IoT-Based Environmental Monitoring System for Heat Stress Assessment in Livestock

Henrique Piscioneri Octaviano - 61450

Dissertation presented to the School of Technology and Management of Bragança to obtain the Master Degree in Electrical and Computers Engineering, in the scope of the double diploma programme with the Federal University of Technology - Paraná.

Work oriented by:

Prof. Paulo Leitão

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Dedication

I dedicate this work to all those who supported me throughout its development, especially my family who gave me the opportunity to complete my studies in another country.

Acknowledgement

I want to express my gratitude to all those who participated in my journey.

Firstly, to my family who supported me throughout this period and also my friends who accompanied me throughout the journey. I would also like to thank my teachers for all the support provided during the development of this work.

Finally, I am grateful to have studied at UTFPR and IPB, two institutions that provided me with knowledge and diverse experiences. Thank you all.

Abstract

This thesis presents the development and evaluation of a low-cost Internet of Things (IoT) system for monitoring environmental parameters related to heat stress in indoor livestock facilities. Commercial solutions are often costly and inflexible, limiting adoption on small and medium-sized farms.

To address this gap, this work proposes an integrated system using affordable IoT technologies structured in three layers: a sensor layer with fixed and mobile nodes, a service layer using Node-RED and InfluxDB, and an interface layer with Grafana dashboards. The system includes grid-powered nodes, battery-powered nodes achieving 23 days of autonomy, and a prototype collar node with LoRa communication. It successfully integrates temperature, humidity, black globe measurements, and external weather data to calculate thermal comfort indices (THI and THIadj) in real-time.

Experimental results demonstrated reliable data acquisition, visualization, and alerting capabilities. This research contributes a scalable, cost-effective solution for livestock environmental monitoring applicable to various facility sizes. Future work includes finalizing the LoRa collar prototype, field testing, expanding sensor integration, and implementing AI-based predictive analytics.

Keywords: Internet of Things, Environmental Monitoring, Heat Stress, Livestock, THI, LoRa, MQTT

Resumo

Esta tese apresenta o desenvolvimento e a avaliação de um sistema de Internet das Coisas (IoT) de baixo custo para monitoramento ambiental relacionado ao estresse térmico em instalações pecuárias internas. Soluções comerciais são frequentemente caras e pouco flexíveis, dificultando a adoção em propriedades de pequeno e médio porte. Para superar essa limitação, propõe-se um sistema integrado baseado em tecnologias acessíveis, com arquitetura composta por três camadas: sensores fixos e móveis, processamento e armazenamento de dados (Node-RED e InfluxDB), e visualização por meio de dashboards Grafana.

Três tipos de dispositivos foram desenvolvidos: um alimentado por rede elétrica, outro por bateria (com autonomia de 23 dias) e um protótipo de colar com comunicação LoRa. O sistema integra sensores de temperatura, umidade e globo negro, além de dados meteorológicos externos (IPB/IPMA), permitindo o cálculo dos índices THI e THIajustado em tempo real. Os testes demonstraram aquisição de dados confiável, visualização eficiente e alertas automatizados.

A solução proposta é modular, escalável e de baixo custo, adequada a diferentes ambientes produtivos. Como trabalhos futuros, destacam-se a finalização do colar LoRa, testes em campo, adição de novos sensores e aplicação de inteligência artificial para análises preditivas.

Palavras-chave: Internet das Coisas, Monitoramento Ambiental, Estresse Térmico, Pecuária, THI, LoRa, MQTT

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Acronyms And Variables

AI Artificial Intelligence.

API Application Programming Interface.

BGHI Black Globe-Humidity Index.

CBPB Compost-Bedded Pack Barns.

CO2 Carbon Dioxide.

CSS Chirp Spread Spectrum.

DC Direct Current.

ESA Escola Superior Agrária.

FR Functional Requirement.

InfluxDB Influx Database.

IoT Internet of Things.

IPB Instituto Politécnico de Bragança.

IPMA Instituto Português do Mar e da Atmosfera.

LoRa Long Range.

LoRaWAN Long Range Wide Area Network.

LPWAN Low-Power Wide-Area Network.

mA Milliampere.

MQTT Message Queuing Telemetry Transport.

NB-IoT Narrowband Internet of Things.

NEB Negative Energy Balance.

NFR Non-Functional Requirement.

PLA Polylactic Acid.

QoS Quality of Service.

Tg Globe Temperature.

THI Temperature-Humidity Index.

Chapter 1

Introduction

Modern animal production faces increasing challenges to simultaneously ensure productive efficiency, animal welfare, and environmental sustainability. In intensive production systems, particularly in indoor environments, controlling environmental conditions is crucial to mitigate stress that can negatively impact animal health, behavior, and performance. According to Das R et al. [1] heat stress can affect the health of dairy animals (directly or indirectly) in the following four areas:

- Physiology;
- Metabolism;
- Hormonal;
- Immunity System;

These effects can occur when temperature and humidity are outside the species-specific thermoneutral zone. Such problems represent a significant concern for the health and production of these animals. Furthermore, in response to heat stress, dairy cows reduce food intake that is directly associated with Negative Energy Balance (NEB), which is largely responsible for decreased milk synthesis [1].

Continuous and accurate monitoring of the environmental conditions to which animals are exposed is therefore essential for the early detection of risk situations, allowing the implementation of management and environmental control strategies (ventilation, cooling, heating) in a timely and effective manner. Some solutions for continuous and accurate indoor monitoring of the conditions to which a group of animals are exposed already exist, but these solutions can be often expensive and not very versatile [2].

1.1 Justification

In this context, due to the rise of technologies associated with Internet of Things (IoT), this solution emerges as a promising approach to the acquisition and monitoring of environmental data to which animals are exposed [3]. The availability of low-cost microcontrollers with integrated connectivity (such as ESP-32), a range of affordable sensors, and flexible cloud platforms allows the development of customized and versatile monitoring solutions [4], adapted to the specific needs of indoor animal production, with a focus on reducing the cost barrier. This dissertation falls within this domain, proposing the development and evaluation of a low-cost IoT-based system for the collection, transmission, storage, and visualization of data relevant to the prediction of heat stress in indoor production animals.

1.2 Problem Statement

Despite the recognized importance of environmental and animal monitoring for heat stress management, the implementation of effective systems on a large scale still faces significant barriers, mainly related to the cost and complexity of commercially available solutions. Many precision monitoring systems are expensive, making their adoption prohibitive for many producers, especially small and medium-sized farms [5]. Furthermore, the integration of different sensors and platforms can be complex and requires specialized technical knowledge for installation and maintenance [6]. Specifically for indoor environments, where microclimate management is more controllable but also more critical due to animal density, there is a need for monitoring systems that are affordable, reliable, versatile and easy to implement. Such systems should be able to collect key environmental data, such as air temperature, relative humidity and, ideally, radiant heat load indicators [6].

Additionally, the exploration of technologies to monitor indicators directly on the animal, even if at the prototype stage, may pave the way for future solutions that allow a more individualized assessment of heat stress, considering the variability between animals and their specific location within the controlled environment [7]. The combination of environmental and animal data has the potential to significantly help any heat stress prediction models to give a more reliable answer [8].

1.3 Objectives

The overall objective of this dissertation is to develop and evaluate a complete system, from data acquisition to visualization, focused on monitoring parameters associated with heat stress in indoor production animals, with emphasis on the use of low-cost IoT technologies and the versatility of the solution. To achieve this overall objective, the following specific objectives were defined:

- Design and implement low-cost fixed sensor nodes for continuous environmental monitoring;
- Develop a prototype of a mobile sensor node for monitoring surface temperature, location, and movement of animals using LoRa communication technology;
- Design and deploy an architecture to receive, process, store, and visualize the collected data;
- Integrate external data sources, including real-time climate data from the Instituto Politécnico de Bragança (IPB) weather station and Instituto Português do Mar e da Atmosfera (IPMA) forecasts via Application Programming Interface (API);
- Configure interactive dashboards and automated alerts in Grafana for real-time monitoring and decision support.

1.4 Thesis Structure

This dissertation is organized as follows:

- **Chapter 1: Introduction** - presents the context of heat stress in livestock production, the justification for developing a low-cost IoT monitoring system, the problem statement, and the specific objectives that guided this research.
- **Chapter 2: State of Art** - reviews the relevant literature on IoT applications in agriculture and animal health monitoring, technologies for environmental monitoring (including LoRa, MQTT, InfluxDB, and Grafana), current challenges, and identifies gaps that this research addresses.
- **Chapter 3: Methodology** - describes the research methodology, including system requirements (functional and non-functional), the established IoT architecture with its three layers (sensor, service, and interface), and details of the system installation process.
- **Chapter 4: Development** - details the development and implementation of the system components, including hardware specifications, LoRa communication setup, data integration through Node-RED, storage in InfluxDB, and visualization dashboards in Grafana.
- **Chapter 5: Tests and Results** - presents the results achieved from testing, including data acquisition and visualization performance, black globe temperature tests, thermal comfort index calculations (THI and THIadj), and battery autonomy tests for mobile nodes.
- **Chapter 6: Conclusion and Future Work** - summarizes the main findings and contributions of the research, and suggests directions for future work to enhance the system's capabilities.

Chapter 2

State of Art

The adoption of IoT solutions has increased significantly in recent years due to their versatility and adaptability across diverse applications. These applications can be used in multiple sectors including Smart Home, healthcare, Industrial Automation, Smart Cities, Agriculture, Energy Management, Environmental Monitoring, and Safety and Security systems [9]. Figure **??** gives an overview of the areas that are using this technology the most, with a trend for the coming years.

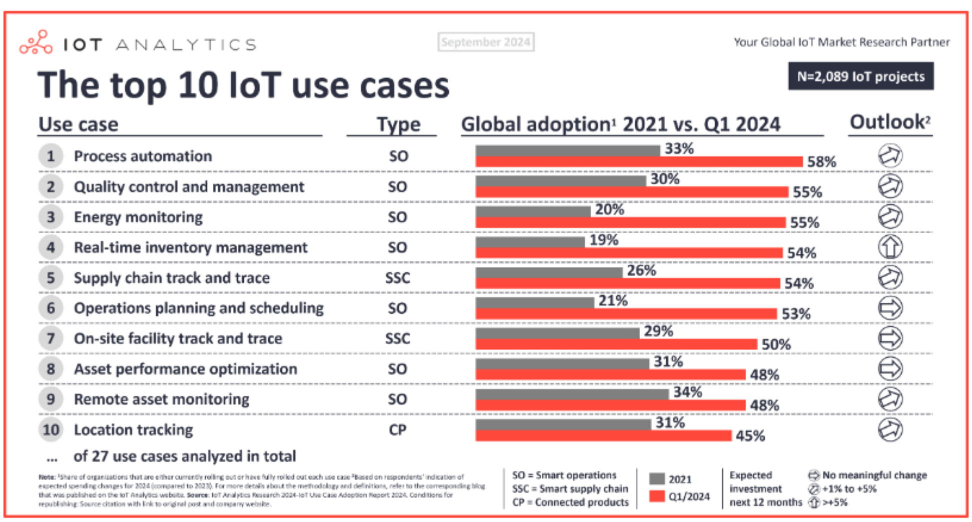

Figure 2.1: Top 10 IoT use Cases 2024 [10].

In IoT applications, the system architecture is commonly structured into several layers, each with distinct responsibilities. These typically are the device layer, network layer, service layer, and interface layer [11][12].

