase 3	Implementation of the ACODAT for the beef-production process. This paper presents the instantiation of one of them.

4 Proposed Architecture

This section presents the proposed architecture for beef production based on PLF. This is one of the main contributions of this work.

4.1 General Architecture

In this research, we propose an architecture for beef production in PLF (see Figure 1), based on the Autonomic-Computing Paradigm [26], [37]. This paradigm is an essential element that guarantees the autonomy and adaptability of the production process. Autonomic properties, like (i) self-configuration, (ii) self-planning, and (iii) self-optimizing, are developed to endow autonomy in the production process. This architecture has four layers: (i) monitoring, (ii) network, (iii) data processing and (iv) business; these layers are described below.

1. ***Monitoring:*** This layer captures soil, water, animal behavior and climate variables through IoT-based sensors. After, data is stored in a cloud server. This layer can be extended by allowing the effective integration of new types of sensors [38]. Some examples of variables captured directly by the sensors, or derived from the sensed data, are the amount of forage per paddock, amount of quality forage per paddock, amount of water in the drinkers, amount of rain per day, movement of animals, pasture yield, among others.

2. ***Network:*** This layer is in charge of communication between the sensors and the server in the cloud.

3. ***Data management:*** This layer stores, verifies, pre-processes, and protects data. These data will be made available to the beef farmer.

4. ***Business:*** This layer is in charge to improve the beef-production process using ACODAT for decision-making. Particularly, data analysis tasks based on everything-mining techniques generate knowledge for the automation of the beef-production process (see the Reflexive Layers in Fig. 1) [30]. Thus, the analytical tasks generate useful information. Some examples of decisions or information that will be obtained in this layer are: the optimal stocking capacity per paddock supported by the livestock farm, detection of animal diseases, forage status per paddock, animal welfare, and weed detection. In addition, the architecture has an alert system –in the reflexive layer– used autonomously by the tasks that require alerts.

The next sections explain in detail the ACODATs we are proposing for holistic management of the entire beef production process, and a case study to explain in detail the implementation of the data analysis tasks for one of them.

4.2 ACODAT in beef production

This section deals with AC design for the beef-production process. We propose a system of ACs (named ACPLF-000, see Fig 2) composed of three ACODAT: (i) preparation of the circuits, (ii) animal fattening, and (iii) animal purchases. ACPLF-000 allows the (i) self-management, (ii) self-planning, and (iii) self-supervision of the production process.

The goal of ACPLF-000 is the self-planning of the rotational grazing in the process of beef production. Specifically, the objective of each AC of ACPLF-000 is the following.

ACPLF-001 (Circuit preparation): This is in charge to prepare paddocks. As an example, to verify the state of: (i) drinking troughs, (ii) electric fences, (iii) pasture capacity, and (iv) animal-carrying capacity per circuit.

ACPLF-002 (Animal purchase): This is in charge (i) to select the best supplier (i.e., another livestock farm or livestock auction), and (ii) to select the animal lot with the best characteristics.

ACPLF-003 (Animal fattening): This is in charge to manage the animal's fattening process. This cycle carries out the tasks of (i) animal weighing, (ii) animal vaccination, (iii) definition of the forage capacity per paddock, (iv) equipment verification, and (v) rotation; depending on the planning process. As an example, if an animal reaches a weight greater than 450kg, then this animal is moved to lots –with special pastures– for its fattening completion.

These three ACs can be executed –in parallel– when there is a production in process, and –in series– when a new production is started. As an example, when a new production is started, it is necessary (i) to prepare the land, (ii) to wait for the grass to grow, (iii) to measure the forage to calculate the stocking rate, (iv) to purchase the animals, and, finally, (v) to monitor their fattening.

