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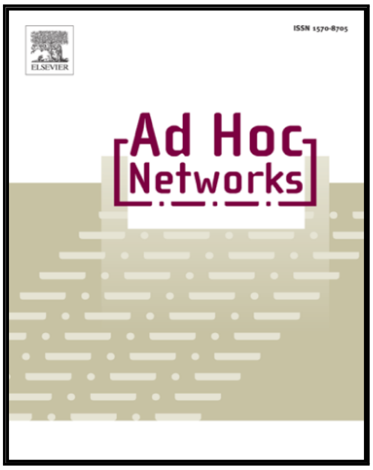

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An intelligent Edge-IoT platform for monitoring livestock and crops in a dairy farming scenario

Ricardo S. Alonso[a,*], Inés Sittón-Candanedo[a], Óscar García[a], Javier Prieto[a,b], Sara Rodríguez-González[a]

[a] *Bisite Research Group, University of Salamanca. Salamanca, SP*
[b] *Air Institute, IoT Digital Innovation Hub, Salamanca, SP*

Abstract

Today's globalized and highly competitive world market has broadened the spectrum of requirements in all the sectors of the agri-food industry. This paper focuses on the dairy industry, on its need to adapt to the current market by becoming more resource efficient, environment-friendly, transparent and secure. The Internet of Things (IoT), Edge Computing (EC) and Distributed Ledger Technologies (DLT) are all crucial to the achievement of those improvements because they allow to digitize all parts of the value chain, providing detailed information to the consumer on the final product and ensuring its safety and quality. In Smart Farming environments, IoT and DLT enable resource monitoring and traceability in the value chain, allowing producers to optimize processes, provide the origin of the produce and guarantee its quality to consumers. In comparison to a centralized cloud, EC manages the Big Data generated by IoT devices by processing them at the network edge, allowing for the implementation of services with shorter response times, and a higher Quality of Service (QoS) and security. This work presents a platform oriented to the application of IoT, Edge Computing, Artificial Intelligence and Blockchain techniques in Smart Farming environments, by means of the novel Global Edge Computing Architecture, and designed to monitor the state of dairy cattle and feed grain in real time, as well as ensure the traceability and sustainability of the different processes involved in production. The platform is deployed and tested in a real scenario on a dairy farm, demonstrating that the implementation of EC contributes to a reduction in data traffic and an improvement in the reliability in communications between the IoT-Edge layers and the Cloud.

[*]Corresponding Author.
Email address: `ralorin@usal.es` (Ricardo S. Alonso)

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1. Introduction

According to the Food and Agriculture Organization (FAO) of the United Nations, it is estimated that there are 750 million people worldwide who are engaged in the milk production sector [1]. Even though the milking yield per cow vary considerably among regions and depends on the use of technology [2], the differences between developed and developing countries are becoming less noticeable as the market becomes increasingly globalized and competitive [3]. Moreover, the challenges faced are applicable to dairy producers worldwide: a need to increase resource efficiency, become more environment-friendly and implement the latest technological trends, able to provide detailed information to the consumer, ensuring the safety and quality of the final product. In this sense, small- and medium-sized farms, in both developed and developing countries, could benefit from the implementation of low-cost technologies for the monitoring and optimization of water and energy resources [4].

Fortunately, technology has become much more accessible and lo[4]w-cost than it has been before and its possibilities are also much greater thanks to advances in communication technologies and technical development. In this sense, the number of sensors and devices that can be implemented in agricultural solutions has increased enormously. The overall technological progress has favored the emergence of IoT and Cloud paradigms, leading to the emergence of different technology-related concepts such as *Precision Agriculture*, which measures and responds to the variability of the agricultural data gathered by sensors [5]; and *Smart Farming*, which applies information and data technologies to perform a more exhaustive analysis of the farming system, taking into account location, historical, real-time and forecast data before taking specific actions [6].

In Smart Farming, the *Internet of Things (IoT)* paradigm [7] is essential in the monitoring of resources by connecting multiple and heterogeneous objects in *mixed dairy farms* (which produce milk from cattle and cultivate feed grain for livestock), such as buildings (e.g., barns), machinery and vehicles (e.g., milking machines or agricultural tractors) or even living organisms (e.g., cattle) [8, 9]. Moreover, if we design, develop and deploy IoT projects and infrastructures according to the *Edge Computing* paradigm [10], it is possible to reduce the costs associated with computing, storage and network resources in the Cloud by deploying services at the edge of the network, which reduce service response times and increase the *Quality of Service (QoS)* and the security of applications [11]. Furthermore, *Distributed Ledger Technologies* can be used in smart farming scenarios as a mechanism by means of which final consumers can track the processes that the produce on sale has went through in the value chain of the agri-food industry, guaranteeing the integrity of the information [12]. In this sense, *Blockchain* technologies are designed as mechanisms that allow some actors to perform verified transactions [13], with features such as *distribution, immutability, transparency, security and auditability* [14].

This work presents a new agro-industry platform which facilitates the application of Edge Computing, Artificial Intelligence and Blockchain techniques in Smart Farming environments. The aim of the platform is to monitor, in real time, the state of dairy cattle and the feed grain, while ensuring the traceability and sustainability of the different processes involved in the production. The novel *Global Edge Computing Architecture* presented by Sittón-Candanedo et al. [15], provides our agro-industry platform with several powerful features, especially its Edge Computing functionalities which reduce the use of computational, storage and network resources in the Cloud, as well as Blockchain technologies that provide security and warrant the integrity and traceability of data. The platform is deployed and tested in a real scenario to validate the benefits of the introduction of Edge Computing, thanks to the application of design rules and features of the Global Edge Computing Architecture, and evaluate the potential reduction of the data traffic between the IoT-Edge layers and the Cloud in both uplink and downlink directions, as well as hypothetical improvement in the reliability of the Edge nodes in their communication with the Cloud.

The rest of this paper is structured as follows. Section 2 identifies the most important trends in the application of Internet of Things and Edge Computing paradigms in Smart Farming scenarios. Furthermore, it describes state-of-the-art Edge-IoT platforms, specifically those designated for agriculture and livestock scenarios. The novel *Global Edge Computing Architecture* (GECA) [15], a tiered architecture with a modular approach that provides and manages numerous solutions for different environments such as Industry 4.0, smart cities, smart energy, or smart farming, is the basis for the new intelligent Edge-IoT agro-industry platform for monitoring livestock and crops on mixed dairy farms, described in Section 3 in depth. Subsequently, Section 4 details the experiments that had been conducted and validates the advantages that the Global Edge Computing Architecture has provided to the agro-industry platform, through its evaluation on a mixed dairy farm. Finally, conclusions and future work are outlined in Section 5.

2. Internet of Things and Edge Computing for Smart Farming

Thanks to technical and communication advances in technology, as well as ease of access, the number of sensors and devices that can be implemented in agricultural solutions has grown enormously. This growth and accessibility have favored the emergence of IoT and Cloud solutions, giving rise to a phenomenon known as *Smart Farming* [5]. The concepts of *Precision Agriculture (PA)* and *Smart Farming* may sometimes be confused, it is therefore important to distinguish between them. In Wolfert et al. [5], PA is said to only consider the variability in the field. On the contrary, Smart Farming provides a more exhaustive analysis, performs precise actions (e.g., decision support information, alerts notifications or task automation), taking into account, location of assets, cattle or humans, and other data enriched by the historical, real-time and forecast information and knowledge [5, 6].

2.1. Trends in IoT and Edge Computing for Smart Farming

The term *Internet of the Things (IoT)* refers to connecting multiple heterogeneous objects, such as machinery, vehicles or buildings with electronic devices such as sensors and actuators, through different communication protocols, in order to gather and extract data [7]. The IoT paradigm serves as the basis for the research and development of solutions in smart homes [16], smart cities [17], Industry 4.0 [18], logistics and transport [19], energy efficiency [20], health care [21], or agriculture [8].

However, for these solutions to be effective, it is necessary to develop global architectures capable of coordinating and managing all the resources involved in an IoT environment, as well as the ingestion of data from heterogeneous sources [22]. Layered IoT data ingestion solutions [23] offer a solution for the effective management of heterogeneous data, through their homogenization and common management in a higher layer. This approach permits the ingestion of big data from multiple scenarios, giving rise to Big Data repositories [24] where Data Analytics and Machine Learning techniques can be applied [25, 26] to provide added value to work environments through real-time analysis and response, pattern recognition, forecasting, etc., [5, 27].

In addition to the challenges encountered in the management of heterogeneous resources, the acquisition, processing and transmission of data also become problematic when dealing with millions of connected data sources [27]. *Edge Computing (EC)* is the competent paradigm when it comes to solving those problems. The main objective of EC is to solve the congestion and bottlenecks at processing and communication levels by moving computational resources and services closer to the end user and the deployed device [28]. Edge Computing deals with the Big Data generated by IoT devices by processing them at the network *edge*, instead of being managed centrally in the Cloud [29]. Thus, the services that are executed in the edge have a fast response time, with a higher *Quality of Service* (QoS) and security, compared with those executed in a centralized Cloud [10].

Thereby, the concept of Edge Computing is essential for the operation of IoT systems, as evidenced by multiple researches that address these two topics jointly. From a conceptual perspective, to reduce the time of response of the devices and increase the quality of the services they offer, Brogi and Forti [30] stated that the data generated by the IoT objects can be processed in the edge of the networks, avoiding the transmission of unprocessed data to a centralized Cloud. This assertion is supported by Lin et al. [11], who asserts that Edge Computing architectures are ideal for IoT solutions due to the efficiency and security that they offer to the users. In this regard, multiple areas have benefited from combining IoT and Edge Computing, such as health care [31], augmented reality [32], video analysis [33], biometric recognition [34], energy and smart grids [35], smart cities [36], smart homes [37] or, as in the case of this research, *Smart Farming* [5, 38].

There are multiple use cases that provide IoT and Edge Computing solutions to specific problems in Smart Farming. Agrawal et al. [39] presented an IoT system that measures the quantity and quality of grain in a silo, using multiple sensors to measure temperature and humidity. Irrigation is another area of interest. Water is a key resource in agriculture so its management, both in quantity and quality, becomes crucial in all agricultural environments. Cambra et al. [40] propose to control irrigation for hydroponic precision farming by means of the combination of multiple sensors and pumps to take smart measurements of the pH and water at the hydroponic facility. Moreover, understanding the behavior of cattle and herds is important to improving animal welfare, which leads to better management, productivity and product quality. An example of this is the smart nest box management system that tracks the performance and behavior of individual hens designed by Chien and Chen [41]. The system makes use of RFID sensors and egg detectors that gather information sent via Wi-Fi and processes it both locally and in the Cloud. There are other solutions focused on increasing the quality of crops by means of the analysis of multi-spectral images [42]. Finally, there are approaches aimed to detect and prevent plagues by means of IoT and Artificial intelligence techniques [43]. Jia et al. [44]

propose an electronic nose that detects apple mold by means of multiple sensors, neural networks, *Linear Discriminant Analysis* and *Support Vector Machines*.

In this sense, it is necessary to design global architectures and platforms that will facilitate the development and application of numerous Smart Farming solutions, regardless of their specific application or technology. In fact, the Smart Farming solutions developed under the umbrella of Edge Computing and IoT often consist of comprehensive platforms.