- **Device Layer:** Comprises sensors, actuators, physical components, and communication hardware. These elements enable interaction with the physical environment and are often referred to as nodes.
- **Network Layer:** Ensures reliable and scalable transmission of data between devices and central systems, typically via protocols suited for low power and constrained environments.
- **Service Layer:** Responsible for data processing, storage, and the application of business logic. This layer includes platforms that enable real-time analytics and system management.
- **Interface Layer:** Acts as the point of interaction for end users, providing dashboards, applications, or APIs that visualize or enable control over the IoT system.

Together, these layers facilitate the collection of data from the physical world, transmission over communication networks, data processing and analysis, and visualization of results through interfaces and dashboards. Figure 2.2 illustrates a layered IoT architecture with representative components at each level.

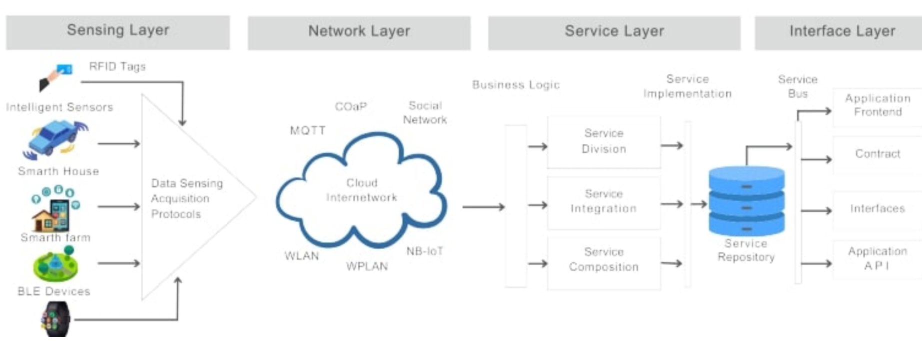

Figure 2.2: Architectural Layers of IoT [13].

This chapter presents a comprehensive review of current research and technological developments related to IoT systems in agriculture, with a focus on animal health monitoring.

- **Section 2.1** explores the applications and benefits of IoT in agricultural contexts, particularly in livestock.

- **Section 2.2** discusses the core technologies used for environmental data acquisition, transmission, and visualization, highlighting the roles of protocols like Long Range Wide Area Network (LoRaWAN) and Message Queuing Telemetry Transport (MQTT), as well as tools like Influx Database (InfluxDB) and Grafana.

- **Section 2.3** addresses the primary challenges faced by IoT deployments in agricultural settings, including sensor calibration, network reliability, and energy consumption.

- **Section 2.4** identifies gaps in the existing literature and outlines how this work contributes to affordable, modular and scalable monitoring solutions, particularly for small and medium-sized farms.

2.1 IoT in Agriculture and Animal Health Monitoring

The integration of IoT technologies into agriculture has transformed traditional farming practices by enabling automated, data-driven approaches to livestock and environmental monitoring. Through the deployment of interconnected sensors and devices, farmers can collect and transmit real-time data related to animal behavior, physiological parameters, and environmental variables such as temperature, humidity, air quality, and radiation levels. This data-driven paradigm is especially impactful in indoor livestock farming, where maintaining optimal environmental conditions is crucial for animal welfare and productivity [13] [11].

The application of IoT technologies for thermal stress monitoring in livestock represents a particularly valuable use case within agricultural IoT systems. These systems can provide early detection of conditions that may lead to heat stress, being especially critical in indoor production environments where microclimate management directly impacts animal welfare and productivity. The integration of real-time monitoring with predictive analytics offers producers the opportunity to implement timely interventions before animals experience significant physiological stress, potentially improving both welfare outcomes and economic performance. A typical architecture used in agricultural IoT systems is shown in Figure 2.3, which highlights key layers and their roles.

In addition to that, the growing availability of low-power wireless communication protocols and technologies (e.g. Long Range (LoRa))), along with efficient messaging protocols such as MQTT, and advanced cloud-based platforms, has made it feasible to deploy cost-effective and scalable monitoring systems even in remote or resource-constrained areas, thus improving overall management.

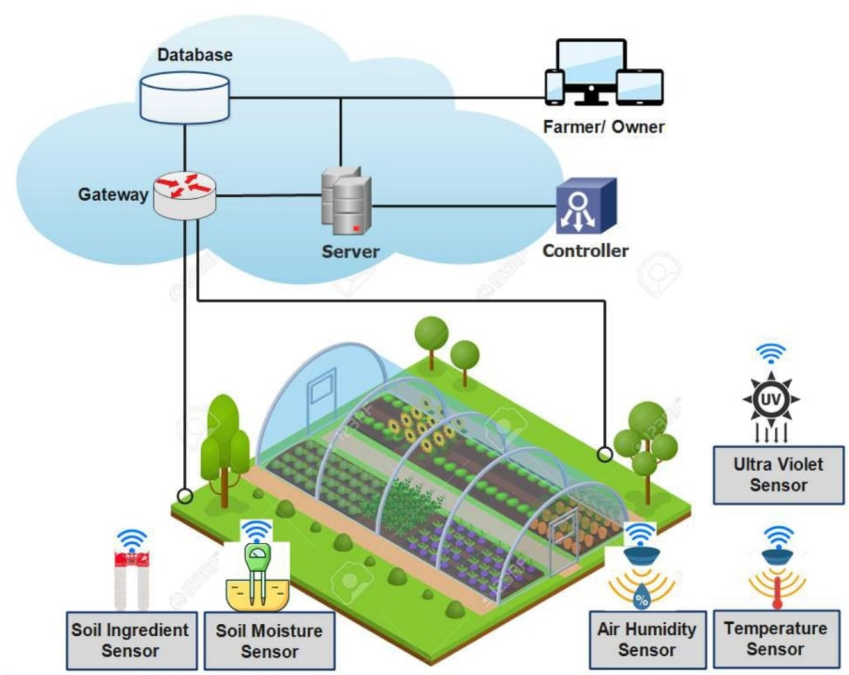

Figure 2.3: Typical architecture of IoT in agriculture, illustrating device, communication, cloud, and interface layers [14].

Recent studies have demonstrated the efficacy of IoT in mitigating environmental stressors such as heat stress in livestock. For instance, Sharma et al. [15] explored non-invasive methods to monitor livestock health using IoT devices, highlighting the importance of accurate data collection in preventing heat-related illnesses. Similarly, Sadeghiniaraki et al. [16] discussed the impact of environmental factors on animal welfare and the role of IoT in monitoring these parameters.

In dairy cattle, Fournel et al. [17] deployed sensor networks to monitor Temperature-Humidity Index (Temperature-Humidity Index (THI)) in freestall barns, enabling automated ventilation control based on real-time conditions. For poultry production, Corkery et al. [18] developed an IoT system that monitors not only environmental parameters but also bird behavior through camera systems, creating a comprehensive approach to heat stress management in broiler houses.

In swine production, Zhang et al. [19] demonstrated the effectiveness of a sensor network that accounts for vertical temperature stratification within confined housing, addressing the unique challenges of maintaining thermal comfort for pigs at different stages of life.

Oliveira et al. [20] conducted a systematic review comparing the health and thermal comfort of dairy cattle housed in compost-bedded pack barns (Compost-Bedded Pack Barns (CBPB)) and other common housing systems. Their findings highlight that CBPB systems, when combined with environmental monitoring technologies, significantly improve thermal comfort, hygiene, and overall animal welfare.

These studies reinforce the growing relevance of IoT approaches in livestock management to improve health outcomes and production efficiency under varying climatic conditions. Furthermore, these species-specific applications highlight the versatility of IoT technologies in addressing particular thermal regulation needs of different livestock with precision environmental control and continuous data acquisition.

2.2 Technologies for Environmental Monitoring

This section explores key technologies used for data transmission and visualization in agricultural IoT systems. These technologies play a central role in enabling real-time monitoring, analysis, and decision-making in precision farming.

For comprehensive thermal stress assessment in livestock environments, advanced sensing technologies go beyond basic temperature and humidity measurements. One such example is the black globe thermometer, which measures radiant heat load, a critical component of thermal comfort that conventional sensors often ignore. Modern black globe sensors designed for IoT integration, such as those described by Nascimento et al. [21], provide digital outputs. This allows seamless integration with IoT platforms while maintaining accuracy, offering more complete data for managing livestock environments.

The following subsections highlight three foundational technologies in agricultural IoT: LoRa for long-range communication, MQTT for lightweight data transmission, and the combined use of InfluxDB and Grafana for time-series data storage and visualization.

2.2.1 LoRa Technology

LoRa is a spread spectrum modulation technique derived from Chirp Spread Spectrum (CSS) technology, developed and patented by Semtech. It enables long-range wireless communication, up to 10 km, while maintaining low power consumption, classifying it as a Low-Power Wide-Area Network (LPWAN) technology [22].

LoRa technology has become a cornerstone in agricultural IoT due to its low power requirements and extended communication range. It enables the deployment of sensor networks across large agricultural areas, supporting real-time monitoring even in remote regions with minimal infrastructure [23].

This communication technology is highly scalable, user-friendly, and capable of long-distance transmission [24]. Its ability to penetrate dense physical environments and overcome signal obstructions makes it a versatile and reliable solution, widely adopted in various IoT applications.

In Chile, a LoRa-based platform was developed for remote monitoring of large-scale farms, demonstrating the system's scalability and ability to handle seasonal climate changes [25]. Similarly, LoRaWAN networks in greenhouses have successfully monitored parameters such as temperature, humidity, and Carbon Dioxide (CO2) levels, contributing to better crop management and disease prevention [26].

In Bragança, Araujo et al. [27] designed an IoT system for monitoring sheep and goats in silvopastoral systems. Their work demonstrated the system's adaptability to different terrains and animal conditions, supporting sustainable land use and livestock management.

Other studies, such as those by Petäjäjärvi et al. [28] and Bor et al. [29], evaluated LoRaWAN's performance in rural settings showing that while LoRa generally performs well, careful optimization of node placement and transmission timing is necessary for consistent reliability.

2.2.2 MQTT Communication Protocol

MQTT is a lightweight messaging protocol standardized by OASIS, widely used in IoT applications. It follows the publish/subscribe communication model, in which a device publishes a message to a topic via a broker, and clients subscribed to that topic receive the message. In this model, new publishers and subscribers can be added dynamically, which simplifies the expansion and configuration of the system. Furthermore, this model enables asynchronous communication and decouples the publisher and subscriber, allowing for flexible and scalable architectures a feature that is particularly useful in dynamic agricultural environments [30].

Due to its low overhead, MQTT is ideal for systems with limited resources, such as devices with limited power, processing capacity, or network bandwidth [31]. MQTT supports essential features such as Quality of Service (QoS) levels, providing a balance between message delivery reliability and network efficiency.

MQTT is highly scalable, making it suitable for deployments involving a large number of connected devices. Its flexibility supports a use cases from simple embedded devices to complex distributed IoT systems. Additionally, the protocol supports high message throughput and low latency, both of which are critical for real-time data processing in

IoT applications.

While technologies like LoRa operate on the physical layer, communication protocols such as MQTT play a vital role in data transmission. MQTT is favored in agriculture IoT application due to its lightweight nature, making it ideal for devices with limited processing power [32].

In livestock applications, MQTT can be used to send real-time data from wearable sensors that monitor variables such as body temperature, activity, and heart rate. This enables rapid interventions that improve animal welfare and productivity [33] [34].