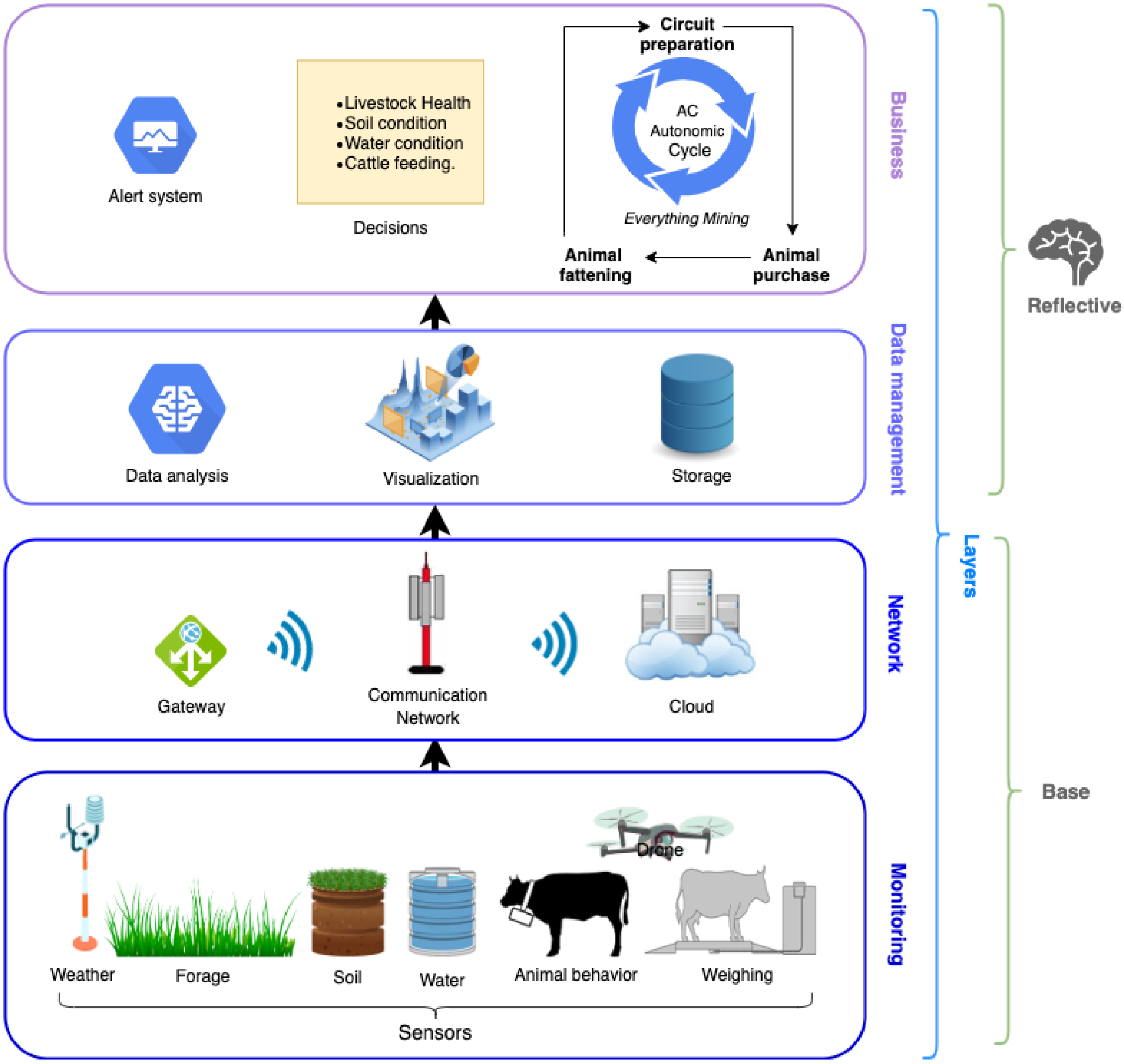

Figure 1: Autonomic architecture for a beef-production process based on PLF

4.2.1 ACPLF-001 Specification: Circuit preparation

The aim of this AC is to verify and configure the process of beef production based on the objective of efficient production. Mainly, this cycle is composed of three tasks (see Fig. 3).

The first task, named the Forage task, is in charge to recommend grass seeds based on the soil characteristics of each paddock. The second task has two subtasks, the first subtask is in charge to detect weeds to determine in which paddock and with what intensity the weeds are found, and the second subtask must calculate the forage capacity per paddock. Finally, the last task estimates the animal carrying per paddock. Table 2 shows the general description of each task of this AC.

Table 2: Description of the Tasks of ACPLF-001. Abbreviations: DB = Data Base.

Task Name	Knowledge models	Data Sources
1. Determine the best seed for a specific paddock.	Recommendation Model	Farm DB (Sensor data), Seed-sale website
2. Determine the amount of weeds	Detection Model	Farm DB (Drone Data)
3. Determine the fodder for each paddock.	Detection Model	Farm DB (Drone Data)

Table 2 continued from the previous page

4. Determine how many animals can be in the pasture depending on the forage (Carrying capacity for paddock).	Estimation Model	Farm DB (Sensor data, Drone Data)

Task 1. Determine the best seed for a specific paddock: This task is a grass-seed recommendation model that uses the soil sensors of the paddocks. This task captures the physicochemical variables of the soil, and, after, it determines which is the best seed to sow depending on the need and type of paddock. Examples of the types of paddocks are (i) quarantine, (ii) fattening and (iii) finishing. In addition, in this task, the attributes and prices of each seed are reviewed on specialized seed websites.