2.2. Edge-IoT Platforms for Smart Farming

Khan et al. [45] presented a generic architecture formed by five layers: *Perception Layer* (Data Ingestion), *Network Layer* (communications), *Middleware Layer* (service management), *Application Layer* (management of application objects) and *Business Layer* (management of the whole system). The approach can cover multiple use cases such as industry, water scarcity, prediction of natural disasters, smart packaging or improved practices. Although this approach has five layers, the solution does not take security issues into account, this can have a negative impact on data management and product traceability.

Ryu et al. [46] present a full-stack solution for a connected farm. The main goal of the solution is to provide a set of devices (sensors and gateway), an IoT Service Server to create virtual IoT devices (*Mobius*) and a middleware management module installed in the devices (*The &Cube*). This module communicates with expert systems and controls the deployment of the IoT systems that monitor crops. However, it lacks flexibility given the great heterogeneity of existing communication devices and protocols. Also security is an aspect that has not been addressed in this work.

Agri-IoT is a framework that favors agricultural data analytics [47]. Its design consists of multiple layers divided into three levels: *lower level* (IoT devices and communication), *intermediate level* (data management and analytics) and *higher level* (application). These levels include multiple software components that permits ingestion, analysis and data visualization. The framework is tested in two scenarios (*Management of fertility dairy cows* and *Soil fertility for crop cultivation*) in which the performance of the framework is verified, however, the need to include open standards that would increase the flexibility of the framework is also evident.

Finally, Park et al. [48] propose a scalable framework for data analysis in which edge nodes pre-process and analyze private data collected before sending the results to a remote server, which collects these results to estimate and predict the total yield of the crop. In the work of Park et al. [48], applying its framework in a real scenario on a tomato farm, the error rate is comparable to the case executed only on the server.

Having analyzed the different IoT and Edge Computing architectures found in the state-of-the-art, it can be observed that all the developments lack security and, in addition, there is a limit to increasing their generalization. The next section presents a novel Edge Computing Reference Architecture that covers these gaps. This new architecture provides the basis for the development of a new platform for application in smart agricultural and livestock environments, also described in depth in next section.

3. An intelligent Edge-IoT platform for monitoring livestock and crops in a dairy farming scenario

The novel *Global Edge Computing Architecture* (GECA) [15], designed as an Industry 4.0-oriented Edge Computing Reference Architecture, has been used to implement a new agro-industry platform, *SmartDairyTracer*. GECA is a tiered architecture with a modular approach that provides and manages numerous solutions for different environments such as Industry 4.0, smart cities, smart energy, or smart farming, and is briefly described in 3.1. The SmartDairyTracer platform, depicted in Section 3.2, is aimed at smart monitoring, sustainability and traceability of dairy products at mixed dairy farms (i.e., crop and livestock farms), dairy industry (e.g., milk, cheese, butter, etc.) and transportation to the end consumer, and its functionalities are enabled by GECA, which provides the platform with Internet of Things, Artificial Intelligence and blockchain technologies. In the first stage of development, focused on livestock and crops, and deeply described in Section 3.3, the new SmartDairyTracer platform is deployed and tested in a real scenario on a mixed dairy farm in Castrillo de la Guareña in the province of Zamora (Spain).

3.1. Global Edge Computing Architecture

The edge computing architecture employed in this study has first been proposed in [15], and it consists of three principal layers: *IoT, Edge and Business Solution layers.* Figure 1 depicts the Global Edge Computing Architecture (GECA) and its layers. Distributed Ledger Technologies are one of the most outstanding features of GECA, because they provide a level of security, from the same IoT Layer (the base layer), to the entire architecture. This makes it possible to encrypt the data generated by sensors and send it to the next layer for processing [13, 49, 14].

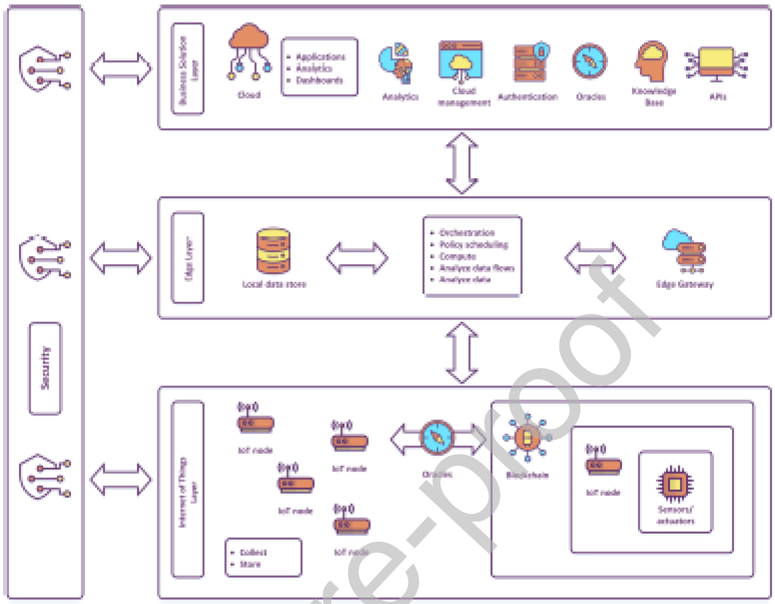

Figure 1: Global Edge Computing Architecture.

The authors of the Global Edge Computing Architecture [15] analyzed four of the most important reference architectures in the field of Edge Computing applications in industrial environments. Their aim was to build an architecture that was complete in all senses and that covered all the important needs of these environments [50, 51, 52, 53].

3.1.1. *GECA IoT layer*

The *GECA IoT Layer* is capable of ingesting data from distinct heterogeneous sensor networks, no matter their standard (SigFox, Wi-Fi, LoRa, ZigBee and others [54, 55, 56, 57, 20]). A set of agents called *oracles* are found in the GECA IoT layer, they act as intermediaries between the data coming from IoT devices and the blockchain [58]. The process starts when the IoT devices send the data to the oracles for verification. GECA oracles apply SHA-256 [59] to the generated data and creates a *hash* that will later be stored in the blockchain. Once verified, the data are sent to the blockchain where they will be used to execute smart contracts. The RSA algorithm [60] is used to encrypt the data that will be sent to the Edge Nodes.

With the SHA-256 algorithm [59], the Edge node that receives the data generates a hash, which can be compared at any time with the one stored in the blockchain to ensure nobody has altered the data. The generated hashes must be the same as this validates the data is correct.

3.1.2. GECA Edge layer

The *GECA Edge layer* manages, in real time, the technological resources that are critical to the processes of an organization, it also manages those processes and the execution of different tasks. As an intermediate layer of the architecture located close to the Edge nodes, it is responsible for the orchestration, monitoring and updating of the technological infrastructure. This includes pre-processing the data it receives from the IoT layer to filter out the data that will be sent to the cloud. To facilitate the implementation of the IoT and Edge layers, data is controlled by low-cost microcomputers such as Raspberry or Orange Pi, creating an open architecture with entry and exit doors. These doors make it easy to connect devices to sensors or to manage IoT device networks from the base layer until the collected data is transferred to the Edge layer. Another important feature of the GECA Edge layer is that it supports the execution of Edge devices that incorporate machine learning techniques (e.g., TensorFlow Lite) enabling different processes, such as Data Analytics, to run on the Edge layer of this architecture, reducing costs and volume per data transferred to the cloud (e.g., Google's Cloud IoT Edge, Microsoft's Azure IoT Edge or Amazon IoT Greengrass).

3.1.3. GECA Business Solution layer

Business Intelligence applications and services, as well as the final storage of the analyzed data for decision making are executed in *GECA Business Solution layer*. GECA enables storage processes to run in both public (commercial servers) and private (organization data centers) clouds. As shown in Figure 1, the main components of the Business solution layer include *Analytics*, *Cloud management*, *Authentication*, *Knowledge base* and *APIs (Application Programming Interfaces)*. Through the *Knowledge base* component, it is possible to implement social machines based on *Virtual Organizations of Agents* or *Decision Support Systems* based on data from IoT sensors [61]. This component is complemented by an orchestration of Cloud-based services that provides the necessary mechanisms for the provisioning, monitoring and updating of the resources used in a scalable and elastic way. The *Authentication* component provides two ways of authenticating new users/nodes of GECA-based platforms or systems: using *non-permissioned* (usual in public environments such as Smart Cities [17]) or *permissioned blockchains* (more common in private environments such as Industry 4.0 or Smart Farming [27]). The use case presented in section 3.3 employs the second one. In this authentication mode, the central authorization entity in the cloud behaves as the initial node and primary administrator of the permissioned blockchain. The primary administrator node mines the first block in which it establishes the working rules. Only existing administrator nodes can assign the role of administrator to a new node, and only administrator nodes can permit IoT nodes to access, which is resolved by means of a *consensus algorithm* [62, 63].

The next section describes the GECA-based platform designed to facilitate the application of IoT, Edge Computing, Artificial Intelligence and Blockchain techniques in smart farming environments. It is designed to monitor, in real-time, the state of dairy cattle and the crops associated with their feeding, as well as the traceability and sustainability of the different processes involved in production, elaboration and transportation of dairy products.

3.2. SmartDairyTracer: Smart Monitoring, Sustainability and Traceability of Dairy products by means of IoT, AI and Blockchain technologies

Nowadays, European dairy industry needs to address common challenges in all countries: to improve their efficiency in the use of resources, to be more environmentally friendly, to improve the digitization in all segments of the value chain and to improve their transparency and security providing detailed information to the consumer, ensuring the safety and quality of the final product [64].

To face these needs, researchers from the University of Salamanca (Spain) and the Digital Innovation Hub (Salamanca, Spain) are building a consortium gathering different profiles (livestock managers, farmers, dairy and cheese industries, IoT technology providers, ICT experts, energy engineers and scientific community researchers) with an extensive background in different activities/technologies (irrigation control, energy management and optimization, cattle welfare monitoring, pests and plague detection in crops) to involve the whole dairy value chain in the roll out of several use cases that, making use of currently available innovative technologies and solutions (IoT, Distributed Ledger Technologies and AI, among others), will provide an integral and open solution in the form of a smart platform based on FIWARE [65] for the improvement of the whole dairy industry, "from the grass to the glass": optimization of processes, reduction of water and energy consumption, reduction of pesticides in associated crops, promotion of a sustainable and environmental friendly production, monitoring of animal welfare and deployment of a reliable agri-food traceability system.

This solution will collect information from each stage (using IoT to monitor cow health and state, milk processing or transport safety) and will share it through a reliable, secure and transparent platform (based on Distributed Ledger Technologies) to provide valuable information to stakeholders (enabling them to optimize their procedures through the integration of AI assisted support) and customers (building a P2P "enabler" between producers and consumers, as well as providing an accurate traceability system and information about the health state and conditions of the livestock).

The projected SmartDairyTracer platform, whose full architecture based on GECA is illustrated in Figure 2, is focused on three main cornerstones: monitoring, through IoT technologies; sustainability, thanks to the application of AI algorithms; and traceability, achieved by means of innovative Distributed Ledger Technologies.