2.2.3 InfluxDB and Grafana

Effective data storage and visualization are critical for agricultural monitoring systems. InfluxDB stores large volumes of timestamped data efficiently, while Grafana provides user-friendly dashboards to visualize trends, detect anomalies, and generate alerts. Together, they enable data-driven decision-making in applications such as irrigation control, weather tracking, soil moisture monitoring, and livestock health analysis [35] [36].

InfluxDB's optimization for time-series data ensures faster queries and better compression compared to traditional databases. When properly configured, these tools can transform raw sensor data into actionable insights, even for users with limited technical skills. Custom dashboards tailored to specific agricultural needs can present complex information in a clear and intuitive way, enhancing operational efficiency and promoting precision agriculture practices. For these purposes, InfluxDB, a high-performance timeseries database, and Grafana, a flexible visualization tool, are widely used [37].

2.3 Challenges and Trends in Agricultural IoT

The implementation of IoT systems in agriculture presents several technical and operational challenges that affect both their scalability and long-term viability. While large-scale farms may have the infrastructure and financial capacity to deploy advanced IoT solutions, small and medium-sized farms often face significant economic and technical constraints that hinder adoption [7]. Bridging these challenges is essential to enable a wider use of precision livestock farming technologies.

One of the major limitations is network reliability, particularly in remote or rural agricultural areas where internet infrastructure is limited or inconsistent. Technologies such as LoRa and Narrowband Internet of Things (NB-IoT) have emerged as viable solutions for long-range, low-power communication. These protocols are specifically designed to address connectivity challenges in rural settings; however, their performance can still be influenced by topography, vegetation, and environmental interference [38]. For instance, LoRa stands out for its extremely low power requirements and long communication range, making it particularly suited for resource-constrained environments and scalable deployments.

Power consumption is another critical concern, especially for devices operating in isolated areas and relying on batteries or solar energy. Ongoing research focuses on reducing energy consumption through techniques such as adaptive transmission intervals, energy-efficient microcontrollers, and the use of energy harvesting mechanisms to prolong device autonomy [39], [40]. LoRa also contributes to energy efficiency by minimizing communication-related power usage, aligning well with these energy-saving strategies.

Maintaining the long-term accuracy of environmental and biometric sensors also poses a challenge. Sensor drift, environmental exposure, and mechanical wear can degrade data quality over time. Regular calibration is necessary, but it can be labor-intensive, particularly in distributed systems. To address this, recent research has explored the development of self-calibrating sensors and remote diagnostic tools to monitor sensor health [41]. Additionally, strategic sensor placement helps reduce physical stress and ensures more consistent data quality [42] [13].

Another significant barrier is the lack of standardized data formats and communication protocols across different platforms and manufacturers. This lack of interoperability complicates system integration and limits the scalability of IoT applications in agriculture [43].

In response to these limitations, several emerging technological trends are shaping the evolution of agricultural IoT. One of them is edge computing, which processes data locally, thereby reducing latency and bandwidth usage. This approach enables faster decision-making and system responsiveness without relying heavily on centralized cloud infrastructure [44]. Another significant trend is the integration of artificial intelligence (Artificial Intelligence (AI)) and machine learning techniques within IoT platforms. These enable predictive analytics and real-time diagnostics, enhancing livestock health monitoring, automating environmental control systems, and optimizing decision-making processes [45]. Finally, as IoT deployments generate increasing volumes of time-series data, the use of scalable big data analytics platforms becomes essential. These platforms support long-term planning and precision agriculture by extracting actionable insights, identifying patterns, and enabling anomaly detection [46].

2.4 Gaps in the Literature

Despite advancements in agricultural IoT, several persistent gaps hinder its broader adoption, particularly among small and medium-sized farms. Affordability remains a significant barrier, as many existing solutions are cost-prohibitive and lack the flexibility to adapt to constrained budgets and infrastructure [7]. Additionally, concerns over data security and privacy are also growing, with few lightweight and secure protocols suited to the limitations of low-power IoT hardware [47]. Moreover, the complexity of current platforms often alienates non-technical users, underscoring the need for more intuitive interfaces and comprehensive training strategies [48].

This work seeks to address these specific gaps by proposing a modular, low-cost, and energy-efficient monitoring system tailored to small and medium scale farms. It emphasizes the use of open-source hardware and software to reduce costs, leverages standardized communication technologies such as LoRa and communication protocols such a MQTT for scalability, adopts efficient power management strategies to support long-term remote deployment, and prioritizes ease of use through simplified interfaces to improve user engagement.

Chapter 3

Methodology

This chapter will present the methodology used to achieve the objectives, specifying the functional and non-functional requirements, the technologies, and the architecture of the system elements.

3.1 System Requirements

To achieve the objectives of this work, some system requirements are designed as functional requirements (Functional Requirement (FR)) and non-functional requirements (Non-Functional Requirement (NFR)).

In the context of this work, functional requirements represent the core operations and architecture of the system, while non-functional requirements establish the operational context and limitations under which these functionalities must operate.

3.1.1 Functional Requirements

Functional requirements define what the system should do, specifying the expected behaviors, operations, and services it must provide. These requirements are closely tied to the type of system being developed, its intended users, and the development strategy employed [49].

In order to better identify the functional requirements of this work, the devices and the architecture's FR have been separated into two subsections.

Functional Requirements of the Devices

The functional requirements of the devices focus on data collection and transmission.

- **FR01** – Devices must be able to operate either on batteries or through a direct connection to the power grid.
- **FR02** – Devices must collect and transmit data at intervals not exceeding 15 minutes.
- **FR03** – Devices must collect environmental temperature and humidity data.
- **FR04** – Devices must receive confirmation upon successful data transmission.
- **FR05** – Devices powered by the electrical grid must include memory to store unsent data.
- **FR06** – Battery-powered devices must enter a low-power mode when idle to conserve energy.
- **FR07** – Devices must support communication with Node-RED using the MQTT protocol.

Functional Requirements of the Architecture

The functional requirements of the system architecture involve data processing, alert generation, data storage, visualization, and integration with external platforms.

- **FR08** – The system must send alerts to users based on temperature and humidity readings.
- **FR09** – The system must retrieve weather forecast data from the IPMA API.

- **FR10** – The system must acquire meteorological data from the IPB weather station located at Escola Superior Agrária (ESA).
- **FR11** – The system must preprocess the collected data before storing it in the database.
- **FR12** – The system must store all collected and processed data in a time-series database.
- **FR13** – The system must present collected data through a visual interface.
- **FR14** – The system must retrieve forecast data from the IPMA API for the current day and the following four days.
- **FR15** – The system must retrieve data from the IPB meteorological station at intervals not exceeding six minutes.

3.1.2 Non-Functional Requirements

On the other hand, non-functional requirements refer to constraints and quality attributes that are not directly related to specific system functionalities but are essential for ensuring performance, usability, reliability, and maintainability. They define the project's contextual and operational constraints, specifying some of the technologies and system limitations [49]. As with the functional requirements, these are also divided into device-related and architecture-related categories.

Non-Functional Requirements of the Devices

- **NFR01** – Devices must be capable of transmitting sensor data to Node-RED.
- **NFR02** – Devices must be reconfigurable to support updates and system changes.

Non-Functional Requirements of the Architecture

- **NFR04** – All technologies employed in the system must be open-source.

- **NFR05** – Communication between devices and Node-RED must follow the publish-subscribe pattern.

- **NFR06** – The protocol used to send data to Node-RED must be efficient and suitable for IoT applications.

- **NFR07** – The system architecture must support multitasking to enhance performance.

- **NFR08** – The data visualization platform must be tailored for IoT use cases.

- **NFR09** – Alerts generated by the system must be displayed on the visualization platform.

- **NFR10** – The database must be time-series based to optimize performance for sequential data.

3.2 System Architecture

This section presents the overall architecture of the system, structured into three layers: the sensor layer, the service layer, and the interface layer. Each layer is responsible for specific functionalities, enabling a modular development.

Figure 3.1 shows a summary of the general architecture of the system divided into the following layers:

- **Sensor**;

- **Service**;

- **Interface**;

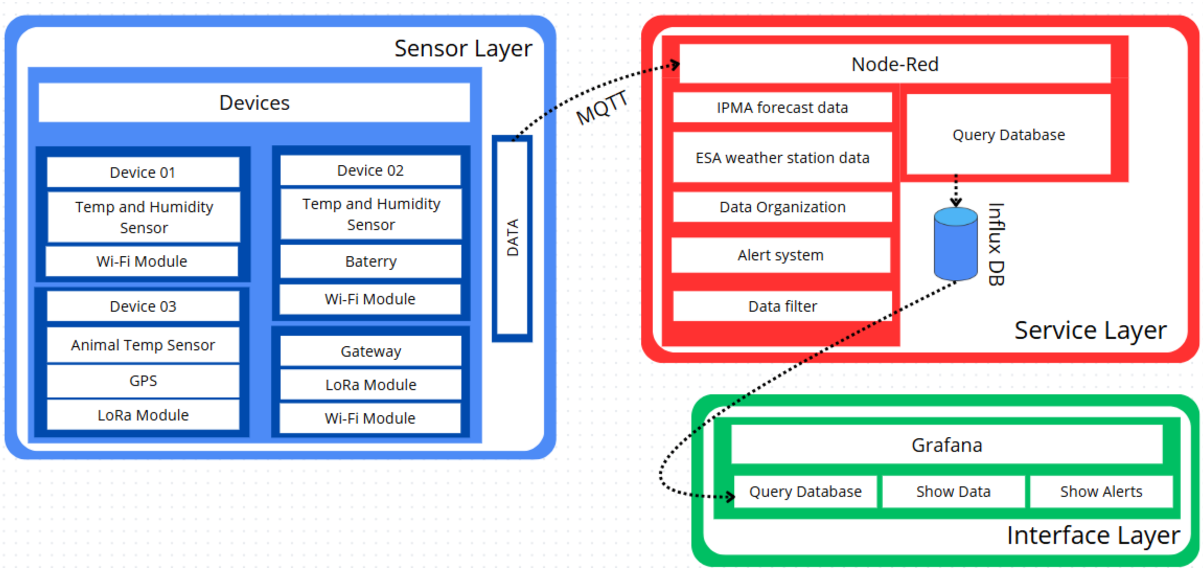

Figure 3.1: Layout of the application

The combination of these layers represents the overall architecture of the system and how the data is managed and delivered to the user who will access the information. Each layer has a specific role within the system architecture, containing a set of crucial functionalities for the system.

This layered design ensures not only modularity but also fault tolerance. By isolating responsibilities within distinct layers, failures or bottlenecks in one component (e.g., a sensor malfunction or database latency) do not compromise the overall system operation. For example, the service layer can temporarily buffer incoming data if the interface layer experiences delays or is temporarily offline. Similarly, the interface layer can still display the most recently stored data even when sensor input is interrupted. This redundancy increases the resilience of the monitoring platform.

By structuring the system into these three layers, the architecture promotes clear functionality boundaries and supports modular development. Each layer can evolve independently, enabling integration of new technologies or features without impacting the entire system.

In the context of heat stress monitoring, each architectural layer plays a vital role in ensuring that actionable environmental insights are reliably generated and presented to stakeholders, including farmers and researchers. Given the physiological impact of thermal discomfort on livestock, a reliable and responsive system architecture is crucial to enabling timely interventions, reducing productivity losses, and ensuring animal welfare.