Task 2. Determine the amount of weeds in each paddock: This task detects the amount of weeds in the paddock (e.g., using images of the paddocks).

Task 3. Determine the fodder of each paddock: This task determines the weight of grass (biomass) per paddock (e.g., using images of the paddocks). Biomass is a fundamental input to calculate animal-carrying capacity.

Task 4. Determine Carrying capacity per paddock: This task determines how many animals can be, in the pasture, depending on the forage. This task invokes an optimization system that defines how many animals each paddock can support. This system uses variables such as climate, forage capacity, pasture type, pasture quality and animal welfare (e.g., percentage of shadow, water availability and feed supplements per paddock).

ACPLF-001 configures the initial conditions for the process of animal fattening on the farm. ACPLF-001 computes initial parameters, such as the number of animals per paddock and pasture inventory.

4.2.2 ACPLF-002 Specification: Animal purchase

The objective of this AC is the selection of suppliers and lots of cattle for purchase. This cycle is composed of two tasks (see Fig. 4). Table 3 shows the data sources used, in this AC, for each task.

Table 3: Description of the Tasks of ACPLF-002. Abbreviations: DB = Data Base.

Task Name	**Mining Techniques**	**Data Sources**
1. Determine the best supplier	Classification model	Social network, Cattle-auction website, Farm DB
2. Determine the best herd of animals	Classification model	Social network, Cattle-auction website, Cameras

Task 1. Determine the best supplier: This task ranks the best cattle supplier using different criteria such as (i) location, (ii) price, (iii) healthy-animal history and (iv) delivery time.

Task 2. Determine the best herd of animals: This task uses a model that estimates the quality of livestock using different data sources. As an example, this task can estimate (i) breed-purity percentage, (ii) best animals and (iii) health condition.

ACPLF-002 is in charge (i) to select the best animal suppliers (using the score of a

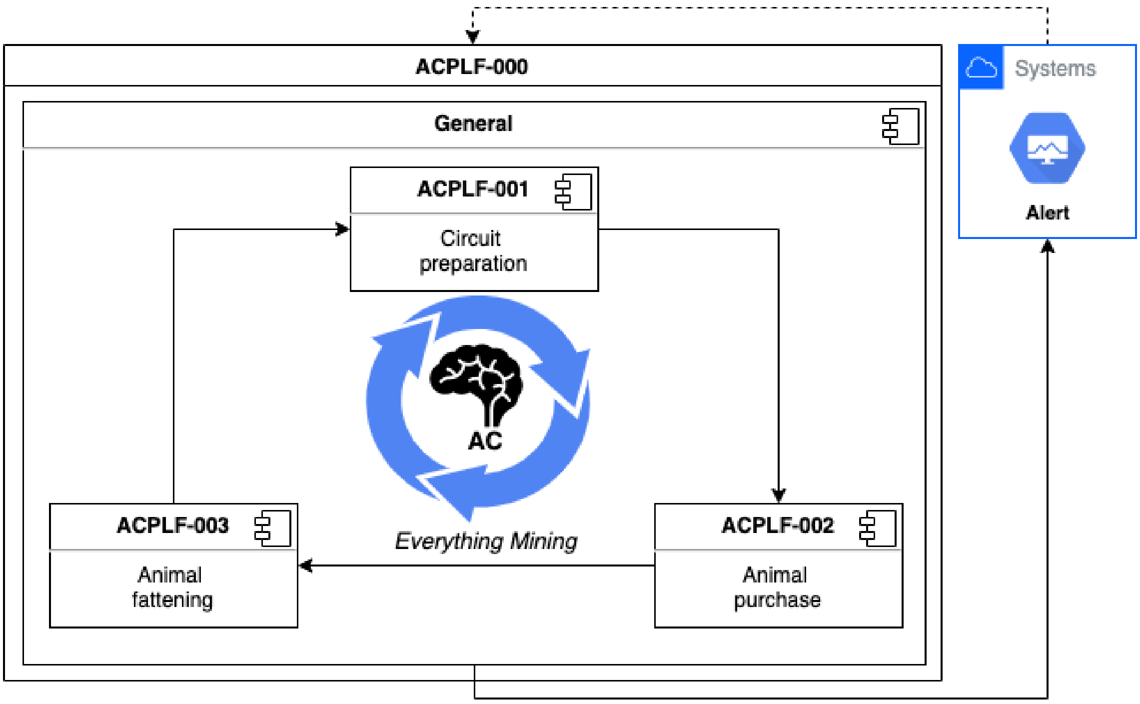

Figure 2: ACPLF-000: AC design for the beef-production process.