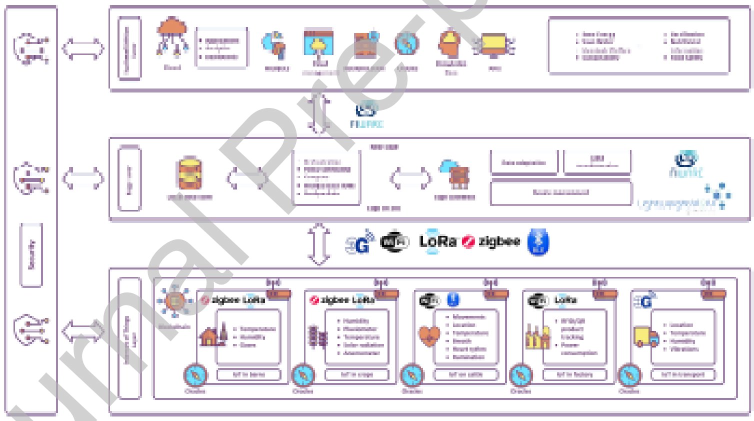

Figure 2: Schema of the complete Smart Dairy Tracer platform following the Global Edge Computing Architecture.

In this regard, SmartDairyTracer will include the following sources and IoT standards:

- *Livestock farms: ambient sensors inside barns* (temperature and relative humidity – to estimate stress – and hazardous gas sensors (methane, hydrogen sulphide, ammonia and formaldehyde), using ZigBee and LoRa technologies; power consumption and solar production auditors, using 3G and Wi-Fi technologies.

- *Agro-meteo stations in crops* used to feed livestock, including rainfall, temperature, relative humidity, anemometer, soil humidity and temperature, and solar radiation, using 3G, ZigBee and LoRa technologies.
- *Cattle sensors:* including real-time location [66], using ZigBee and BLE (Bluetooth Low Energy); as well as livestock health conditions, including body temperature, breath, heart rhythm and rumination, using Wi-Fi technologies.
- *Factories:* RFID tags and QR codes will be incorporated for the traceability of the different packaged products (milk, cheese, butter, etc.), as well as smart meters for monitoring energy consumption in the factories.
- *Transportation:* Finally, the time and conditions of transport (temperature, humidity, vibrations, etc.) to the consumer will be controlled in order to guarantee the quality of the final product. If the agreed conditions are not met, the distributor will be penalized by means of *smart contracts.*

The values of the monitored parameters will be gathered through the above-mentioned wireless IoT technologies, managed by means of Lightweight M2M [67] and transferred using FIWARE [65] to IoT Service and Mediation layers, respectively. Auxiliary gateways and proxies will be deployed when necessary both in the *Edge on Site* and the *Near Edge.*

AI techniques will be used to process this information (ad-hoc ontologies for the implementation of Smart Data solutions in the dairy industry, Deep Learning to infer knowledge from the data and Decision Support Systems which facilitate the inclusion of extracted conclusions in the decision-making process) and to detect stress and illness in livestock (increasing production), prevent fungi and pests in crops (reduce the use of pesticides), optimize energy consumption (shifting some processes when it is possible to produce renewable energy) and reduce the consumption of resources (smart irrigation or smart waste management and circular economy), resulting in a more sustainable production.

Finally, to build a reliable system, innovative Distributed Ledger Technologies (DLT) will be used. They will provide a tamper-proof framework which will ensure the traceability of all the information in systems. This will help guarantee the safety and quality of the product by certifying its origin and giving detailed information of all the processes that the produce will undergo, from the farm to the table. Thus, DLT are an effective means of preventing food fraud and health risks.

3.3. First stage: a new platform for monitoring and managing mixed crop-livestock farming

The first version of the SmartDairyTracer platform has been implemented following the Industry 4.0-oriented Edge Computing reference architecture (GECA). Its main objective is to lay the foundations of the whole SmartDairyTracer platform and, in accordance, develop an agro-industry platform designed to monitor, track and optimize the management tasks of mixed crop-livestock farms.

Thus, to test and validate the new agro-industry platform, it has been deployed in a real scenario in a dairy cow farm located in Castrillo de la Guareña, in the province of Zamora (Castile and León, Spain). The farm has two barns of 1850 and 1650 m^2, respectively, which hold 180 dairy cows. This dairy farm also has 302 ha of associated crops, including corn, alfalfa and rye used as fodder for the livestock.

The main objective of implementing this use case is to monitor, by means of IoT and Edge Computing technologies, all the resources used in milk production, the parameters related to the livestock, their environment and the associated crops (alfalfa, corn, rye) used to feed the livestock. Monitoring has a twofold purpose; it allows to optimize the resources used in milk production, through Business Intelligence, Data Analytics and Machine Learning techniques. Moreover, monitoring makes it possible to track the produce in the milk value chain, from its origin to its retail location; this includes the daily conditions and the feed grain of the livestock, milking, the processes that the produce undergoes at the treatment and packaging plant, and its transport. Traceability is achieved by means of Distributed Ledger Technologies (blockchain). However, the transportation of the milk to the processing and packaging plant, as well as the final transport to the consumer, are issues that will be addressed in the future, in the second stage of development that will complete the implementation of the SmartDairyTracer platform.

In this scenario, the main advantages of using the GECA reference architecture [15] in designing the agro-industry platform include the following:

- *Flexibility and scalability:* thanks to the design of the IoT and Edge layers, it is possible to dynamically incorporate new sensors for monitoring and tracking of facilities, livestock and crops through the platform.
- *Availability of real-time information*: thanks to the entire layer structure of the architecture, from the IoT layer to the Business Solution

layer, applications and users have remote access to monitoring and traceability information in real-time.

- *Knowledge and value-added information:* both the Edge layer and the Business Solution layer provide Artificial Intelligence techniques for the detection of irregular patterns in the behaviour and vital signs of livestock (stress, diseases) or water stress in crops by means of Case Based Reasoning mechanisms in the Business Solution layer or Machine Learning in the Edge (through TensorFlow Lite [68]).

Following the requirements of the first stage to be implemented within the SmartDairyTracer platform, as well as the design patterns of the Global Edge Computing Architecture, the following specifications were defined for each of the three layers of the architecture, which can be seen reflected in the platform in Figure 3.

- *IoT Layer:* This layer includes all IoT devices designated for monitoring livestock-related parameters (location, activity patterns and health status through bio-metric sensors) and their environment (ambient conditions of the barns in order to detect potential stress and hazardous concentration of gases), as well as the feed grain (through agro-meteorological stations to monitor rain and irrigation, air temperature and humidity, solar radiation, wind conditions, as well as soil humidity and temperature). Therefore, by means of this layer, the agro-industry platform collects context information from a set of heterogeneous Wireless Sensor Networks [69].

- *Edge Layer:* collects all the information gathered by the IoT devices in the lower layer. It is in charge of pre-processing those data before before they reach the Business Solution Layer which is deployed in the Cloud. In this layer, the Crypto IoT chips in the IoT devices (as *IoT oracles* at the IoT Layer) or IoT-Edge gateways, hash the information and it is stored in becoming part of the blockchain and maintaining the inviolability of the data to ensure traceability. On the one hand, all the information collected by the sensors becomes part of the distributed ledger from this point using On the other hand, the data are pre-processed and filtered by Data Analytics techniques, generating knowledge in the same Edge and reducing data traffic and transmission costs to the Cloud.

- *Business Solution Layer:* is deployed in the agro-industry platform as a set of coordinated components. SQL and NoSQL databases, back-end Web Services are deployed through Serverless *Function as a Service*, as well as Artificial Intelligence algorithms of the Cloud Computing platform. In this layer a *Virtual Organization of agents* works as a social machine [70], which provides the Decision Support System (DSS) with decision-making features. The decisions are made on the basis of the physical quantities gathered by the different heterogeneous Wireless Sensor Networks at the IoT Layer. Moreover, the agro-industry platform includes additional features such as data visualization technologies and an alert management system which sends warning messages and corrective actions when the values obtained by heterogeneous IoT networks indicate a hazardous situation.

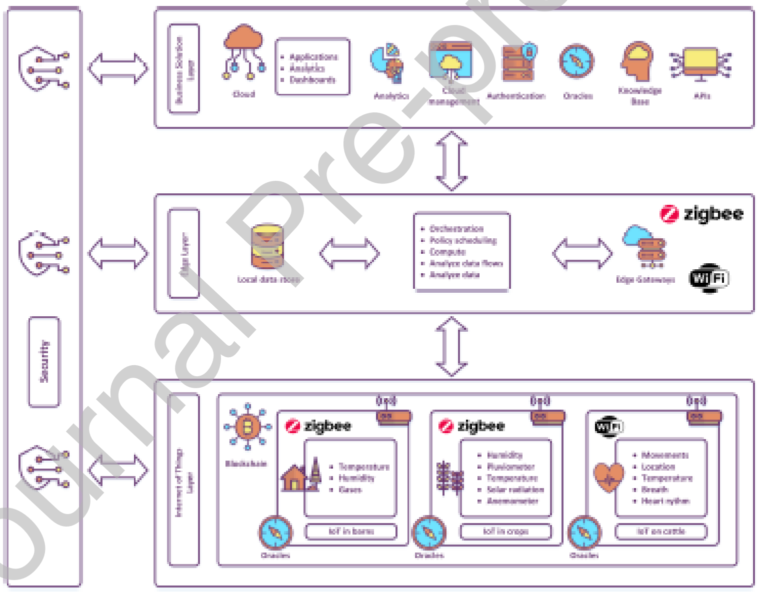

Figure 3: The first version of the agro-industry platform based on the novel Edge Computing reference architecture (GECA).

Thank to the GECA reference architecture, the new platform is organized in a set of layers that allow to add and remove components dynamically, making it possible to scale the implemented systems horizontally over time. The Cloud provides flexibility to the Business Solution Layer thanks to data pre-filtering in the Edge layer, as well as knowledge extraction at both layers. Moreover, thanks to the distributed ledger technologies underlying the entire architecture, the data read and collected by the sensors and devices at the IoT layer are unalterable as they are recorded for traceability through the Edge and Business Solution layers.

3.3.1. IoT Layer

There are three heterogeneous, IoT-based wireless sensor networks in this scenario, each of them is different and is in charge of monitoring different elements (buildings, crops and cattle):

The IoT Layer of the agro-industry platform can be divided into three blocks of heterogeneous IoT networks. However, the architecture of the GECA-based SmartDairyTracer platform is modular and scalable, therefore new IoT networks can be added in the future.

- *Barn sensors:* the platform includes ambient sensors with the aim of measuring the conditions where dairy cows live (barns) and how this affects their health:
  - Sensors to estimate the *temperature-humidity index*, which is related to stress in dairy cattle [71]:
    - *Air thermometer* to measure air temperature inside barns.
    - *Hygrometer* to measure the relative humidity of the air inside barns.
  - *Gas sensors* to measure potentially dangerous levels of gases in the air inside barns:
    - CH_4 (methane)
    - H_2S (hydrogen sulphide)
    - NH_3 (ammonia)
    - CH_2O / H-CHO (formaldehyde)
- *Agro-meteo station in crops:* the platform contemplates a series of agro-meteorological stations to measure and collect different physical quantities of the air and soil where the different crops used to feed livestock are found and take optimal decisions about whether or not to irrigate crops. In the case study in Castrillo de la Guareña these crops include alfalfa, corn and rye, but the stations are indeed independent of the crop. The agro-meteo stations include the following sensors:
  - *Pluviometer* to measure both rainfall and artificial irrigation.

- *Soil thermometer* to measure ground temperature.
- *Soil moisture sensor* to measure ground moisture.
- *Air thermometer* to measure air temperature.
- *Hygrometer* to measure the relative humidity of the air.
- *Anemometer* to measure wind speed and direction.
- *Pyranometer* to measure solar radiation, which can be utilized to estimate crop evapotranspiration levels [72].