The detailed description of the implementation of each component, outlining how the designed architecture was realized using specific hardware and software solutions will be presented in Chapter 04.

3.2.1 Sensor Layer

This layer comprises the devices responsible for acquiring environmental data. All devices are equipped with temperature and humidity sensors; some devices also include motion, location, and LoRa communication modules, depending on their deployment context. These devices measure these parameters and transmit then to the **Service Layer**. The design of this layer ensures flexibility, allowing integration of different types of sensors and communication technologies suited to the deployment environment. This modularity supports scalability and adaptability to various use cases.

Additionally, each device was configured to support updates, enabling firmware upgrades. Power consumption was also a key consideration: components were selected based on their energy efficiency, and firmware routines were optimized to enter deep-sleep modes during idle periods. These features extend battery life and support sustainable operation in off-grid environments.

3.2.2 Service Layer

This layer acts as the system's data processing core. It handles incoming data streams by performing tasks such as data filtering, aggregation, alert generation, and storage. This layer is designed to facilitate efficient management of data flows from multiple sensor nodes, providing a centralized point for data integration. It also incorporates mechanisms to interface with external data sources, enhancing the system's overall context with heat stress.

Additionally, by aggregating historical sensor data alongside forecast and weather data from public APIs, the service layer supports a more comprehensive environmental assessment. This hybrid data strategy enhances the contextual relevance of the information displayed to users and lays a solid foundation for future predictive.

3.2.3 Interface Layer

This layer is responsible for presenting processed information to end users. Through interactive dashboards, users can visualize environmental data, monitor system status, and receive alerts. The interface is designed to be user-friendly, offering customization options to focus on relevant parameters and time-frames. This approach supports effective monitoring and timely responses to changing environmental conditions.

The interface was developed using tools optimized for IoT dashboards, emphasizing low-latency data rendering and compatibility across multiple platforms. Special attention was given to accessibility and visual clarity, using intuitive layouts, color coding, and alert markers to highlight critical conditions. This design prioritizes usability by nontechnical users such as farmers, thereby reducing the gap between complex environmental data and real-world decision making.

Chapter 4

Development, Design and Implementation

This chapter details the development, design, and implementation of the environmental monitoring system. It covers the hardware construction, data integration and storage strategies, visualization approaches, and alert mechanisms. These efforts address the key functional requirements **FR08**, **FR09**, **FR10** as well as non-functional requirements **NFR07**, **NFR08**, and **NFR10**.

The established system forms the basis for the analysis and evaluation discussed in Chapter 5.

4.1 IoT Devices

This section provides an overview of the physical components composing the monitoring system in the sensor layer and the system installation. These devices were developed in accordance with the functional and non-functional requirements outlined previously.

Figure 4.1 illustrates the primary hardware modules integrated into the monitoring devices: an ADXL345 accelerometer, a DHT11 temperature and humidity sensor, a Grove GPS Air530 module, the ESP32-WROOM-32E microcontroller, and the TTGO LoRa32 OLED module.

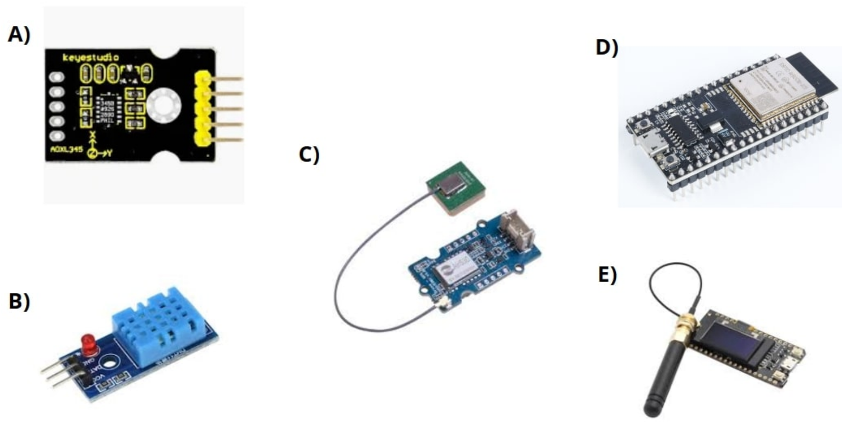

Figure 4.1: Device modules and sensors: (a) ADXL345 accelerometer; (b) DHT11 temperature and humidity sensor; (c) Grove GPS Air530; (d) ESP32-WROOM-32E; (e) TTGO LoRa32 OLED ESP module

4.1.1 Temperature and Humidity IoT Device

This section details the design, implementation, and functionality of the Temperature and Humidity IoT Device. The primary objective of this device is to continuously monitor ambient temperature and relative humidity in indoor environments. Three such devices were developed and deployed to provide comprehensive coverage within the ESTIG laboratories.

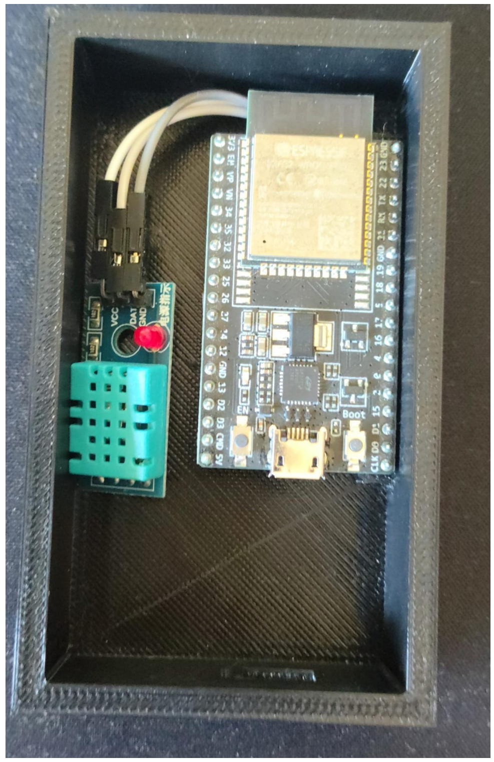

Figure 4.2: Temperature and Humidity IoT Device

Figure 4.2 illustrates the physical implementation of the device. The core components include an ESP32-WROOM-32E microcontroller and a DHT11 temperature and humidity sensor. The ESP32-WROOM-32E serves as the central processing unit, offering integrated Wi-Fi connectivity and sufficient processing power for data acquisition and transmission. The DHT11 sensor is responsible for collecting accurate temperature and humidity readings, providing a humidity accuracy of ±5% RH and temperature accuracy of ±2°C. These components were selected for their reliability, cost-effectiveness, and ease of integration in IoT applications.

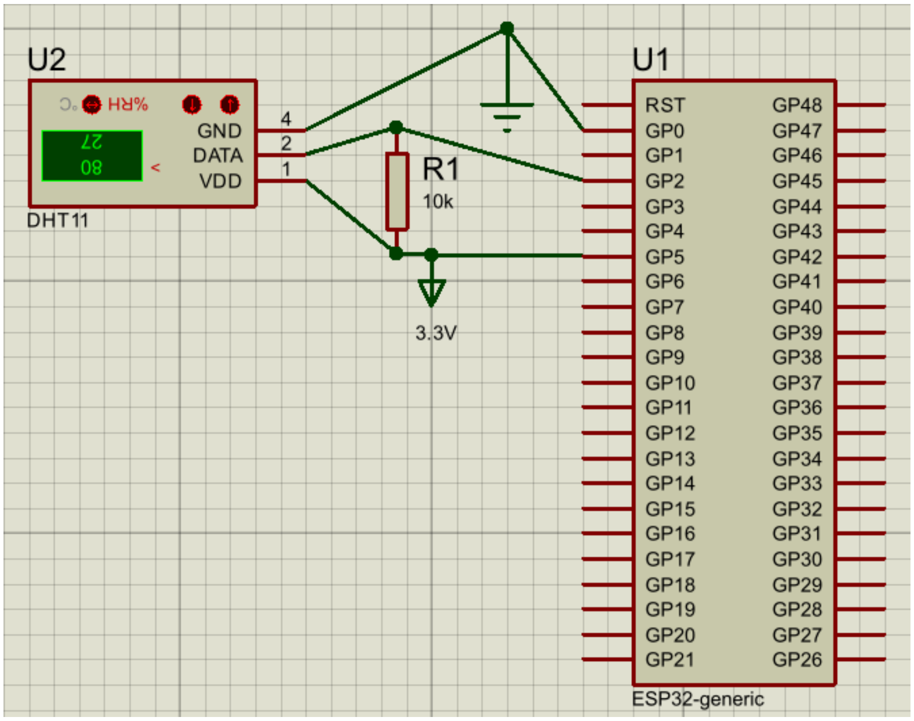

Figure 4.3: Temperature and Humidity IoT Device Electrical Schematic

The electrical schematic in Figure 4.3 shows the connections between the ESP32 and the DHT11 sensor. Data collected by the DHT11 sensor is processed by the ESP32 and transmitted via Wi-Fi using the MQTT protocol. The MQTT protocol was chosen for its lightweight nature and efficiency in IoT environments, ensuring reliable communication between the devices and the central computational application. The devices are powered directly from the electrical grid, ensuring continuous operation without the need for battery management. The main data collected by these devices are temperature and relative humidity. These devices were installed in the ESTIG laboratories to monitor the environmental conditions within the facility.

4.1.2 Temperature, Humidity, Black Globe Thermometer IoT Device

This section describes the Temperature, Humidity, and Black Globe Thermometer IoT Device, designed for comprehensive environmental monitoring, including radiant heat.

One such device was developed and installed at ESTIG.

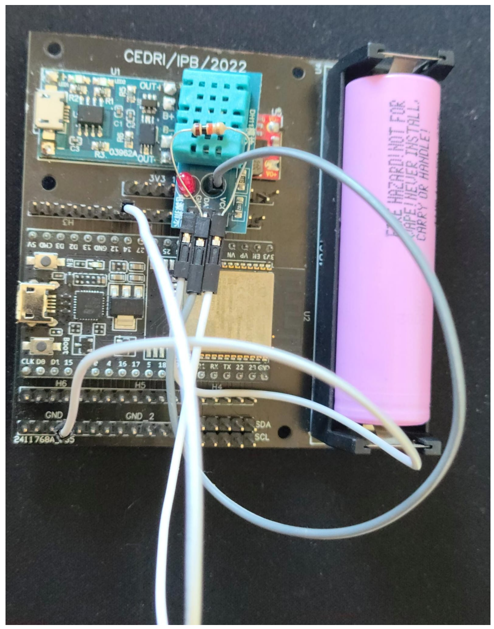

Figure 4.4: Temperature, Humidity, Black Globe Thermometer IoT Device

Figure 4.4 displays the physical implementation of this device. It integrates an ESP32-WROOM-32E microcontroller, a DHT11 temperature and humidity sensor, and a custom-built black globe thermometer. The ESP32 handles data acquisition and transmission, leveraging its integrated Wi-Fi capabilities. The DHT11 provides accurate ambient temperature and humidity readings. The black globe thermometer, housed in a 3D-printed sphere, measures radiant heat, which is crucial for calculating thermal comfort indices like WBGT.