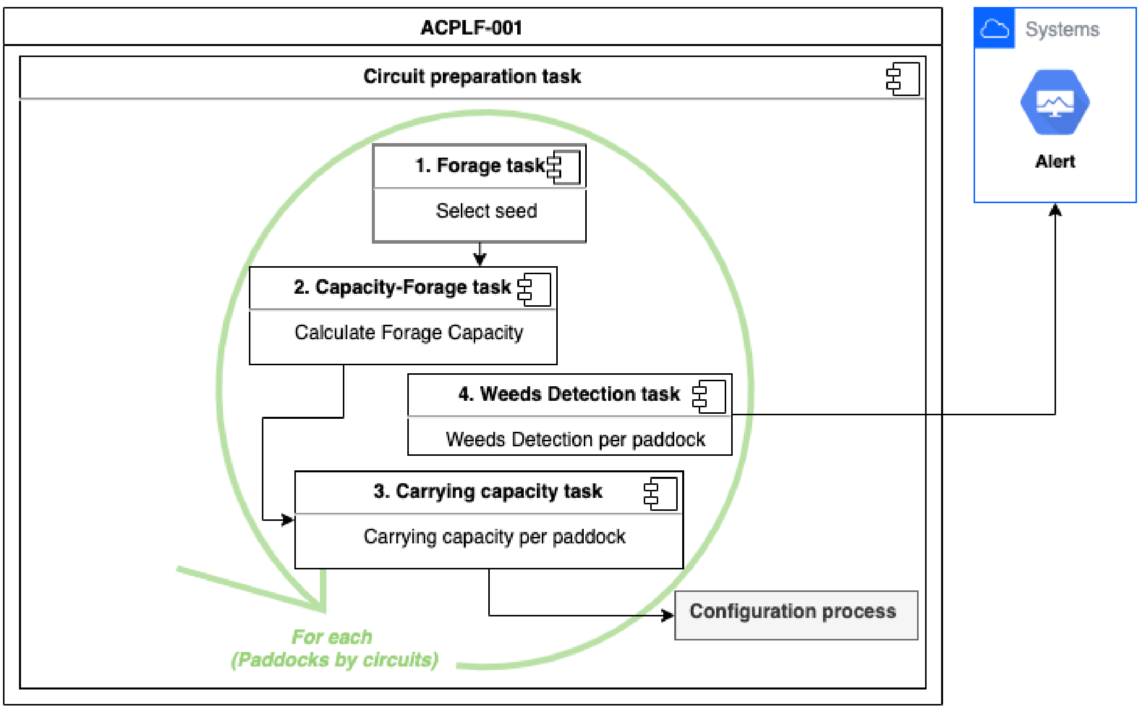

Figure 3: ACPLF-001: Circuit preparation

supplier in the system), and (ii) to select the best herd of animals for purchase (considering season and market prices).

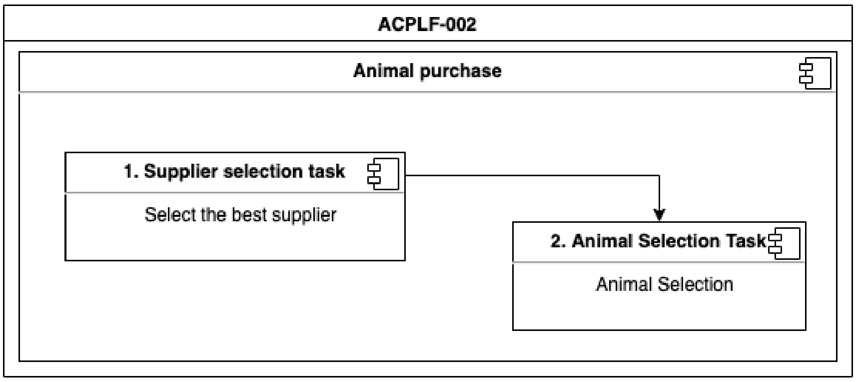

Figure 4: ACPLF-002: Animal purchase

4.2.3 ACPLF-003 Specification: Animal fattening

This AC is in charge to monitor animal's fattening by performing (i) animal weighing, (ii) animal vaccination and (iii) animal rotation (see Fig. 5). In this AC, there is a planning process of animal rotation, depending on different characteristics, such as (i) forage, ii) climate, (iii) animal health, (iv) soil and (v) season. Table 4 shows data sources used, in this AC, for each task.