- *Cattle sensors:* This sensor group includes the different bio-metric devices and sensors responsible for locating cattle and gathering measurements of physical quantities directly linked to the cows' bodies, allowing to detect indications of illnesses (e.g., fevers) and other possible problems (e.g., stress) that affect their health conditions, as well as dairy production:
  - *Thermometer* to measure cattle's body temperature.
  - *Pulsometer* to measure heart rate.
  - *Respiration monitor* to measure breathing rate (indeed, this quantity is estimated from the heart rate by a DSP at the collar).
  - *Accelerometers and gyroscopes* to calculate the position and inclination of the animal's head, making it possible to estimate if the cattle is moving, eating, ruminating or just resting, also important to estimate dairy production levels [73].
  - Location (by means of Real-Time Locating Systems based on wireless signals [66]) important for the detection of anomalous behavior patterns and possible areas with more temperature-humidity stress inside barns.

To connect the wireless devices in the IoT Layer (IoT sensors) with the Edge Layer, different communication standards can be used to implement IoT-Edge gateways, including LoRa, Wi-Fi, 3G or ZigBee [74]. In the current version of the presented use case, ZigBee is used as a communication standard for gathering data from both agro-meteo stations installed in crops and sensors deployed in barns. Wi-Fi is used as a transmission standard for collecting data from cattle sensors, and it will be also used by the Real-Time Locating System to track cattle.

These IoT-Edge gateways collect sensor information received from the devices at the IoT layer and forward this data to the devices (i.e., micro computers) in the Edge Layer as described in Section 3.1.2. These micro computers at the Edge, filter, pre-process and transfer IoT data and Edge-extracted knowledge to the upper Business Solution Layer through Internet via cellular networks or *Digital Subscriber Lines* (DSL), as fiber optics or cable connections are normally unavailable in rural environments.

The use of *IoT oracles* is key at this point, as explained in Section 3.1.1. These IoT oracles allow for the interaction between data from *Input and Output* (I/O) ports at the sensor and actuator devices and the blockchain, following the Global Edge Computing Architecture by means of specific *Crypto-IoT* boards, as shown in Figure 4. These Crypto-IoT boards have been designed by the blockchain and electronics teams from the BISITE Research Group of the University of Salamanca [15]. These data-agnostic electronic boards are intended to work as generic gateways aimed at developing systems and applications following the *blockchained* IoT paradigm, by ensuring the security, integrity and reliability of the data read and collected from the different elements of the environment at the IoT Layer before transferring it to the upper layers (Edge and Business Solution).

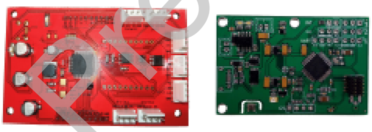

Figure 4: Crypto-IoT boards version 1.0 (left-hand) and version 2.0 (right-hand).

The features of the Crypto-IoT devices are important because they meet the design requirements of the Global Edge Computing Architecture and are therefore necessary for the overall functioning of the agro-industry platform. Moreover, they warrant the integrity of data in the SmartDairyTracer, making traceability in the dairy value-chain possible. These features include:

- ATSHA204A encryption chip including SHA-256 technology to cipher and hash data to be incorporated in the blockchain.

- XBee module which allows to integrate different radio transceivers (Wi-Fi, Bluetooth, ZigBee, LoRa, FM Radio or RPMA) for data transmission and reception between IoT and Edge.

- A USB module that allows the Crypto-IoT board to connect with other devices, working as USB host. Moreover, the USB module allows it to connect with neural processing modules which pre-process and implement Machine Learning at the IoT or Edge Layers, if needed.

- I^{2}C communication bus [75] to *plug-and-play* any kind of I^{2}C sensors acting as slave devices.

Figure 5 shows a map of an area on the mixed dairy farm in Castrillo de la Guareña, in the province of Zamora, Castile and León (Spain), where the agro-industry platform has been implemented. This Figure indicates the location of the management and engineering office, the two barns where the livestock live and the associated crops used as feed grain.

Regarding the buildings (office and barns), a set of ZigBee nodes, described in Table 1 have been deployed to gather the ambient conditions of the livestock and forward data from Edge to Business Solution Layers:

Table 1: IoT nodes deployed in office and barns in the mixed dairy use case.

Node	Description	Collecting node
Node #0	IoT-Edge gateway placed at the management and engineering office for the collection of data coming from the sensor nodes both in the two barns and at the agro-meteorological stations. This IoT-Edge gateway collects ZigBee frames coming from sensor nodes and forwards filtered data to the Business Solution Layer in the remote Cloud using an Ethernet/DSL Internet connection, it is described in depth in 3.3.2.	Business Solution Layer
Node #1	Ambient sensor node in barn #1, including air thermometer and hygrometer for stress detection, as well as gas sensors for detecting hazardous levels of CH_4, H_2S, NH_3 and CH_2O.	Node #0
Node #2	Ambient sensor node in barn #2, including air thermometer and hygrometer for stress detection, as well as gas sensors for detecting hazardous levels of CH_4, H_2S, NH_3 and CH_2O.	Node #0

By combining air temperature and relative humidity values we obtain the *temperature-humidity index (THI)* [71], which represents stress that affects dairy cattle in terms of both milk production and reproductive efficiency:

$$THI = 0.8T + ((RH/100)(T - 14.3)) + 46.4 \tag{1}$$

where T is air temperature (in Celsius degrees) and RH is the relative humidity (expressed as a percentage between 0% and 100%). The THI is designed to be typically between 70 and 80. Values under 72 represent no stress in cattle; values between 72 and 78 represent moderate stress; and values over 78 are indicative of high stress in dairy cattle.

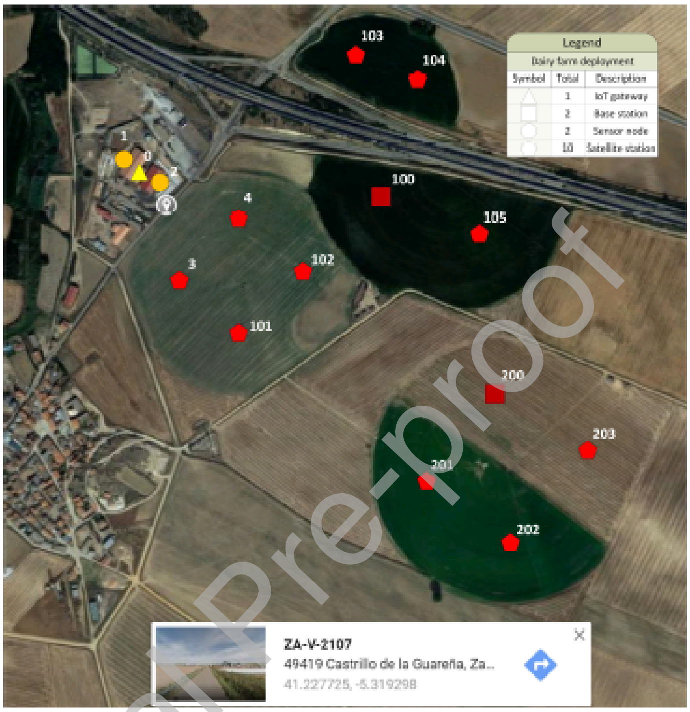

Figure 5: Deployment of the Edge-IoT gateway in the office, the IoT sensor nodes in the two barns and the 12 IoT agro-meteorological stations placed in the associated crops.

Figure 6 illustrates the physical appearance of the IoT barn sensors in the laboratory before they had been installed in the mixed dairy farm (top left), an image showing an IoT device installed in barn #1 in the real scenario (top right), as well as a functional design schema that depicts the different components of the each IoT barn sensor (bottom). Table 2 includes a summary of the sensors included in each IoT barn node.

In addition to the power supply module, the Single-on-Chip (SoC) micro-controller and ZigBee transceiver (ATmega1281) with 9dBi antenna, four analog sensors have been incorporated for the detection of hazardous gases. These sensors are digitized by the *Analog-Digital Converter* (ADC) module (ADS1115) before passing to the I^2C port [75] at the micro-controller. This module includes four input channels. In addition, temperature and air humidity are measured by means of the SHT20 sensor probe which provides

Table 2: Sensors integrated into IoT barn nodes (nodes #1 and #2).

Sensor	Description
SHT20	Air temperature and relative humidity to calculate stress in cattle (THI).
MQ-4	CH_4 (methane)
MQ-136	H_2S (hydrogen sulphide)
MQ-137	NH_3 (ammonia)
MQ-138	CH_2O / $H\text{-}CHO$ (formaldehyde)

these physical quantities as digital I^{2}C packets.

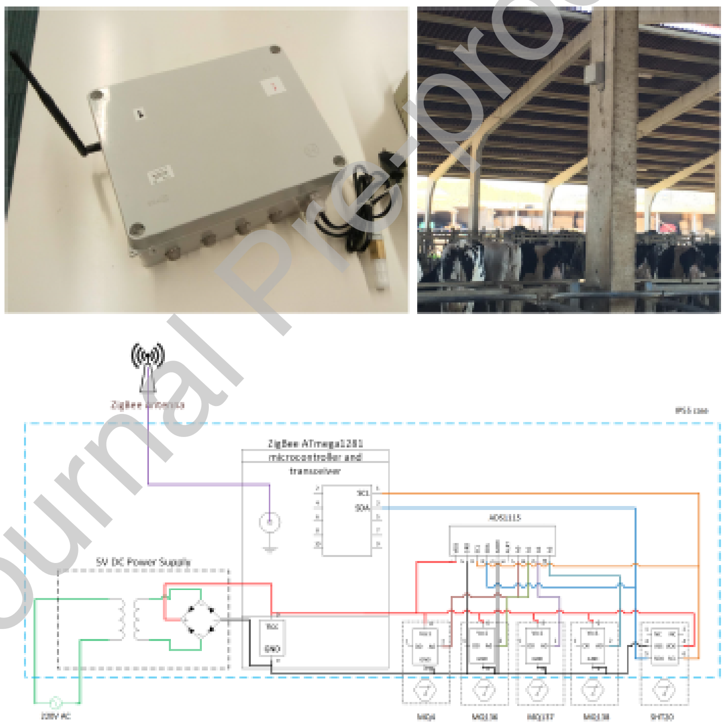

Figure 6: The physical appearance of an ambient sensor node in the laboratory before installation in barns (top left-hand side), its appearance one installed in one of the barns (top rigth-hand side) and schematic blocks of the ambient sensor nodes (bottom).

Figure 5 also shows the IoT agro-meteorological stations installed in the associated crops (alfalfa, corn and rye) used to feed cattle in the case study in Castrillo de la Guareña, and represented by nodes #3, #4, #10x and #20x. In this research, two versions of IoT agro-meteorological stations have been deployed for crop monitoring: *base stations* and *satellite stations* (i.e., auxiliary stations). *Base stations* are capable of measuring all the ambient (air and soil) conditions at the installed location because they incorporate sensors for the measurement of all the required physical quantities. On the contrary, *satellite stations* (i.e., auxiliary stations or *non-base stations*) have limited capabilities and only include the sensors that are used to measure natural precipitation and artificial irrigation, as well as soil temperature and moisture. These sensors must be deployed at shorter distances (i.e., the scenario requires the collection of granular data) because these physical quantities vary over short distances, especially when artificial irrigation is performed by means of *irrigation pivots*, that usually spin slowly over the ground. Other physical quantities, such as air temperature or solar radiation do not vary significantly over short distances and farmers can reduce costs by deploying fewer sensors at large distances from each other. The set of measurements gathered by satellite stations are transmitted to the base stations by means of ZigBee radio transmission, which in turn buffer and forward them to the Edge layer at the main management and engineering offices by retransmitting ZigBee packets. Table 3 provides a list of the IoT agro-meteorological stations, including their type and the corresponding collecting node.