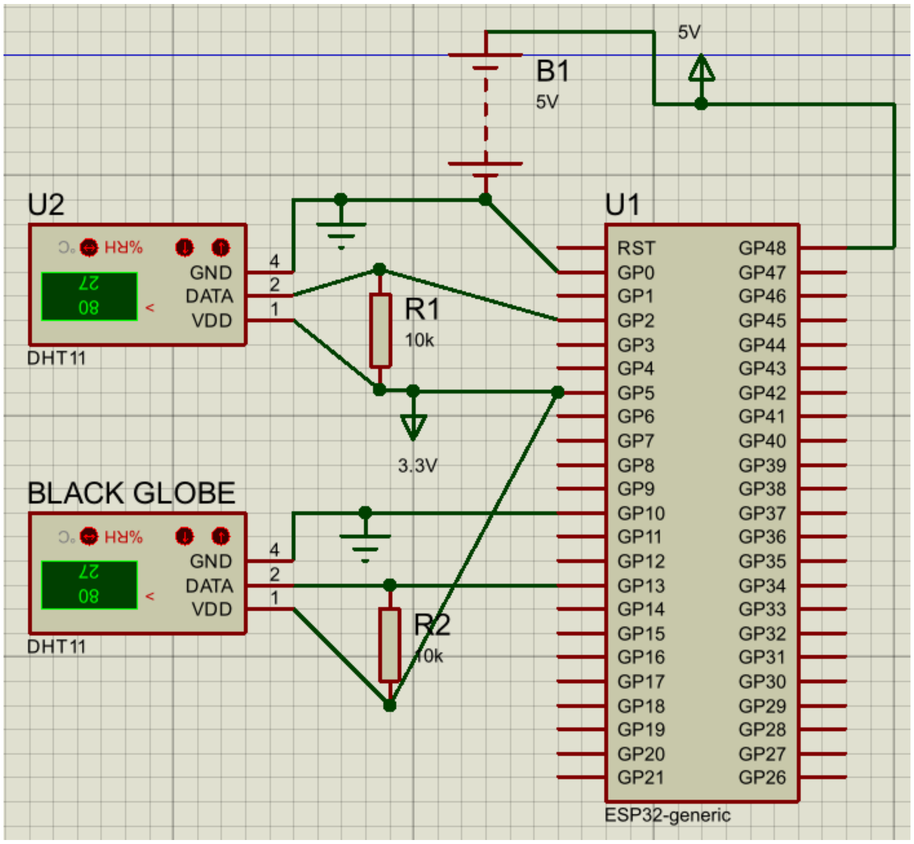

Figure 4.5: Temperature, Humidity, Black Globe Thermometer IoT Device Electrical Schematic

As shown in the electrical schematic in Figure 4.5, the components are interconnected to ensure proper data flow. Communication is established via Wi-Fi using the MQTT protocol, allowing for efficient and reliable data transfer to the computational application. This device is primarily battery-powered, utilizing rechargeable INR18650-35E lithium-ion batteries. To maximize battery life, the ESP32's deep sleep mode is extensively used. The data collected includes ambient temperature, relative humidity, and black globe temperature. This device was installed at ESTIG to provide detailed environmental data, including radiant heat exposure.

4.1.3 Collar IoT Device

This section describes the Collar IoT Device, an experimental prototype designed for future animal-mounted monitoring. Its primary objective is to collect surface temperature, accelerometer-based movement, and GPS data to assess animal behavior and physiological responses. One such prototype was developed.

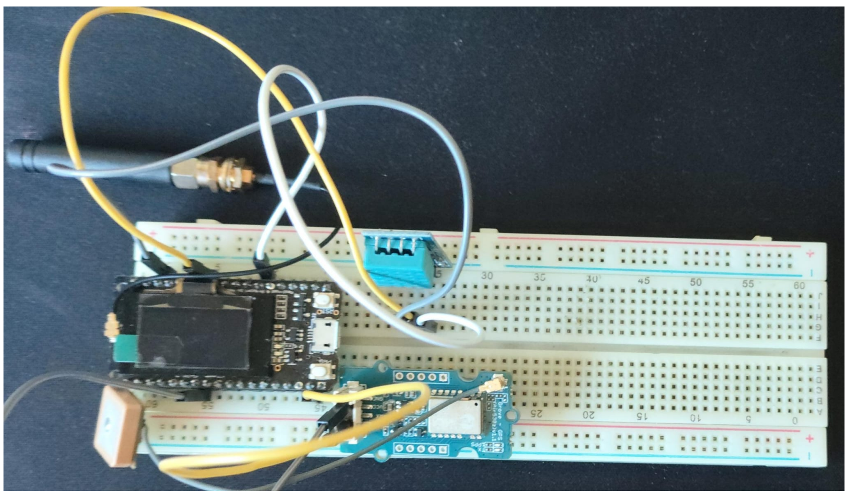

Figure 4.6: Collar IoT Device Prototype

Figure 4.6 illustrates the physical assembly of the collar prototype. The device integrates an ESP32-WROOM-32E microcontroller, an ADXL345 accelerometer, a Grove GPS Air530 module, and a TTGO LoRa32 OLED module. The ESP32 serves as the central processing unit, managing data acquisition and communication. The ADXL345 accelerometer provides 3-axis acceleration sensing, enabling motion detection and behavioral monitoring, configured via I2C at a 25 Hz data rate. The Grove GPS Air530 module offers precise geolocation capabilities, supporting multiple satellite systems and communicating via UART. The TTGO LoRa32 OLED module integrates an ESP32 microcontroller with a Semtech SX1276 LoRa transceiver, operating in the 868/915 MHz ISM bands, and includes an onboard OLED display and LiPo battery charger.

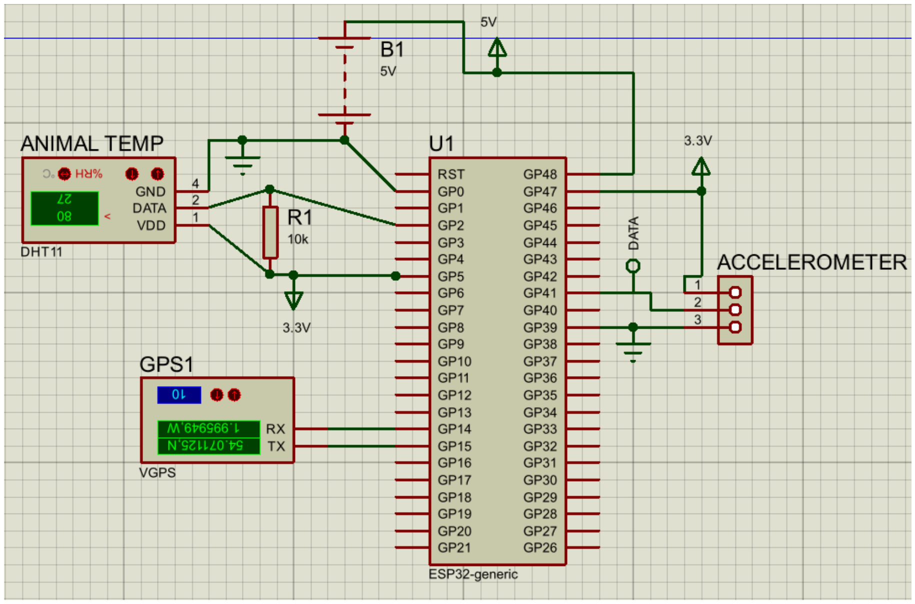

Figure 4.7: Collar IoT Device Electrical Schematic

The electrical schematic in Figure 4.7 details the connections between these components. The device transmits information via LoRa to a gateway. LoRa technology was chosen for its long-range, low-power communication capabilities, making it suitable for remote monitoring in agricultural environments. The data collected includes surface temperature, acceleration data (for movement patterns), and GPS coordinates (for location tracking). The device is powered by rechargeable INR18650-35E lithium-ion batteries, and leverages the ESP32 deep sleep mode to maximize battery life. This prototype was designed for potential installation on animals to monitor their welfare and behavior in extensive farming systems.

4.2 LoRa Communication Setup

LoRa wireless technology is crucial for enabling connectivity in large geographic areas or remote locations lacking Wi-Fi access. To achieve long-range, low-power communication, both the collar prototype and the gateway are equipped with LoRa modules. The collar prototype transmits environmental data via LoRa to the gateway using a TTGO LoRa32 development board. This development board integrates an ESP32 microcontroller with a

Semtech SX1276 LoRa transceiver, operating in the 868/915 MHz ISM bands, featuring an onboard OLED display and LiPo battery charger [50], facilitating standalone operation and enabling independent operation from local network infrastructure.

The LoRa module implemented is the standard or "Module A" version of the SX1276 transceiver, which is widely adopted for IoT applications due to its robust performance in terms of sensitivity (up to -148 dBm) and output power (up to +20 dBm), enabling reliable long-range communication with low power consumption [51]. This module supports Chirp Spread Spectrum (CSS) modulation, making it resilient to interference and multipath fading, essential for outdoor and agricultural environments.

Data from the TTGO LoRa32 board is received by a Dragino DLOS8N LoRaWAN gateway, configured in LoRaWAN mode. This setup ensures scalability and robust communication in agricultural environments lacking Wi-Fi infrastructure.

Figure 4.8: LoRaWAN gateway employed in the system

4.3 Data Integration and Storage

This section outlines the software architecture facilitating data collection, processing, and storage present in the service layer. The computational application manages data flow and processing, while InfluxDB serves as the time-series database, enabling efficient storage and retrieval.

4.3.1 MQTT Server

A public MQTT broker hosted by EMQX (`broker.emqx.io`) is used to facilitate communication in this project. MQTT is a lightweight publish/subscribe protocol widely adopted in IoT systems for its robustness and scalability. Using MQTT satisfies non-functional requirements NFR01, NFR05, NFR06, and functional requirement FR07, ensuring reliable communication between sensor devices and the computational application.

4.3.2 Computational App

The computational application, implemented using Node-RED, is a flow-based development tool designed to integrate hardware devices, APIs, and online services [52]. It offers a low-code visual programming environment where application logic is created through interconnected nodes representing specific functions or interactions. With a web-based graphical user interface and an event-driven Node.js back-end, this application enables rapid prototyping and scalable IoT application development. Its extensive library of preinstalled and community-contributed nodes supports numerous IoT protocols and services, facilitating interoperability across different systems.

In this project, the computational application functions as the central data orchestrator, subscribing to messages published by the devices to the EMQX broker and requesting external climate data from the IPMA API and the IPB weather station located at ESA. Its responsibilities include data filtering, formatting, analysis, and alert generation, forwarding processed data to InfluxDB. This architecture supports functional requirements **FR08**, **FR11** and non-functional requirements **NFR04**, **NFR07**.

Flows are categorized as follows:

- Data Collection and Processing;
- Data Formatting;
- Alerts Generation;
- Climate Data Acquisition;
- Collar Prototype Data;

Data Collection, Processing, and Formatting

This flow segment aggregates data from devices, applies initial filtering, and formats the data appropriately for storage. It meets **FR03** and supports **FR15**, while ensuring IoT-efficient processing aligned with **NFR06**.

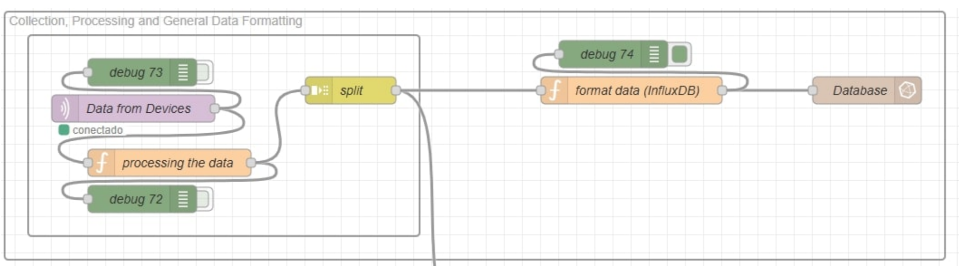

Figure 4.9: Computational App flow for data collection, processing, and formatting

Alerts Generation

Incoming data is analyzed to detect threshold violations or anomalies. Alerts are tagged with metadata and stored in InfluxDB to enable real-time monitoring and notifications, fulfilling **FR08** and **NFR09**.