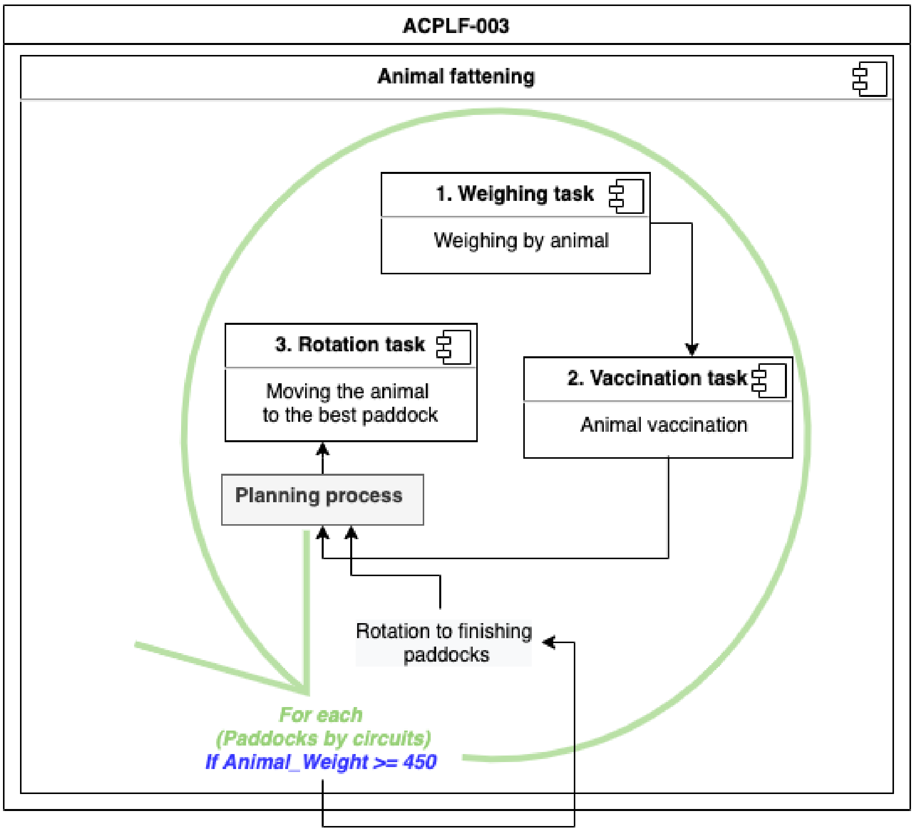

Figure 5: ACPLF-003: Animal fattening

Table 4: Description of the Tasks of ACPLF-003. Abbreviations: DB = Data Base.

Task Name	Mining Techniques	Data Sources
1. Weighing task	Estimation model	Farm DB
2. Vaccination task	Prescriptive models	Farm DB
3. Rotation task.	Assignment Model	Farm DB

Task 1. Weighing task: This task uses the history of the previous weighing and estimates cattle weight and health status.

Task 2. Vaccination task: This task is based on a prescriptive model to determine the actions to follow in the vaccination plan (including deworming and vitamins). The main objective of this task is to reduce costs and improve profits.

Task 3. Rotation task: This task uses data from sensors located throughout the farm, and other data sources (e.g., images of the farm, climate, pasture type and animal-welfare variables), to assign the best paddock available for weight gain.

4.2.4 Data model

The multidimensional data model, for the previous ACs, is defined in this section.