Table 3: IoT agro-meteorological stations at associated crops.

Node	Type	Collecting node
Node #3	Satellite	Node #0
Node #4	Satellite	Node #0
Node #100	Base	Node #0
Node #101	Satellite	Node #100
Node #102	Satellite	Node #100
Node #103	Satellite	Node #100
Node #104	Satellite	Node #100
Node #105	Satellite	Node #100
Node #200	Base	Node #0
Node #201	Satellite	Node #200
Node #202	Satellite	Node #200
Node #203	Satellite	Node #200

Table 4 summarizes the different components and features of each type of IoT agro-meteorological station at associated crops. In this regard, base stations use their ZigBee transceiver to collect the data transmitted by satellite stations and forward them to the Edge Layer located in management and engineering offices, while satellite stations use their ZigBee transceiver to transmit data to base stations, which will forward them to the Edge Layer in main offices.

Table 4: Features of each type of IoT agro-meteorological station at associated crops.

Component	Base stations	Satellite stations
Solar panel for harvesting energy	✓	✓
Battery for storing energy	✓	✓
Power supply (energy coming from solar panel and battery)	✓	✓
Battery level sensor	✓	✓
Pluviometer to measure both rainfall and artificial irrigation	✓	✓
Soil thermometer to measure ground temperature	✓	✓
Soil moisture sensor to measure ground moisture	✓	✓
Air thermometer to measure air temperature	✓	-
Hygrometer to measure the relative humidity of the air	✓	-
Anemometer to measure wind speed and direction	✓	-
Pyranometer to measure solar radiation (used to estimate evapotranspiration levels)	✓	-
Single-on-Chip (SoC) micro-controller and ZigBee transceiver (ATmega1281)	✓	✓
Antenna 2.4GHz 9dbi omni-directional	✓	✓
IoT Crypto chip for blockchain features	✓	-

Each base station includes all the sensors required to measure all the physical quantities at the place at which they are installed, and it forwards both its own ambient (air and soil) data and the ambient data coming from the satellite stations connected to it. Figure 7 shows the physical aspect of a IoT agro-meteorological base station in an alfalfa crop in the monitoring scenario use case (left-hand side) and its functional design diagram (right-hand side).

On the other hand, the non-base satellite stations do not include the air thermometer, the hygrometer, the anemometer, the pyranometer or the IoT Crypto chip electronic board with blockchain capabilities (as the correspond-

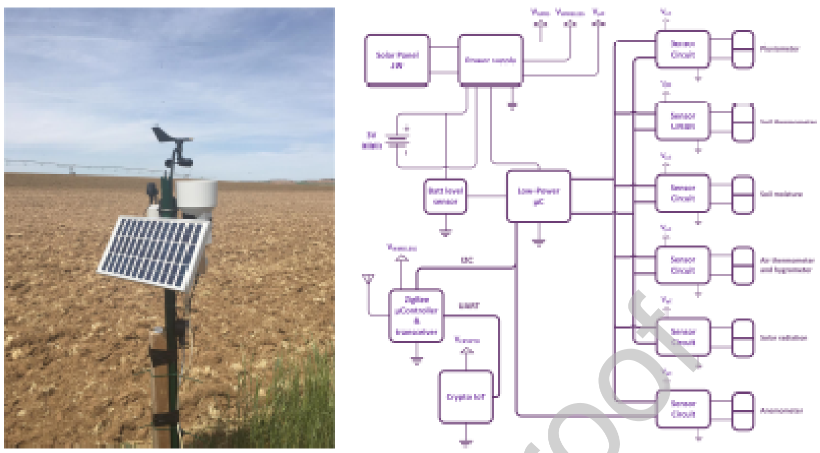

Figure 7: The physical aspect of an agro-meteorological base station in an alfalfa crop in the use case monitoring scenario (left-hand side) and its functional design diagram (right-hand side).

ing base station ciphers the data before forwarding them to the IoT-Edge gateway). Figure 8 shows the physical appearance of an agro-meteorological satellite (i.e., non-base) station in a real alfalfa crop monitoring scenario (left-hand side) and the functional design diagram of an agro-meteorological satellite station (non-base) (right-hand side).

Finally, Figure 9 shows the physical aspect of an IoT device used for monitoring bio-metric indicators in livestock (left-hand side) and how one of those devices is worn by cattle (right-hand side). These IoT cattle devices include bio-metric sensors for monitoring different health indicators in dairy cattle. The set of sensors intended for reading and collecting physical quantities related to dairy cattle include the following:

- 5V battery (typically 21-day lifetime when transmitting data every 5 minutes) and power supply.
- Microprocessor for processing (by means of Digital Signal Processing techniques) received signals with physical quantities from sensors and sending information through its Wi-Fi transceiver.
- Wi-Fi transceiver for the transmission of health and activity information to the specific IoT-Edge gateway at the management and engineering office, which receives Wi-Fi frames, filters, pre-processes and

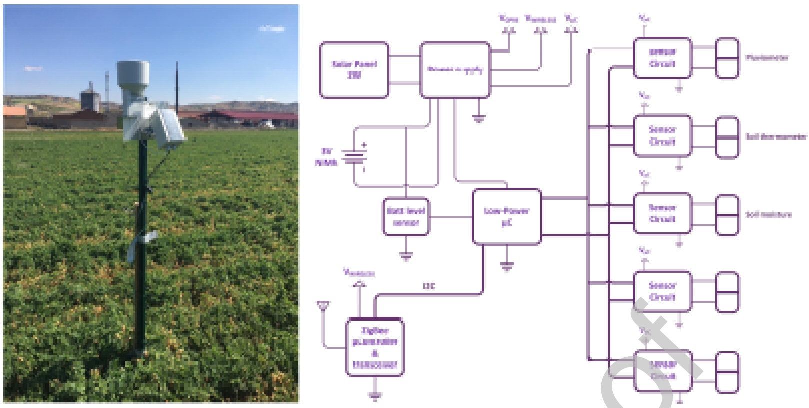

Figure 8: The physical appearance of an agro-meteorological satellite station (i.e., non-base) in an alfalfa crop in the use case monitoring scenario (left-hand side) and its functional design diagram (right-hand side).

forwards them as IP packets until they reach the Business Solution Layer at the Cloud.

  – Wi-Fi signals come from the Wi-Fi transceiver and arrive at the IoT-Edge gateway. Furthermore, additional Wi-Fi access points are used for location purposes (by means of Real-Time Locating Systems based on wireless signals [66]), necessary for detecting anomalous behavior patterns, as well as possible stress due to the temperature-humidity index throughout barns.

- Bio-metric sensors:
  – *Thermometer* to measure cattle body temperature.
  – *Pulsometer* to measure heart rate.
  – *Respiration monitor* to measure breathing rate.
  – *Accelerometers and gyroscopes* to calculate the position and inclination of the animal's head, allowing to estimate if the cattle is moving, eating, ruminating or resting.

3.3.2. Edge Layer

In the previous section, we have talked about node #0. This node is the IoT-Edge gateway intended for gathering data from the IoT barn sensors and IoT agro-meteorological stations (which had previously obtained

Figure 9: The physical aspect of an IoT device used for monitoring bio-metric indicators in livestock (left-hand side) and how one of those devices is worn by cattle (right-hand side).

information from satellite stations). In both cases, the data are obtained by means of the ZigBee wireless standard. This IoT-Edge gateway is located in the office building (the management and engineering office) located between the two barns (where nodes #1 and #2 are placed). Figure 10 shows both the physical aspect of this IoT-Edge gateway in laboratory (left-hand) and its functional design diagram (right-hand). The functional design diagram shows the power supply of the IoT-Edge gateway, the Single-on-Chip (SoC) micro-controller and ZigBee transceiver (ATmega1281), the Crypto-IoT chip board (which belongs to the IoT Layer in the GECA reference architecture) with blockchain features, as well as the Ethernet expansion module with the aim of tunnelling hashed data between the IoT nodes and the Edge node (described below) which filters, pre-processes and forwards data to the Business Solution Layer in the remote Cloud via a suitable Internet connection (via radio in the use case because of the lack of DSL or cable access in this rural area). Regarding the environmental conditions, the expansion boards of the IoT-Edge gateway can be replaced to incorporate data collecting technologies such as LoRa instead of ZigBee, as well as data tunneling technologies such as Wi-Fi, GPRS or LTE instead of Ethernet.

Regarding the Edge node itself, and as mentioned, this node collects all data coming from the different IoT nodes associated to it and filters, pre-

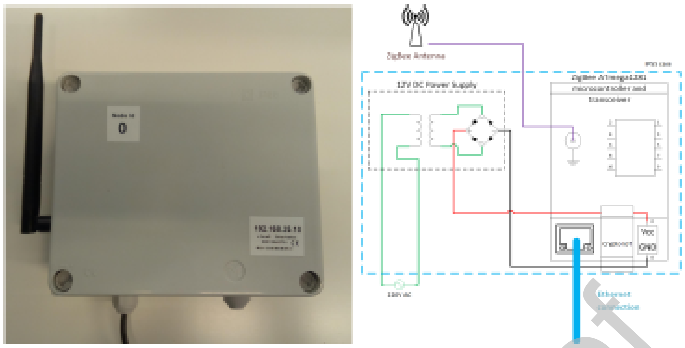

Figure 10: Physical aspect in laboratory (left-hand) and functional design (right-hand) of the IoT data collecting gateway (node #0) at the IoT-Edge layers.

processes and buffers these IoT data before forwarding it to the Business Solution Layer in the remote Cloud. These filtering and pre-processing stages can include Machine Learning techniques at the Edge, and can be implemented by a micro-computer which allows to extract knowledge at the Edge and reduce the data traffic from the Edge to the Cloud, thus reducing energy and transmission costs due to Cloud fees. In the described use case, this Edge node is formed by a Raspberry Pi 3 Model B, which has been configured to provide the computing, storage and communication characteristics depicted in Table 5.

Table 5: Computing, storage and communication features of the micro-computer used as Edge node in the mixed dairy farm use case.

Component	Description
CPU	Broadcom BCM2837 SoC ARMv8-A 64-bit/32-bit instruction set 4 Cortex-A53 cores working at 1.2 GHz.
RAM	1 GB shared with GPU.
Storage	16 GB microSD card (10 MB/s).
I/O	4 USB 17x GPIO, some of them shared with specific buses such as UART, I^2C and SPI.
Networking	10/100 Mbit/s Ethernet 802.11b/g/n (2.4 GHz single band) Bluetooth 4.1

This Raspberry Pi 3 Model B acts as an Edge node that filters and pre-processes IoT data with the assistance of TensorFlow Lite libraries [68] using an ECMAScript run on a Node.js- and Express.js-based server. This server collects IoT sensor data that come from IoT-Edge gateways, it also filters and eliminates possible noise, discards repeated frames to avoid unnecessary transmissions to the Cloud, serves summarized information through a Web interface that can be accessed from the same LAN at the Edge (i.e., within the mixed dairy farm) with no need for an Internet connection with the Cloud and finally forwards only valuable and value-added data, as well as extracted knowledge, to the Business solution layer in the remote Cloud.