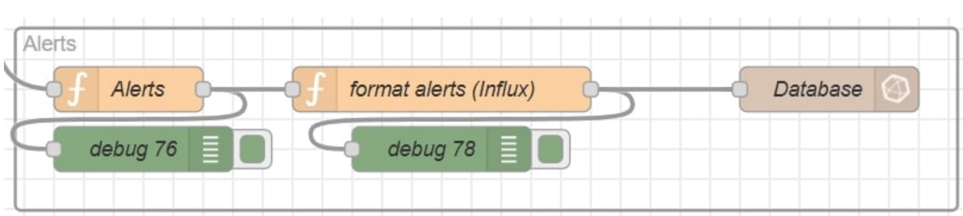

Figure 4.10: Computational App flow segment responsible for alerts generation

Climate Data Acquisition

This flow collects weather data from the IPMA API and IPB weather station at ESA via a http request node, after that the data is formatted in a function node and tagged accordingly before being sent to InfluxDB. Additionally the data collected passes to another function node to calculate some thermal comfort indices such as WBGT, THI, and THI_{adj}. Processed data is tagged and stored, supporting **FR09**, **FR10**, and **NFR07**.

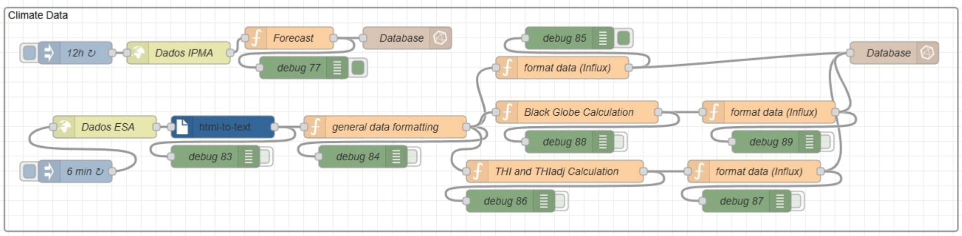

Figure 4.11: Computational App flow for climate data acquisition and processing

Collar Prototype Data

Data from the collar device undergoes collection from an MQTT node, then it is formatted and tagged using a function node before sending it to InfluxDB, enabling further analysis and visualization.

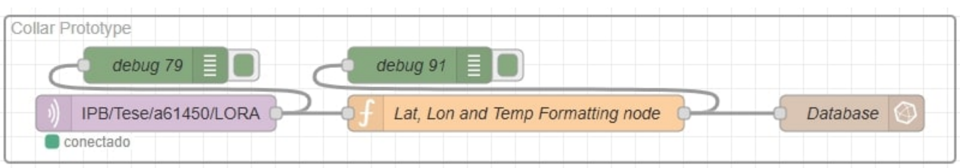

Figure 4.12: Computational App flow handling collar prototype data

4.3.3 Database

InfluxDB, an open-source time-series database, is used to store and manage the vast volume of temporal sensor data [53]. It is optimized for fast data ingestion, efficient querying, and low latency, essential for continuous environmental monitoring.

InfluxDB's column-oriented architecture and distributed model support high performance and horizontal scalability, allowing the addition of nodes to handle increasing data demands. It also provides native support for temporal aggregations, advanced analytics, and integration with visualization tools like Grafana and the computational application.

InfluxDB organizes data into buckets optimized for time-series data [53]. Measurements are classified into sensor readings, climate data, and alerts. Each record includes timestamps, fields (e.g., temperature, humidity), and zone identifiers, enabling efficient, scalable querying and clear data organization. Alerts are similarly structured, facilitating their retrieval and display in the Grafana dashboards. Using InfluxDB meets non-functional requirement **NFR10** and fulfills functional requirement **FR12** related to data storage.

4.4 Data Visualization

This section describes how the system's collected data and alerts are visually presented using Grafana dashboards, providing intuitive, interactive access to information in real time.

Grafana Dashboards

Grafana is an open-source data visualization and analysis platform. It allows the creation of customizable dashboards to monitor data from multiple sources, including relational and time-series databases, cloud services, and APIs [54]. Its extensive visualization options enable dynamic data analysis. Grafanaś optimized architecture ensures high performance with large data volumes.

The active community ecosystem provides numerous plugins and integrations, enhancing functionality. Grafana was selected to meet non-functional requirement **NFR08** and functional requirement **FR13**.

Grafana works by querying the InfluxDB database directly and displaying the data via interactive panels. These panels support dynamic filtering by zone, device, or time range, enabling users to tailor their view to specific operational needs. Data updates occur at configurable intervals, ensuring near-real-time monitoring.

Planned dashboard features include visualization of alerts, temperature and humidity collected from the devices responsible for the environmental data, forecast data from IPMA, environmental data from the IPB weather station (e.g. wind speed and direction, solar radiation, dew point), geolocation and temperature form the collar prototype device, and a dashboard responsible for showing the THI, THI_{adj}, and estimated WBGT.

Each dashboard was designed with specific monitoring objectives in mind, aligning with the data sources and functional needs of the system. For instance, environmental dashboards focus on visualizing raw sensor data such as temperature and humidity trends, while the forecast dashboard integrates external APIs to provide forward-looking insights. The collar prototype dashboard combines GPS tracking and thermal monitoring to offer real-time situational awareness of animal activity. Additionally, a dedicated thermal comfort dashboard aggregates and processes sensor data to present derived indices such as THI, THI_{adj}, and estimated WBGT, aiding in heat stress risk assessment. These dashboards collectively form the user-facing layer of the system, transforming raw time-series data into actionable intelligence through Grafanaś rich visualization capabilities. Each of them will be presented in detail in the following subsections.

Alerts Dashboard

A dedicated alerts dashboard (Figure 4.13) lists active and historical alerts, sorted by severity and zone. This interface allows prompt response to critical events affecting animal welfare or system performance.

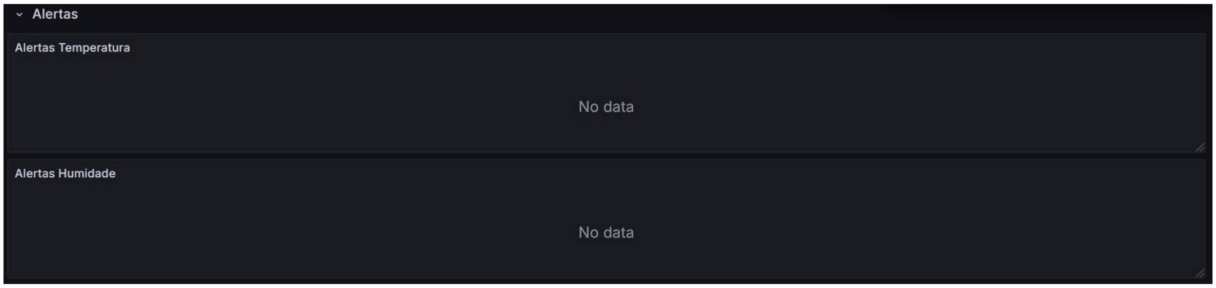

Figure 4.13: Alerts dashboard displaying system notifications and threshold violations

Temperature and Humidity Dashboard

This group of panels presents the environmental data collected by the devices, specifically temperature and relative humidity. The data is displayed in two main formats: a time series graph, which shows the variation of the parameters over time, and a set of smaller panels, which highlight the last recorded values for each zone, as shown in Figure 4.14. This visualization approach allows for both trend analysis and quick status checks, meeting the functional requirement **FR13**.

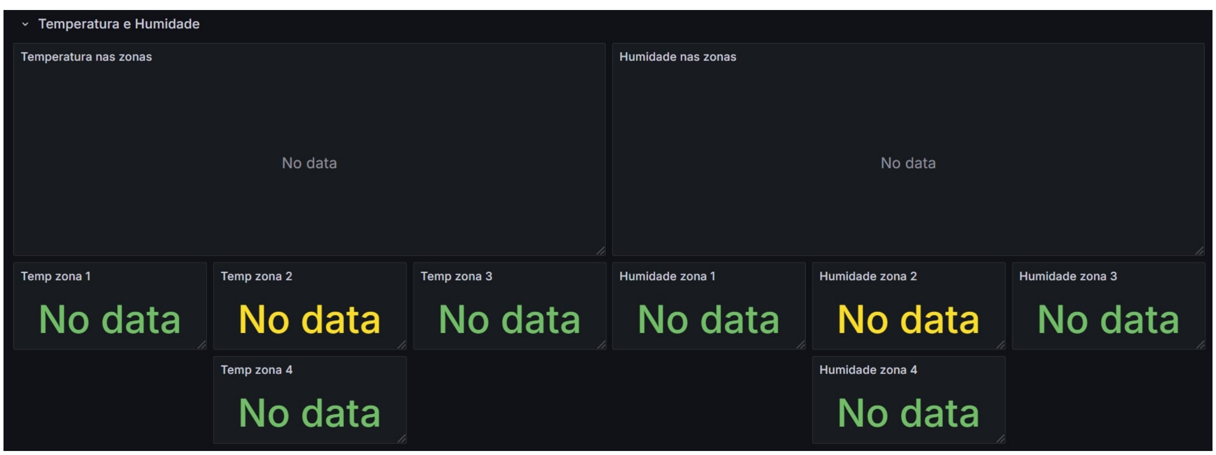

Figure 4.14: Temperature and Humidity - Grafana

Weather and Forecast Dashboard

This group of panels presents data from external sources, specifically the IPB weather station and the IPMA forecast service. The data is displayed in various formats, including time series graphs for historical weather data, tables for forecast information, and specialized visualizations for wind direction and speed, as shown in Figure 4.15. This comprehensive view of external environmental conditions provides context for the locally collected data, fulfilling the functional requirements **FR09** and **FR10**.

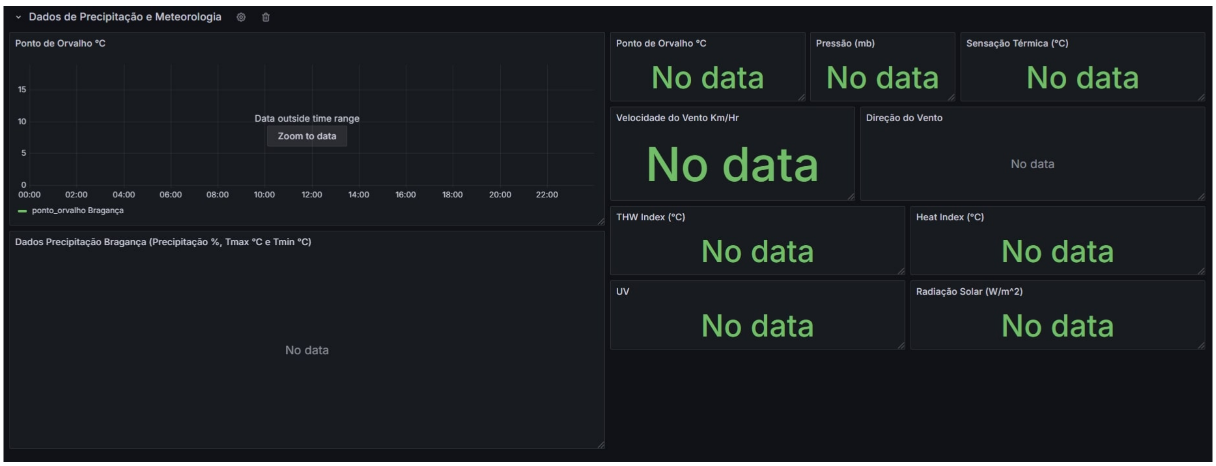

Figure 4.15: Weather and Forecast Data - Grafana

Black Globe, THI and THI$_{adj}$ Dashboard

This group of panels presents the Black Globe, THI and THI$_{adj}$ data calculated by the system using the data from the IPB weather station. The data is displayed in two formats: a set of smaller panels, which highlight the last values recorded within the selected time interval and a table to show the context of the WBGT estimated value (e.g. day with direct sunlight or night without direct sunlight), as shown in Figure 4.16. This visualization approach allows for trend analysis of thermal comfort indices, meeting the functional requirement **FR13**.