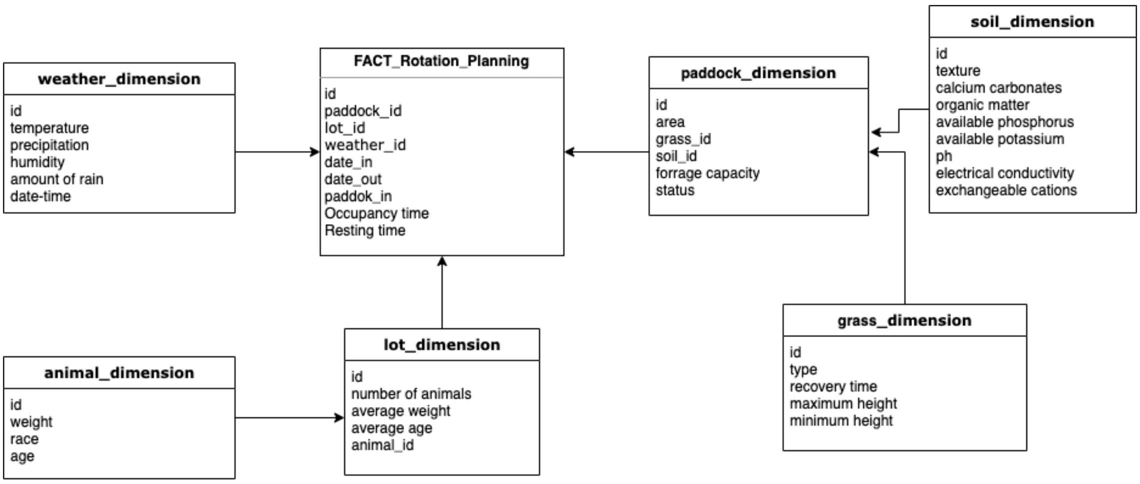

Figure 6: Multidimensional Model

Figure 6 describes the multidimensional data model required by the ACODAT for smart farm management. Each dimension represents and characterizes each information source (animal, paddock, etc.) necessary during the management process. The data model in Figure 6 includes data from different sources, specifically, from farm databases (e.g., livestock-inventory systems), climate data obtained from the Internet, and sensor data captured in the monitoring layer that are in cloud servers, among others. Data from each source is included in a different dimension in the data model, according to its characteristics. The dimensions are the following.

Weather dimension: Contains weather data; for instance, temperature and the amount of water on the farm.

Paddock dimension: Stores data of the paddocks on the farm; for instance, area and forage capacity.

Soil dimension: Stores soil data; for instance, physicochemical variables of each paddock.

Animal dimension: Stores animal data; for instance, weight, breed and age.

Lot dimension: Stores data of the batches of animals that are in the process of fattening.

Grass dimension: Stores the data of the pasture; for instance, its type, maximum height and minimum height.

In general, data is extracted from different sources following different strategies. For example, when they are extracted from farm databases they follow a traditional data extract-transform-load approach, when they are extracted from the Internet is used a natural language processing approach, and so on for the rest of the sources. Then, they go through a phase in the data management layer that is in charge of data pre-processing, which includes data cleaning and normalization, the elimination of invalid and atypical data, among other things, and culminates with a feature engineering process that allows determining the variables required for the construction of the different knowledge models of the ACODAT data analysis tasks.

5 Case study: "El Rosario" cattle farm

For this case study, this section presents the experimental context and the instantiation of ACPLF-003 (Animal monitoring).

5.1 Experimental context

In this case study, we used data from "El Rosario" cattle farm, located 5 km from the city of Monteria, Colombia. This farm focuses on beef-production with fattening cattle. The farm is certified in good cattle-raising practices by the *Colombian Agricultural Institute (in Spanish, ICA)* [39]. The farm is on the road to obtain the *Rainforest Alliance certification*. Rainforest Alliance is an international non-governmental organization that works to conserve biodiversity and ensure sustainable livelihoods [40].

To illustrate the functionality of ACPLF-000, this case study discusses ACPLF-003, in an animal monitoring process, according to the following scenario. The cattle farm has 18 lots of animals with an average of 45 animals per lot, equivalent to 810 fattening animals. These animals begin their fattening process with an average of 300 to 350 kilograms, with an average age of two years old. The animals must arrive to the slaughterhouse with an average of 450 to 550 kilograms, in a maximum of 14 months of fattening (which means they gain an average of 20 kilograms per month).

In the process of weight gain, the farmer must have enough food, water and nutrients to meet the weight gain demands required by the market. The fattening process requires a constant monitoring of different variables; for instance, climate, forage, animal weight and animal health. During the 14 months of fattening, the farmer, based on his experience and the advice of a veterinarian, or when necessary due to any eventuality that may arise during the process (e.g., infection, worms or skin cuts), vaccinates –frequently– the animals with antiparasitics, gives vitamins.

During the fattening, decisions are also taken about the paddocks, and the batch of animals that should be moved to based on the farmer's experience. The farmer chooses, empirically, which paddock should be occupied or not depending on (i) forage capacity, (ii) watering capacity, and (iii) which paddock has shade to improve animal welfare.

5.2 Instantiation of ACPLF-003: Animal Fattening

The instantiation of ACPLF-003 must consider, for instance, disease detection, vaccination plan, paddock availability and climate. The following steps describe how ACPLF-003 is instanced for this case study.

Task 1. Weighing task: The first task is to –automatically– determine the weight of cattle, for which a prediction model is used. The prediction model is built with historical data found in the farm's livestock software. The prediction model also uses variables such as i) breed, ii) age, (iii) sex, (iv) climate, (v) temperature and (vi) pasture quality to explain an increase or decrease in weight. In what follows, two cases of this task are presented.

- ***Case 1:*** An animal weighs 340 kg. The model estimates that it should have gained 338 kg. In this case, Task 2 would not be performed, since the animal gained the desired weight gain.
- ***Case 2:*** An animal weighs 300 kg, but the model estimated that it should have gained 325 kg, as presented in Table 5 (see Animal Id 00734). Since the conditions were favorable for weight gain (e.g., quality of pasture and climate), in this case, a warning to the farmer is generated so that he can take the appropriate decisions.