3.3.3. Business solution Layer

In order to verify the performance of the Business Solution Layer with a use case, a new online platform known as Rural-IoT was implemented. In this use case, a mixed dairy farm scenario was developed, which runs as a Web Server and follows a Platform as a Service approach (PaaS, App Engine on Google Cloud). This online platform collects pre-processed information arriving from the Edge node and it is intended to scale and be extended to many dairy farms providing milk to the same dairy producer in the province of Zamora (Spain), thus exploiting the benefits of Edge Computing. This platform is developed using .NET Core for the backend, and HTML5, Bootstrap 4 and Vue.js for the frontend. The platform relies on a MySQL (Google Cloud SQL) database for the relational part including configuration and the relationship of buildings, cattle, devices, sensors or stations, and Google BigQuery as database for storing massive sensor data coming from IoT and Edge Layers. Figure 11 shows some screenshots of the Rural-IoT platform accessed from a web browser, and several views of the platform:

- *Top*: An interactive map (using Leaflet.js library and OpenStreetMap as data source) showing the different IoT devices, including barn sensors and agro-meteorological stations.

- *Middle*: Interface for the configuration of the different sensors at each IoT node in the platform. The platform automatically detects when a node sends data to the platform using the IoT-Edge gateways. Although the node must authenticate the platform, users can authorize, reject or configure the sensor data streams and how they affect the rest of the components in the system.

- *Bottom*: Some monitored and stored bio-metric quantities of a sample dairy cattle. The *Graphical User Interface* (GUI) in the figure shows, according to a user search, two graphs with information on the activity (movements from accelerometers) and health (possible fever) of a selected cattle.

– *Top graph*: The graph in the upper part of the GUI displays a specific index associated with the activity of a selected cattle during a defined period of time, which is estimated according to its movements measured by the accelerometers and gyroscopes on its Wi-Fi collar.

– *Bottom graph*: The graph in the lower part of the GUI displays a fever indicator combining the temperature, breathing rhythm and heart rate of the cattle over time, also read by the set of sensors attached to the cattle's Wi-Fi collar.

4. Experimentation and results

Cloud providers such as Amazon Web Services, Microsoft Azure or Google Cloud offer pricing plans based on the amount of resources customers over a certain period of time [76]. Cloud pricing plans are quite complex to describe, but, without going into much detail, cloud providers charge for computing resources (use of CPU in terms of $cores \times GHz \times s$, as well as RAM in terms of $GB \times s$), storage and database resources (in terms of $GB \times month$, as well as total read and write operations per month), as well as network resources (in terms of amount of the incoming and outgoing traffic), among others that currently include advanced services, such as *Machine Learning as a Service* (e.g., Natural Language Processing APIs) or highly-specialized *Infrastructure as a Service* (e.g., Tensor Processing Units or TPUs) [77]. Thus, Edge Computing, can help reduce the data traffic that moves to the Cloud and the amount of data stored on it, and, most importantly in terms of costs, the computing resources and the data traffic that moves out of the Cloud.

To validate the benefits of the agro-industry platform (i.e., the benefits that come from the Global Edge Computing Architecture on which the platform is deployed), the platform was evaluated in a use case conducted on a mixed dairy farm in Castrillo de la Guareña (Zamora, Spain). The aspect that was considered was the reduced cost of transmitting incoming (from IoT devices or Edge nodes to Cloud) and outgoing (from Cloud to the IoT devices or Edge nodes) data. The first experiment was divided into

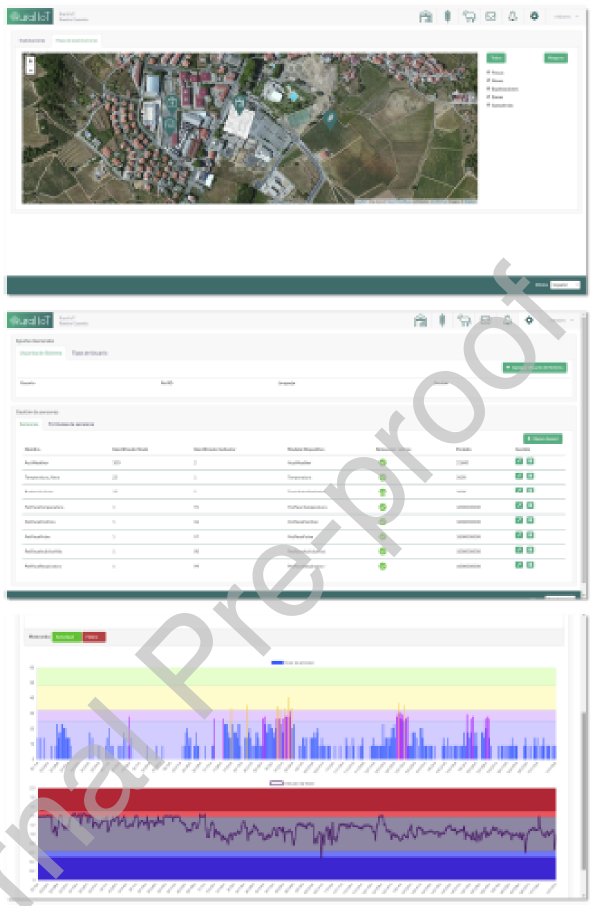

Figure 11: Screenshots of the dairy cow monitoring application on the agro-industry platform running on the Business Solution layer.

two one-month (30 calendar days each one) stages, performed in different time periods. The first test started on September 1st 2018 and finished on September 30th 2018, and the second test started on October 8th 2018 and finished on November 6th 2018.

The first stage of the test was in fact a baseline period with no Edge Layer present, just the IoT (IoT devices and IoT-Cloud gateway) and Business Solution Layers in the Cloud. The second test was carried out to evaluate and verify the possibility of optimizing the data transmission costs of the same system. For that, the Edge layer was incorporated by means of the full application of the Global Edge Computing Architecture, that is, with IoT Layer, Edge Layer and Business Solution Layer on Cloud, presented and running within the platform. The two tests were subjected to similar conditions in terms of IoT data sources.

In the first test, the amount of data transmitted by the previous version (non-Edge) of the system was measured between the devices at the IoT Layer and the remote Cloud, both uplink traffic (from the devices at the IoT Layer to the remote Cloud) and downlink traffic (from the remote Cloud to the devices at the IoT Layer). This version could not benefit from the features provided by the Edge Layer of the Global Edge Computing Architecture. In the second test, a similar evaluation was carried out to assess the new version (i.e., Edge-based) of the agro-industry platform which included the new Edge Layer and the new Crypto-IoT boards. In this regards, during the second test data transmission was monitored in two links: uplink and downlink traffic between the IoT sensors and the Edge layer (from IoT devices to Edge nodes, and from Edge nodes to IoT devices, respectively) and uplink and downlink traffic between the Edge layer and the Cloud (from Edge nodes to remote Cloud, and from remote Cloud to Edge nodes, respectively).

On the one hand, the platform deployed and running in the first experiment test was a previous version which did not include the Crypto-IoT boards, the Edge elements (i.e., Raspberry Pi 3 Model B micro-computers running TensorFlow Lite libraries) or blockchain features. In this sense, during the first test, the IoT-Cloud gateways collected the data by means of Wi-Fi and ZigBee and forwarded them directly to the remote Cloud via a radio-based Internet connection without encrypting, filtering or pre-processing them. On the other hand, during the second test, the Crypto-IoT boards and the new Edge devices (i.e., Raspberry Pi 3 Model B micro-computers running TensorFlow Lite libraries) were incorporated, thus following the full features and design rules provided by the Global Edge Computing Architecture.

In both tests, the same number of IoT data sources (described on Table 6) was used. On the one hand, there was 1 Wi-Fi router collecting data from 12 collars for cattle sensitization (body temperature, heart rate, respiration rhythm and activity). Every 5 minutes, each collar sent 4 quantities, one for each of the parameters measured. On the other hand, there was 1 ZigBee collecting node gathering data from the 2 ambient devices in the two barns, as well as the 12 agro-meteorological stations in the associated crops used for feeding cattle. Each one of the 2 nodes in barns (nodes #1 and #2) measured 6 quantities (air temperature, relative humidity and four types of potentially hazardous gases), and sent each of these quantities every 10 minutes. From the 12 agro-meteorological stations, 2 were base stations (nodes #100 and #200, with 8 physical quantities) and the other 10 were satellite stations (measuring 3 physical quantities). Every station sent each of its values every 15 minutes.

The Business Solution Layer of the agro-industry platform was deployed on Google Cloud using the App Engine as PaaS (*Platform as a Service*) to provide the backend of the platform (developed under .NET Core), the Google Cloud SQL to provide the relational database (configuration, users, node setup, etc.), Google Functions as FaaS (*Function as a Service*) to provide the different REST APIs of the platform and Google BigQuery to provide database for storing massive sensor data coming from IoT and Edge Layers. Furthermore, for developing the frontend, HTML5, Bootstrap 4 and Vue.js technologies were utilized.

On the one hand, Figure 12 shows a graphical comparison between the uplink traffic (from IoT devices to Edge nodes, from IoT devices to remote Cloud and from Edge nodes to remote Cloud) in the two one-month tests, non-Edge and Edge-based, respectively. On the other hand, Figure 13 depicts the same comparison between the download traffic (from Edge nodes to IoT devices, from Cloud to IoT nodes and from Cloud to Edge nodes) in the two tests.

Finally, Table 7 shows the total amount of data transferred uplink and downlink during the two one-month tests. The data in the table demonstrate that applying the design of the Global Edge Reference Architecture when building the agro-industry platform and providing it with the Edge Layer allow to reduce the amount of total data transferred to the Cloud in a mixed dairy farming scenario with the same conditions of use and sensitization by a 46.72% (38.86% in uplink and 64.10% in downlink). This reduction may be even greater in other scenarios that take more advantage of the use of filtering and/or pre-processing stages at the Edge Layer.

From the above results, it is clear that an Edge Computing approach can reduce the volume of traffic required to be transmitted the Cloud, either from IoT devices, in the case of the non-Edge version (test 1), or pre-processed and filtered data transmitted from Edge nodes, in the case of the Edge-based version of the platform (test 2). Nonetheless, the introduction of Edge nodes must have, in return, implications for the energy consumption of the devices themselves, which were not previously present, as well as the acquisition and maintenance costs of Edge nodes. Both energy consumption and the acquisition of Edge nodes are easy to quantify, and comparing the advantages between the scenario without Edge nodes and the scenario with

Table 6: IoT nodes deployed in the mixed dairy farming scenario for the two tests.