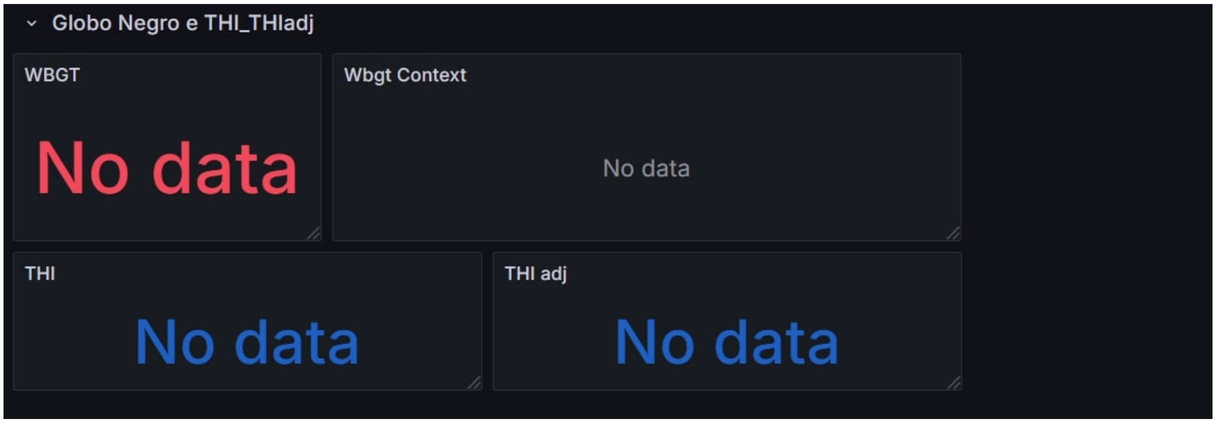

Figure 4.16: Black Globe, THI and THI_{adj} Dashboards - Grafana

Collar Prototype Dashboard

Figure 4.17 shows the dashboard for the collar prototype collected data, serving as a central interface for monitoring this data in real time. The geolocation panel provides a visual representation of the animalś movements over time, plotted on an interactive map using GPS data. This allows for tracking patterns such as grazing areas, resting zones, and potential behavioral anomalies. The time-series graph of temperature data enables the continuous assessment of surface body temperature, which can be a useful proxy for detecting early signs of heat stress or illness in livestock.

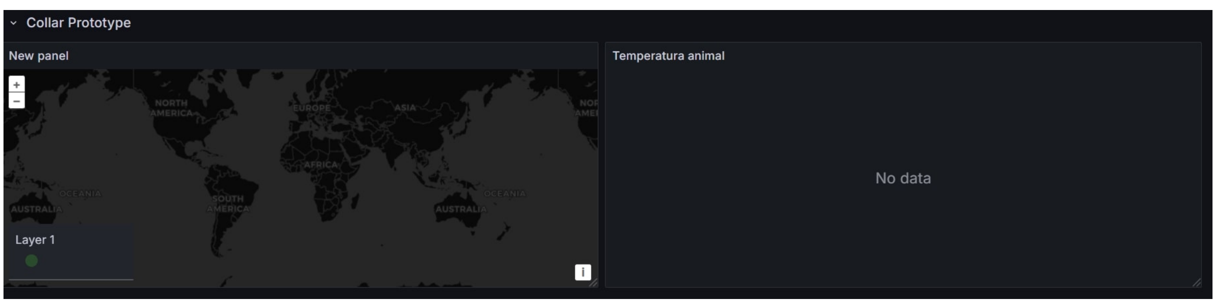

Figure 4.17: Geolocation and Animal Temperature Data - Grafana

By combining geolocation and thermal data in a unified view, this dashboard exemplifies the integration of IoT sensing and decision-support interfaces, reinforcing the system's role in precision livestock management.

Chapter 5

Tests and Results

This chapter presents the experimental evaluation of the IoT-based environmental monitoring system developed in this project. The main objectives of the tests were to assess the system's ability to collect and visualize environmental data and evaluate the energy performance of the battery-powered prototype. The system was deployed in laboratory environments at IPB, simulating its future application.

5.1 Data Acquisition and Visualization

During testing, three device configurations were used, those included a grid-powered environmental node, a battery-powered environmental node, and a LoRa-enabled collar prototype. Each device was configured to acquire specific types of data, such as temperature and humidity for environmental monitoring, and GPS and temperature for livestock tracking. A dedicated black globe sensor, connected to the battery-powered node, was used to measure radiant heat for the estimation of thermal comfort indices such as WBGT, THI, and $\mathrm{THI}_{\mathrm{adj}}$.

All collected data was transmitted to an MQTT broker and processed through Node-RED, which also retrieved forecast and real-time weather information from the IPMA API and IPB weather station. The resulting dataset composed of sensor values and derived indices was stored in an InfluxDB time-series database and visualized using Grafana dashboards. This pipeline enabled comprehensive monitoring and analysis of environmental conditions and animal well-being in real time.

Figures 5.1 through 5.4 illustrate various Grafana dashboards populated with real-time data, confirming the end-to-end functionality of the system's data acquisition and visualization pipeline.

Figure 5.1 shows the alerts dashboard, where real-time system alerts are displayed along with their respective timestamps and reasons for the alert to trigger.

Figure 5.1: Alerts with example data

Figure 5.2 presents temperature and humidity readings collected by both the grid-powered and battery-powered environmental devices. These measurements are visualized as time series plots and current values, enabling both short-term analysis and historical trend observation.

Figure 5.2: Temperature and Humidity Dashboards with example data

Figure 5.3 presents weather and forecast data obtained from the IPB weather station and IPMA APIs. The information includes wind speed, direction, solar radiation, and forecasted conditions for five days, providing context for interpreting and enabling better environmental planning.

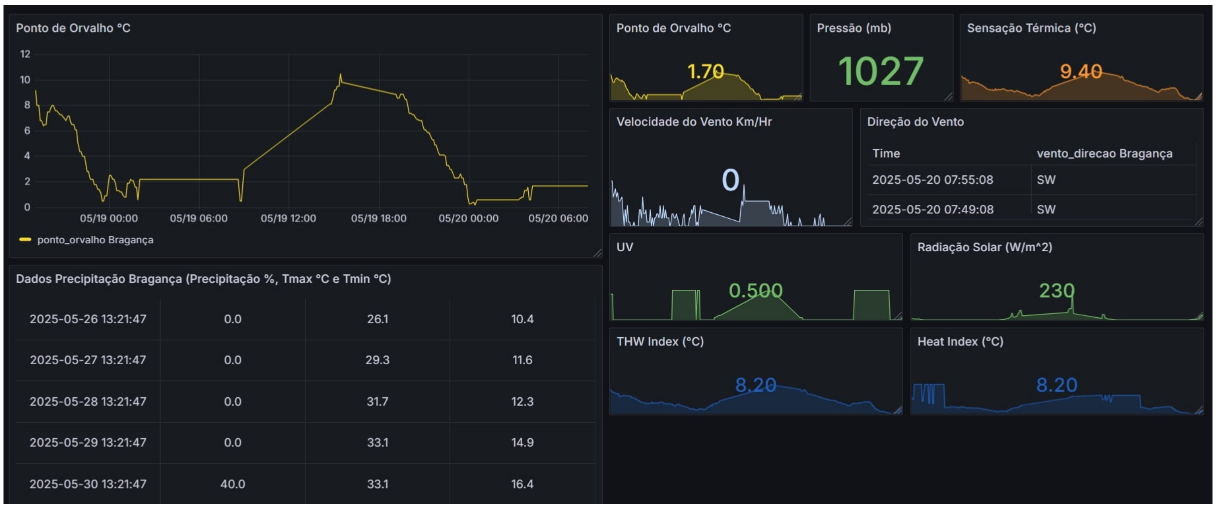

Figure 5.3: Weather and Forecast Dashboards with example data

Figure 5.4 shows the collar prototype's data in real time. The dashboard combines GPS-based geolocation and temperature tracking, supporting use cases related to animal welfare monitoring and behavior assessment.

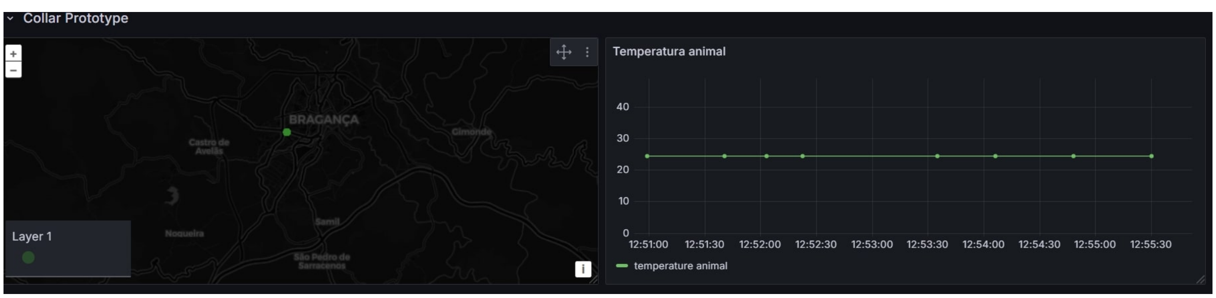

Figure 5.4: Geolocation and Animal Temperature Dashboards with example data

Although accelerometer data was collected as part of the collar prototype's sensor suite, it is not currently displayed on any of the Grafana dashboards. The raw values, typically represented as X, Y, and Z acceleration components, do not provide immediate value to end users without additional context or processing (e.g., activity classification or motion pattern detection). At this stage, the data is being stored for future use, where it could support advanced applications such as animal behavior monitoring, posture analysis, or movement-based alerts. The infrastructure is in place for later integration of processed insights derived from this data.

To ensure data consistency across different nodes and external sources, all sensors were configured to operate with a fixed sampling interval of 15 minutes. This synchronization simplifies the temporal alignment of values across different data, which is critical for accurate index computation and reliable alert triggering. The consistency also allows for straightforward data aggregation and trend analysis in Grafana, improving the usability of the dashboards.

During the testing period, the system demonstrated stable performance with no major failures or data loss, even under variable network conditions in the laboratory environment. The use of an MQTT broker, the decoupled architecture of Node-RED flows, and the configuration made in the codes for each device provided resilience to temporary communication drops, allowing the system to recover and resume normal operation without manual intervention. These results support the robustness of the system's architecture for continuous monitoring applications.