Table 5: Predictions generated by the weighting task

Lot Id	Animal Id	Age	Weight	Predicted weight
L20-034	00732	1,5	330	327
L20-034	00733	1,6	320	319
L20-034	00734	1,6	300	325
L20-034	00735	1,4	340	338

Task 2. Vaccination task: The second task uses a prescriptive model, which is built with the (i) farm's historical data, (ii) websites selling animal-feed supplements, (iii) animal medications, and a (iv) database of bovine diseases or parasites. The prescriptive model is activated depending on the weight gain/loss in the first task. As an example, in the second case, presented in Task 1, an animal weighs 300 kg and Task 1 estimated that it should weight 325 kg. This condition would invoke the prescriptive model to define a nutrition plan with vitamins or other supplements, as presented in Table 6.

Table 6: Prescription generated by the vaccination task

Lot Id	Animal Id	Prescription
L20-034	00734	Anti-partisan
L20-034	00734	Genabilic acid
L20-034	00734	Mineralized salt

Task 3. Rotation task: In the third task, the system will use an assignment model that uses environmental data to make an intelligent planning about where it is best to move a batch of animals. The assignment model takes into account (i) the quality of pasture, (ii) resting times, (iii) occupation, (iv) climate and (v) animal welfare (e.g., percentage of shade and access to water). Thus, this task will assign the best paddock to move the batch of animals to maximize meat production based on a self-planning scheme. As an example, the assignment model of Table 7 shows the planning of animal rotation (to which paddock to rotate), the duration of the occupancy, and the resting times of the paddocks.

Table 7: Assignment model generated by the rotation task

Lot ID	Quantity of animals	Average weight	Date in	Date out	Paddock	Occupancy time	Resting time
L20-034	28	300	4/01/20	8/01/20	P045	4	45
L20-034	28	303,6	8/01/20	12/01/20	P048	4	35
L20-034	28	305,4	12/01/20	14/01/20	P049	2	36
L20-034	28	307,2	14/01/20	16/01/20	P050	2	37
L20-034	28	309,9	16/01/20	19/01/20	P055	3	38
L20-034	28	311,7	19/01/20	21/01/20	P052	2	39
L20-034	28	314,4	21/01/20	24/01/20	P059	3	45
L20-034	28	316,2	24/01/20	26/01/20	P060	2	30
L20-034	28	318	26/01/20	28/01/20	P065	2	35

6 General Analysis

6.1 Comparison with Previous Works

In this section, we propose criteria to analyze beef-production automation in the context of PLF. The criteria that have been considered are desired aspects in PLF. For example, carry out everything-mining to exploit the available data. Also, automate the entire beef production process, considering the variables that directly or indirectly affect the animal, such as the pasture. On the other hand, the third criterion points to a holistic vision of the problem that must consider the relationship between soil, forage and animal. Finally, the possibility of adding aspects of environmental sustainability to model the beef production process, in order to assess its benefits, is a very important element to consider. These general criteria are within the scope of the PLF and are aspired to be achieved. In this section, we have focused on determining whether the works comply with some of these aspects, and not on how they methodologically do so. Next, we make a comparison of this work with previous works based on these criteria.

Criterion 1: The entire beef-production process is automatized.

Criterion 2: Everything-mining techniques are used in the production process.

Criterion 3: Grazing and animal welfare are analyzed together.

Criterion 4: Efficient and environmentally-friendly production is considered.

In Table 8, a qualitative comparison with related works is made, based on previous criteria (✓means the work meets that criteria and ✗means it doesn't).

Table 8: Comparison with previous works.

	Criterion 1	Criterion 2	Criterion 3	Criterion 4
[17]	✗	✓	✓	✗
[18]	✗	✓	✗	✗
[19]	✗	✗	✗	✗
[20]	✗	✓	✓	✗
[21]	✗	✗	✓	✗
[22]	✗	✗	✓	✗
This work	✓	✓	✓	✓

As shown in Table 8, related papers did not satisfy all the criteria. Specifically, in criterion 1, this research allows, by means of ACs, the automation of the whole production process. For this automation, paradigms such as multi-agent systems need to be used, in conjunction with the ACODAT architecture, to model the entire production process [41].

For criterion 2, Segerkvist *et al.* [17] and Feng *et al.* [18] worked on the estimation of animal weight based on data mining. The basis of our proposal is an autonomous decision-making through data, with knowledge extracted from animal production. Thus, this work is based on everything-mining techniques.