IoT node	Nodes	Quantities per node	Transmission period per quantity
Livestock			
Collars for livestock sensitization • Body temperature • Heart rate • Respiration rhythm • Activity from accelerometers	15	4	5 minutes
Barn devices			
Ambient sensors in the two barns • Air temperature • Relative humidity • CH_4 (methane) • H_2S (hydrogen sulphide) • NH_3 (ammonia) • CH_2O / H-CHO (formaldehyde)	2	6	10 minutes
Agro-meteo stations			
Base stations • Rain/irrigation • Soil temperature • Soil moisture • Air temperature • Relative humidity • Wind speed and direction • Solar radiation	2	8	15 minutes
Satellite stations • Rain/irrigation • Soil temperature • Soil moisture	10	3	15 minutes

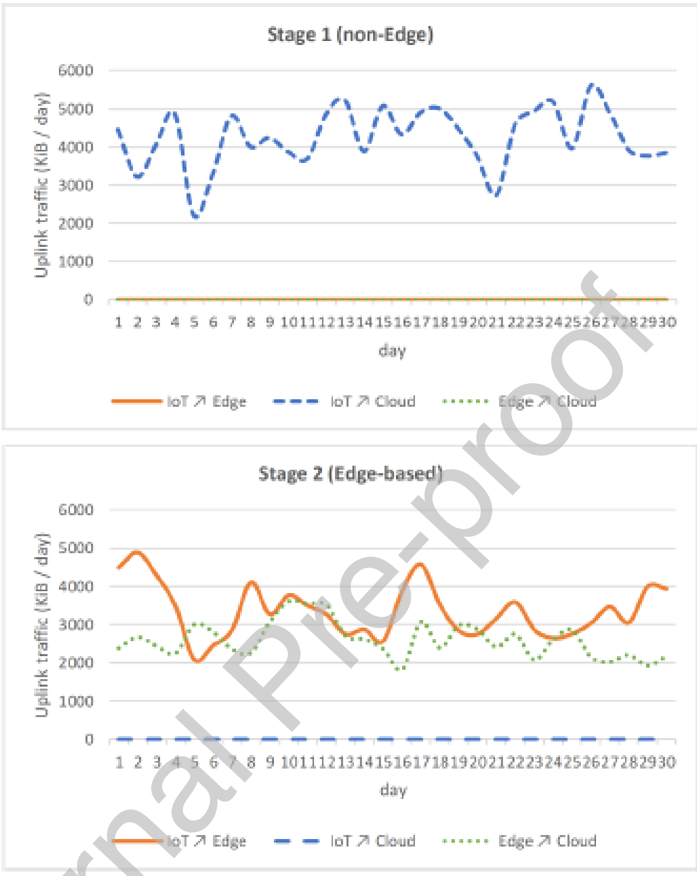

Figure 12: Comparison of the amount of data transferred in the two tests (uplink).

Table 7: Data transferred between the different IoT, Edge and Cloud components during the two tests.

Uplink (↗) / downlink (↙)	Test 1 (non-Edge)	Test 2 (Edge-based)
IoT devices ↗ Edge nodes	0 KiB / month	100,538 KiB / month
IoT devices ↙ Edge nodes	0 KiB / month	34,819 KiB / month
IoT devices ↗ Cloud	127,605 KiB / month	0 KiB / month
IoT devices ↙ Cloud	57,755 KiB / month	0 KiB / month
Edge nodes ↗ Cloud	0 KiB / month	78,020 KiB / month
Edge nodes ↙ Cloud	0 KiB / month	20,733 KiB / month

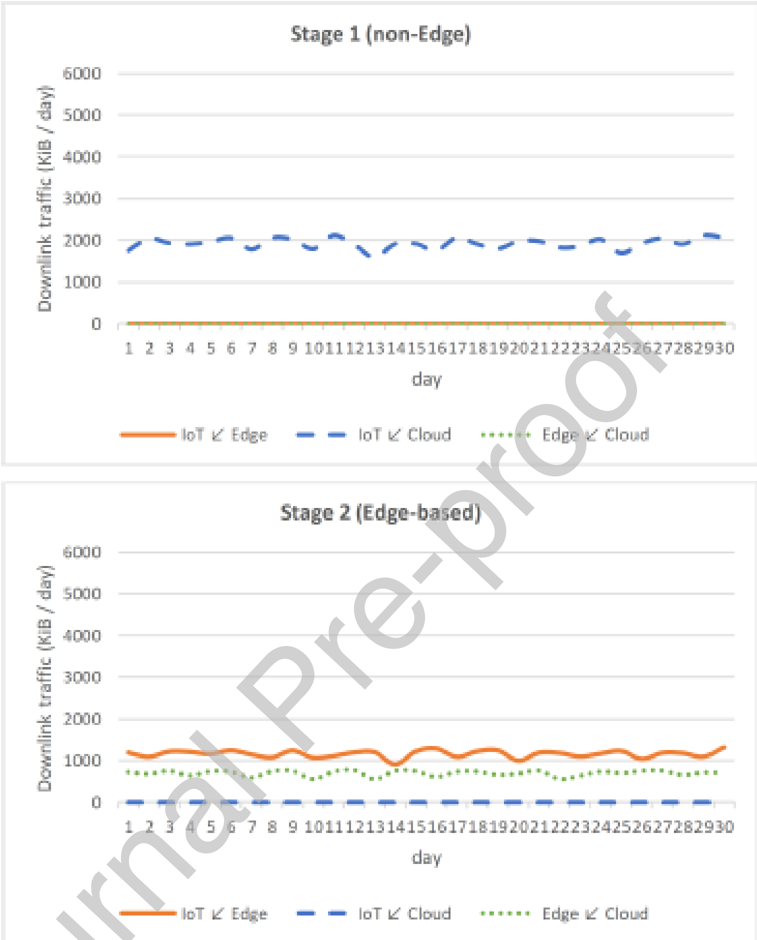

Figure 13: Comparison of the amount of data transferred in the two tests (downlink).

Edge nodes depends on the average life time of the Edge devices, the Cloud provider's costs in both scenarios and the amortization period considered in the acquisition of the devices.

This comparison therefore includes certain parameters that are difficult to measure in the short and medium term (the average lifespan of the devices in the conditions of use of the platform) and others that are influenced by a selection that is sometimes relatively arbitrary or subjective on the part of analysts (the amortization period considered). On the other hand, this type of comparison with the acquisition of Edge computing resources or their rental to service providers in the Cloud has already been carried out by other authors [78].

Therefore, after verifying the advantages of applying an Edge Computing approach provided by the application of the GECA architecture on the SmartDairyTracer platform in terms of reducing the volume of traffic required between IoT/Edge layers to the Cloud, with the consequent reduction in costs associated with the use of computing and storage resources in the Cloud, service logs and resulting database were inspected to learn more about how the new approach affects the performance of the wireless transmission protocols from the IoT nodes, as well as the hypothetical improvement in the reliability of the Edge nodes in their communication with the Cloud.

In this sense, the values of LQI (*Link Quality Indicator*) registered in ZigBee packets transmitted from IoT devices based on this protocol were observed in both tests (i.e., agrometeorological stations and ambient sensors in the barns) and whose value is encapsulated in the application protocol used, in such a way that the original LQI value always reaches the application that parses it. The importance of LQI lies in the fact that it is a value that ZigBee transceivers statistically calculate as a value between 0 and 255 related to PER (*Packet Error Rate*) [79], where a LQI value = 255 (0xff) indicates the optimum signal quality in the medium (i.e., a PER = 0), and a LQI value = 0 (0x00) would indicate the worst signal quality (i.e., a PER = 1).

It is important to note four issues regarding the registered LQI measurements. First, the LQI is measured between the source node (the IoT device in both tests) and the packet destination node (i.e., the collecting node associated to each of the IoT devices according to the Tables 1 and 3). Secondly, it is important to note that PER is related to the number of retransmissions that need to be made in the physical and medium access layers (i.e., PHY and MAC) of the ZigBee network to send a packet, and it depends on the noise in the medium, which will be higher the more packets are sent by more nodes in the network, if the rest of the interference level in the medium is the same (for example, other wireless networks working in 2.4GHz, in this case). However, it also depends on the distance between the source and destination nodes (for large distances even in the absence of noise there is a greater probability of having to retransmit a packet due to the attenuation of the signal). Third, the LQI measurement that comes with each packet does not mean that that particular packet would have to be retransmitted or not, as it is a statistical measure that transceivers calculate over time based on the necessary retransmissions during a time window. Fourthly, although the table 6 tells us how often a packet with a measurement will be sent from each of the nodes, due to retransmissions in the different layers of the ZigBee stack, a packet with information from a sensor may arrive several times at its destination or even never arrive at all, so there may be several LQI measurements for a single measurement expected in time.

Table 8: Comparison between the day-average LQI between each IoT node and its collecting node during the two tests.

Node	**Test 1 (non-Edge)**	**Test 2 (Edge-based)**	Total theoretical packets	Weight
Node #1	190.00	187.83	25,920	0.1184
Node #2	188.60	183.77	25,920	0.1184
Node #3	147.97	145.13	25,920	0.1184
Node #4	152.10	143.17	25,920	0.1184
Node #100	113.00	108.27	23,040	0.1053
Node #101	110.30	95.17	8,640	0.0395
Node #102	133.80	117.30	8,640	0.0395
Node #103	128.73	119.80	8,640	0.0395
Node #104	131.17	125.00	8,640	0.0395
Node #105	137.13	140.67	8,640	0.0395
Node #200	98.57	92.10	23,040	0.1053
Node #201	183.97	172.43	8,640	0.0395
Node #202	182.63	175.10	8,640	0.0395
Node #203	169.17	158.53	8,640	0.0395
Average	149.10	142.82		
Total			218,880	1.0000

As can be seen in the Table 8, there is a weighted average decrease of 4.21% in the value of the LQI in test 2 with respect to test 1. A priori it might seem that there is no noticeable difference in this sense between the two scenarios, although this decrease could be due to the fact that the Edge nodes have a greater computational load at the time of attending the received packets with respect to the IoT-Cloud gateways, which only forward packets without further processing on them. In any case, the computational capacity of the Edge nodes is also higher than the IoT-Cloud gateways, so the results are not considered conclusive.

Furthermore, in order to estimate the possible improvement in the reliability of communications between the Edge/IoT layers and the Cloud, the number of failed insertions in the Big Data in the Cloud was observed. In other words, the number of data from IoT sensors expected to be received

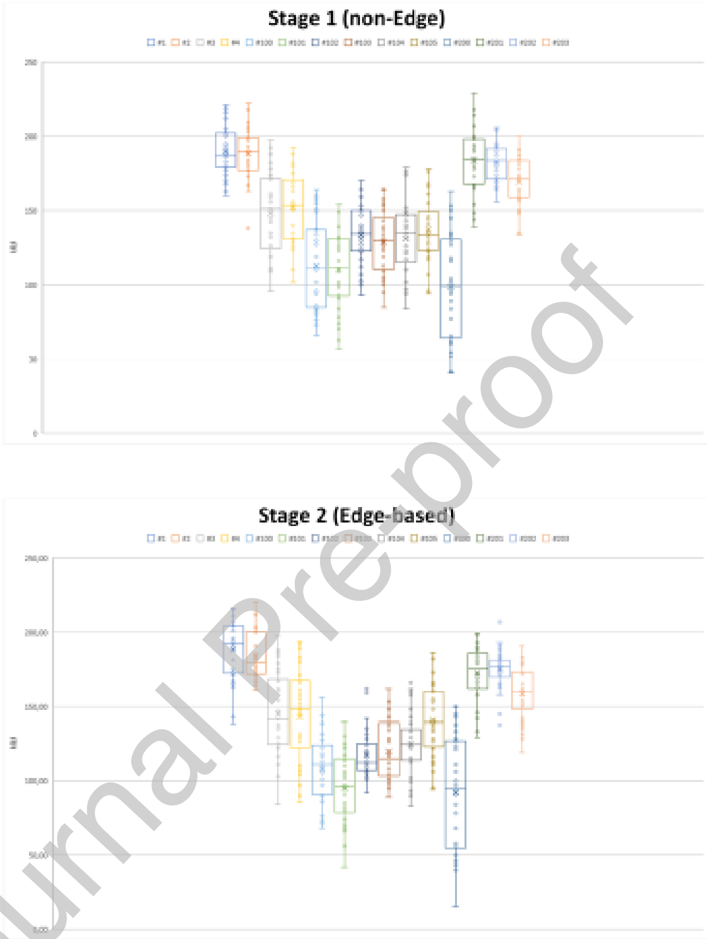

Figure 14: Comparison of the LQI between the ZigBee IoT nodes and its associated collecting node in the two tests.