For criterion 3, Segerkvist *et al.* focused on the detection of infections that reduce weight gain, something fundamental for animal welfare. In addition, Fuentes *et al.* [20] focused on animal welfare, specifically, in the reduction of heat stress by providing an automatic evaluation of animal welfare. Jung *et al.* [19] used wireless sensor networks, to monitor farm animals, using IoT equipment and cloud platforms. Vayssade *et al.* [21] and Li *et al.* [22] worked with drones for farm-data capture and monitoring tasks. Vayssade *et al.* used image processing for animal activity detection, and Li *et al.* used drones to autonomously track and monitor livestock. This proposal takes into account animal-welfare, soil, and pasture to perform rotations, in addition, this proposal includes a prescriptive model to improve animal health.

Finally, for criterion 4, this proposal meets the criterion of efficient and environmentally-friendly production because the farmer can know what is the maximum number of animals per season that can support her/his farm. This reduces greenhouse gases, and makes the farm more productive and sustainable.

6.2 Discussion of Preliminary Results

As mentioned before, in this work, the theoretical design of several ACODATs for self-management of the beef production process has been presented. However, the development of some of the tasks defined in these ACODATs have been carried out in previous works. For example, the ACODAT responsible for the animal fattening supervision process has two tasks, the detection of abnormalities in the fattening process and the diagnosis of what may be happening in the animal. Both tasks have already been carried out in previous works, with very stimulating results.

For example, the task that defines the animal fattening identification model was performed in [14], which allows the detection of anomalies in cattle weight gain over time. For the development of this task, the CRISP-DM methodology was used. In that work, the performance of various machine learning techniques was compared, and an outlier detection process was performed to identify outlier weights. In general, the results showed a performance with an average Mean Absolute Error (MAE) of 5.4 kg, which is quite good for cattle weights of the order of 400 kg.

Regarding the task to diagnose the anomaly detected in the fattening process of cattle in rotational grazing, a fuzzy classification system was used in [15]. For the development of this task, the KDD methodology was used. The fuzzy classifier uses the fuzzy reasoning to determine the current situation before a given input and the genetic algorithms to optimize the rules to improve diagnosis. The results of the tests carried out indicate that the quality of the fuzzy classification system is very good. The value of the Area Under the Curve that measures the sensitivity and specificity of the system is 1 (indicates a precision of 100% in the diagnosis); and the certainty of the rules it optimizes (determines the average degree of their firing), in the end, have a value of 0.85, which is very good.

Specifically, this paper shows the implementation of the autonomous self-planning cycle as the first step toward semi-autonomous production processes, in the context of PLF. The described autonomous cycle was methodologically detailed using MIDANO, to achieve the desired results. This means that this AC achieved the designed objectives of animal-rotation planning, aiming to incorporate autonomy in the beef production process. The preliminary results indicated in this section show the viability of our proposal, and motivate the future development of all the ACODATs defined in this work.

7 Conclusions and Future Work Directions

This paper presents an architecture to integrate and inter-operate actors in the context of PLF. The architecture combines multiple variables; for instance, soil, animal welfare, pasture, climate. The proposed architecture uses ACODAT and proposes several ACs to give autonomy to the beef-production process. In addition, this article shows the instantiation of an autonomous self-planning cycle as the first step towards efficient and effective beef-production processes.

Other results of this research are (i) the use of environmental variables to make decisions on optimal grazing, (ii) the ability to use everything-mining techniques to improve the knowledge of the system and decision-making processes (.e.g., data mining, text mining and web-mining techniques), (iii) real-time analysis for a sustainable and environmentally-friendly livestock production , and (iv) use of PLF and PAF combined and managed by CAs capable of adapting to the beef production process. Thanks to the concept of "autonomous data analysis cycles", the model can self-adjust to new environmental constraints, as well as to growth/decrease in forage demand, among other events. For this purpose, several data analytics techniques are used, which autonomously work to make decisions.

Particularly, the case study shows that everything-mining techniques are needed to address self-planning in rotational grazing. This case study serves as a guide to incorporate self-management in a beef-production process. Finally, the implementation of this case study will allow us to evaluate the impact of this self-management approach of beef-production processes, in the context of PLF, based on the autonomous-computing paradigm and everything-mining techniques.

Future work is aimed to implement this framework in a simulated environment to verify the functionalities of this solution. In this sense, we plan to use historical data of "El Rosario" Cattle Farm to develop the different data-analysis tasks (e.g., to determine weight gains or losses in the rotation of animal flocks). Another important future work is to develop specific ACs to evaluate autonomic processes to configure and reconfigure a livestock farm, in the context of PLF, according to this architecture.

Finally, one of the biggest challenges to implement this type of system is the cost associated with the sensors for data acquisition. In addition to the optimal distribution of these sensors, Internet connectivity and stable electricity-flow on the farm are big challenges. Future studies should analyze these uncertain aspects and how to consider them in the proposed architecture.

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