(23,424 insertions per day, according to the data in the Table 6) and which were not finally present in the database (Big Query in Google Cloud). It is important to note that the data may be missing for several reasons: an error in the transmission from the original IoT device, an error in the collecting nodes when retransmitting the data or an error in the devices that forward the data to the Cloud (the IoT-Cloud gateway in the first test or the Edge node in the second test).

In the first test, moreover, an absence can come from a specific error in the communication or in the availability of the service in the Cloud (timeout) when the data is sent from the IoT-Cloud gateway. This type of error cannot occur in test 2, since the service running on the Edge node has a mechanism to retransmit later measurements that do not reach the Cloud (even if the Edge node is restarted, since these readings are stored in the persistent local memory of the Edge node). This mechanism does not exist in the IoT-Cloud gateway, since this device is only capable of forwarding packets through a data tunnel over TCP/IP to the Cloud. For the same reason, it is not possible to have a log file in the IoT-Cloud gateway that would allow differentiating which data reached the IoT-Cloud gateway correctly from the IoT devices, but did not reach the Cloud correctly due to some problem in the communication with Big Query.

As can be seen in the figure 15, the number of absences in the database is much lower in the case of test 2 than in the case of test 1. In the case of test 1 (non-Edge) the total number of absences in the database during the 30 days is 756 lost values, representing a loss of 0.01076% of the total expected values in the database. In the case of test 2 (Edge-based) the total number of absences is 350 lost values, representing a loss of 0.00498% of the values in the database. That is, by incorporating the Edge nodes, a 53.71% decrease in the total number of missing values in the database is achieved.

5. Conclusions and Future Work

5.1. Conclusions

Globalization has facilitated global trade with agricultural outputs. Farmers and stockbreeders must make themselves stand out by providing their consumers with high-quality products, information about the origin of the product and the processes it has gone through in the value chain, until it reaches the retail location. To this end, the agri-food industry must implement technologies such as the Internet of Things and Distributed Ledger Technologies, such as Blockchain, which offer monitoring and traceability features.

For this to be possible, it is necessary to facilitate the access to those technologies for farmers and stockbreeders. In this regard, the Edge Computing paradigm makes it possible to reduce the costs associated with computing, storage and network resources in the Cloud, through the implementation of services in low-cost Edge nodes, such as microcomputers like Raspberry Pi

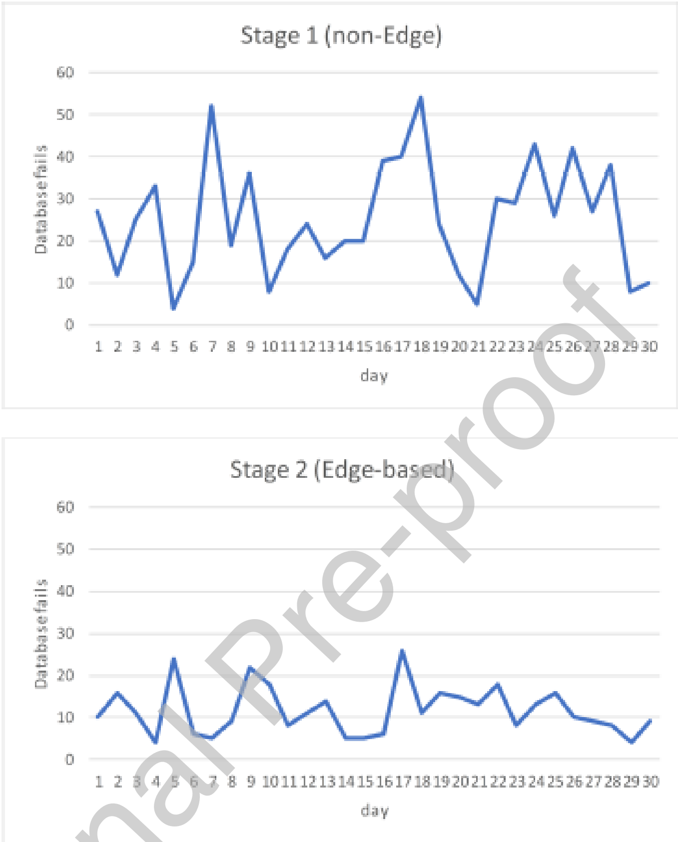

Figure 15: Comparison of the number of absences in the database in the two tests.

3 Model B and similar, through which it is even possible to use Machine Learning algorithms in the same Edge using TensorFlow Lite libraries.

In this work, it has been demonstrated that it is possible to reduce the costs associated with the transfer of data between the IoT and the remote Cloud by introducing design rules coming from a reference architecture, such as the Global Edge Computing Architecture in an agro-industry platform aimed at monitoring, traceability and optimization of resources and processes carried out in the value chain in a mixed dairy scenario. Moreover, the introduction of Edge nodes improves the reliability of communications to the Cloud by means of a reduction in the number of missing values in the database in the cloud.

The Edge nodes of the Global Edge Computing Architecture filter and pre-process data coming from devices in the IoT layer. Moreover, they are responsible for discarding the values that have been repeated due to the retransmission of frames from the physical sublayers (ZigBee, Wi-Fi) to the IoT layer. They can also perform averages and regression data analysis which takes place in the same Edge. In both cases, the amount of data and the cost of its transmission that is transmitted to the Cloud is reduced, reducing the costs of data traffic, as well as the need for calculation and storage in the Cloud.

Furthermore, at a qualitative level, the new version of the agro-industry platform benefits in terms of security, traceability and data integrity, due to the characteristics provided by the elements associated with the Distributed Ledger Technologies of the Global Edge Computing Architecture, including the blockchain itself and the Crypto-IoT boards and oracles. In addition, thanks to Edge elements, users can access accumulated data from IoT sensors from the last 30 days, as well as averages, trends and alert levels detected in the data patterns, even if the connection to the Cloud is interrupted.

5.2. Future Work

Future work principally involves the implementation of the platform on not one but on several dairy farms in the same region. In this extended scenario, the platform will be equipped with innovative consensus algorithms under research, designed to detect stress or potential health problems in cows, through the measurement of different parameters (ranging from bio-metric sensors to environmental sensors). These experiments will be conducted simultaneously on multiple farms where Machine Learning techniques will be applied to learn about the different conditions in which cows suffer stress or illnesses that affect productivity.

Moreover, authors will complete the development of the SmartDairyTracer platform which will give the agri-food industry and all those involved in it, such as farmers and stockbreeders, an opportunity to foster loyalty and gain new consumers. The IoT devices and methodologies used by the SmartDairyTracer platform will make it an innovative product in agriculture where all processes in the dairy chain are monitored and shown to the consumer, from the feed grain and livestock to the product packaging and the transportation until the consumer.

Thus, the platform will provide transparency; the quality of the product and the processes that the product has gone through will be made known to the user. The SmartDairyTracer platform will use public and distributed databases (i.e., Distributed Ledger Technologies) to guarantee data persistence and integrity, and avoid data alteration or corruption. Consumers will be able to access and analyze all the data regarding the goods for sale. IoT devices will be included in the platform by means of compatible open-source and open-standard hardware, at an affordable price.

All these features will contribute to the development of a better solution. Moreover, they will be a source of continuous feedback at all stages of pilot deployment, making it possible to enhance the accuracy of the SmartDairyTracer platform. This will result in a powerful tool that will increase the competitiveness of the whole value chain, providing a reliable source of information for consumers and supporting them in their decisions.

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Declaration of Competing Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript.

Biography

Ricardo S. Alonso is a Telecommunications Engineer from the University of Valladolid (Spain), Master's Degree in Intelligent Systems from the University of Salamanca (Spain) and is currently developing his PhD in Computer Engineering at the University of Salamanca. He is currently working as a researcher in the BISITE Research Group (Bioinformatics, Intelligent Systems and Educational Technology) at the University of Salamanca. He is also a collaborating professor in the Master in Big Data and Visual Analytics at the International University of La Rioja (Spain). He has published more than 10 research articles in international journals and more than 30 in international conferences. His main research and development interests include Internet of Things technologies, Edge Computing, Embedded Systems, Indoor Location Systems, Cloud Computing and Artificial Intelligence.

Inés Sittón-Candanedo earned a degree in Computer Systems Engineer from the University Latina of Panama and a Master's in Technologies and Information Systems from the UNACHI - University of Chiriquí, Panama. She is currently working on her Ph.D. in Computer Engineering as a member of the BISITE research group. As a researcher, her interests are focused on Internet of Things, Industry 4.0, Edge Computing, blockchain and other fields.

Óscar García was awarded his PhD in Computer Science and the Extraordinary Performance Award for Doctorate Studies from the University of Salamanca in 2017. He also holds the Telecommunication Engineer degree from the University of Valladolid since 2016. Throughout his career, Dr García has collaborated with private and public research entities, including the University of Valladolid and the University of Salamanca, and he currently collaborates with the BISITE research group. Óscar also serves as Lecturer in the Master Big Data and Visual Analytics and the Master Industry 4.0 at the UNIR. He has published more than 30 papers in international journals, books and conferences, participated in more than 10 research projects, and been author of four Spanish patents. His research interests include Data Analytics, Machine Learning, IoT and Artificial Intelligence focused on energy efficiency, smart cities and smart farming.

Javier Prieto holds a PhD in Information Technology and Telecommunications from the University of Valladolid since 2012 and an Extraordinary Doctorate Award. At the same University he obtained his degree in Telecommunication Engineering (2008) and his degree in Market Research and Techniques (2010). Since 2007, Javier Prieto has worked in different public and private research centers, including the University of Valladolid or the Massachusetts Institute of Technology. He is currently a distinguished researcher in the BISITE group at the University of Salamanca. He has published more than 50 articles in international journals, books and conferences, has participated in more than 35 research projects, and is the author of 2 national patents. His research interests include social computing and artificial intelligence, to create smarter and safer cities and industries, location and navigation technologies, to guide in both indoor and outdoor environments, Bayesian inference techniques, to improve social welfare and sustainable development, as well as Blockchain technologies for automation and safety of everyday processes.

Sara Rodríguez-González received a Ph.D. in Computer Science from the University of Salamanca in 2010. She pursued her studies of Ph.D. in this University. She obtained a Technical Engineering in Systems Computer Sciences degree in 2004, an Engineering in Computer Sciences degree in 2007 at the University of Salamanca. She is Associate Professor at the University of Salamanca and researcher at the BISITE research group (http://bisite.usal.es). She has participated as a coauthor in papers published in recognized international conferences and symposiums.