This general configuration for data acquisition and visualization validated the data flow of the system, from sensor acquisition and external data retrieval to storage and visualization, demonstrating its feasibility for continuous and remote monitoring in agricultural environments. The dashboards confirm the system's ability to present diverse and synchronized data streams in a coherent and actionable manner in real time.

5.1.1 Black Globe Temperature Test

To assess the system's capability for monitoring thermal comfort, a comparative test was carried out using a 3D-printed black globe. The Globe Temperature (Tg) is a critical variable in the calculation of the Black Globe-Humidity Index (BGHI), an established index to evaluate heat stress in livestock environments.

The black globe was fabricated using Polylactic Acid (PLA) filament and equipped with a temperature sensor placed at its geometric center to simulate standard globe temperature readings.

To validate the performance of the 3D-printed globe, its measurements were compared with those of a standard ambient air temperature sensor positioned nearby. Furthermore, theoretical globe temperatures were calculated using data from the IPB weather station, including solar radiation, wind speed, and air temperature, according to the thermodynamic model proposed by Buffington et al. [55]. The results of this comparative analysis are illustrated in Figure 5.5.

The data revealed several important findings. First, the black globe temperature (orange line) consistently registered higher values than the ambient temperature sensor (blue line), with an initial difference of approximately 5°C that gradually decreased as both temperatures converged toward the end of the measurement period. This pattern aligns with the expected behavior of a black globe thermometer, which captures both convective and radiative heat components.

Second, the theoretically estimated globe temperature (gray line) was significantly lower than both measured values, remaining approximately 15°C below the actual globe temperature throughout the test period. This substantial discrepancy suggests that the theoretical model may not adequately account for all environmental factors present in the test conditions, particularly the indoor environment where the measurements were taken.

The convergence between the globe and ambient sensor readings toward the end of the test period indicates that radiative heat sources became less influential over time, possibly due to changes in the environment. However, the consistent difference between the measured and estimated values highlights the importance of direct measurement for accurate thermal comfort assessment in specific environments.

These findings demonstrate that the 3D-printed black globe provides valuable additional information beyond standard air temperature measurements, particularly in environments with significant radiative heat components. The integration of this sensor into the monitoring system enhances its capability for comprehensive thermal comfort assessment in livestock facilities.

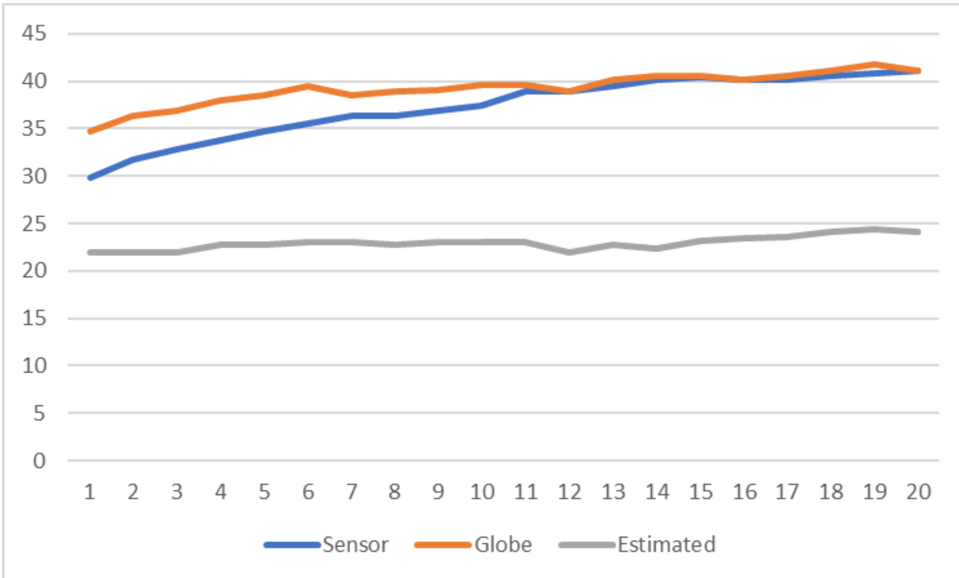

Figure 5.5: Comparison data between regular sensor, black globe sensor and estimated calculation

5.1.2 Thermal Comfort Index Calculation: THI and $\mathrm{THI}_{\mathrm{adj}}$

To assess the thermal comfort of livestock environments, the system was extended to compute two widely used indicators: the **Temperature-Humidity Index (THI)** and the **Adjusted Temperature-Humidity Index** ($\mathrm{THI}_{\mathrm{adj}}$). These indices are essential tools for evaluating heat stress in animals, which can significantly affect productivity, health, and welfare.

THI Calculation

The *THI* is calculated based on ambient temperature and relative humidity using the following formula [56]:

$$\mathrm{THI} = T_{db} - (0.55 - 0.0055 \times RH) \times (T_{db} - 14.5) \tag{5.1}$$

Where:

- T_{db}: Dry-bulb temperature in °C
- RH: Relative humidity in %

THI values are interpreted according to the following thresholds:

- $<$ **72**: No stress
- **72–78**: Mild stress
- **78–84**: Moderate stress
- $>$ **84**: Severe stress

$\mathbf{THI_{adj}}$ Calculation

To refine the heat stress assessment, the system also includes the *Adjusted THI* (THI_{adj}), which incorporates solar radiation and wind speed into the thermal comfort model, following the formula proposed by Dikmen and Hansen [57]:

$$\mathrm{THI}_{adj} = \mathrm{THI} + f_{rad} - f_{wind} \tag{5.2}$$

Where:

- $f_{rad} = 0.3 \times SR$ (solar radiation in kW/m²)
- $f_{wind} = 0.5 \times WS$ (wind speed in m/s)

These adjustments reflect the additional thermal load from solar exposure and the cooling effect of air movement, respectively.

The data for these indices were collected using sensors for temperature, humidity, solar radiation and wind speed (via external data APIs). The THI and $\mathrm{THI}_{\mathrm{adj}}$ values were computed in real time and stored alongside the raw sensor data in InfluxDB. Visualization panels were created in Grafana to display the thermal comfort indicators, enabling quick interpretation by farm managers (Figure 5.6).

Figure 5.6: THI and THI_{adj} example data in Grafana

This functionality significantly improves the capability of the system, providing actionable insights for possible adjustments in ventilation, shading, and hydration strategies to mitigate thermal stress in animal housing.

5.2 Battery Test

The energy efficiency of the battery device was evaluated to understand the viability of battery-operated devices in field deployments.

The test was performed by measuring the current consumption in each operational phase using a Direct Current (DC) power supply. The device operates in fixed 15-minute cycles, divided as follows:

- **Phase 1 (Start-up)**
- **Phase 2 (Data collection and Transmission)**
- **Phase 3 (Acknowledgment wait)**
- **Phase 4 (Deep sleep)**

Table 5.1 shows the current and duration values for each phase:

Table 5.1: Current consumption and duration per cycle phase (15-minute cycle)

Phase	**Current (mA)**	**Duration (s)**
Phase 1 (Start-up)	90	3.0
Phase 2 (Data collection and transmission)	140	0.5
Phase 3 (Acknowledgment wait)	100	0.5
Phase 4 (Deep sleep)	6	896.0

The average current consumption per cycle is computed as:

$$I_{\text{avg}} = \frac{\sum_{i=1}^{n} I_i \cdot t_i}{T_{\text{cycle}}} \quad \text{(Equation 1, adapted from [48])} \tag{5.3}$$

where I_i is the current in mA for each phase i, t_i is the duration in seconds, and T_{cycle} is the total cycle time (900 s).

$$I_{\text{avg}} = \frac{(90 \times 3.0) + (140 \times 0.5) + (100 \times 0.5) + (6 \times 896)}{900} \tag{5.4}$$

$$I_{\text{avg}} = \frac{270 + 70 + 50 + 5376}{900} = \frac{5766}{900} \approx 6.41 \text{ mA} \tag{5.5}$$

Using this value, the battery life can be estimated with:

$$\text{Battery life (hours)} = \frac{\text{Battery capacity (mAh)}}{I_{\text{avg}}} \quad \text{(Equation 2, based on [47])} \tag{5.6}$$

Assuming a 3500 Milliampere (mA)h battery, the estimated theoretical autonomy is:

$$\text{Battery life} = \frac{3500}{6.41} \approx 546.02 \text{ hours} \approx 22.75 \text{ days} \tag{5.7}$$

Table 5.2 summarizes the main parameters and the estimated battery performance:

Table 5.2: Estimated battery life

Parameter	**Value**
Battery capacity	3500 mAh
Average current draw	6.41 mA
Estimated autonomy	22.75 days
Measurement interval	15 minutes

These results indicate that this device can operate for approximately 23 days on a full charge using a 3500 mAh battery. This confirms its suitability for medium-term deployment in agricultural settings where power access is limited, and suggests that further optimizations (e.g., reduced transmission frequency or lower deep sleep current) could improve longevity even more.

Chapter 6

Conclusion and Future Work

This work presented the development and evaluation of an IoT-based system for environmental monitoring in an agricultural contexts, with a focus on applications in livestock health and facility management. By integrating temperature and humidity sensors alongside weather and forecast data with wireless communication protocols, the system enables real-time data collection, storage, and visualization using tools such as MQTT, Node-RED, InfluxDB, and Grafana.

The system was deployed and tested in laboratory environments at IPB, where it demonstrated reliable performance in both data acquisition and visualization. Three sensor nodes were developed, each simulating different deployment conditions: one powered by the electrical grid, one battery powered, and one designed for long-range communication using LoRa.

The battery test yielded particularly promising results. The battery-powered node achieved an estimated 23 days of autonomous operation in a 15-minute transmission cycle, confirming the feasibility of using optimized Wi-Fi-based IoT nodes in environments with limited access to power. Furthermore, data visualization dashboards enabled intuitive real-time monitoring of environmental conditions essential for effective decision-making in precision agriculture.

Although the LoRa-enabled prototype was not finalized, its partial development demonstrated the flexibility of the system and its potential for future expansion to support large-scale deployments in remote farming areas.

Additionally, the implementation of comfort indices such as THI and THIadj provided an effective method for evaluating thermal stress in livestock environments. These indices, computed in real time using collected sensor data, offer valuable insight into the immediate conditions affecting animal well-being. The inclusion of a 3D-printed black globe sensor further enhanced the system's capacity for measuring radiant heat, demonstrating the potential of low-cost components in replicating traditional environmental metrics.

The architecture developed in this project proves to be highly modular and extensible. Its use of standard protocols and open-source tools allows for future upgrades and seamless integration with additional devices or services. The combination of low-cost hardware and scalable software services ensures that the system remains adaptable to a wide range of operational conditions, from small farms to large facilities.

Future Work

Building on the foundations laid in this project, several avenues for future development and improvement are identified.

The first being the finalization and testing of the collar-based LoRa prototype and evaluating its performance. This will provide insights into long-range, low-power applications for animal monitoring in the field. Not only that, but testing the system in a real farm environment will help validate its robustness, communication reliability, and practical utility in diverse conditions.

Integrating new sensors (e.g., for air quality and superficial temperature) can enhance the system's capacity to detect early signs of animal discomfort. Furthermore, studying the possible construction of another device with sensors capable of collecting the data from respiratory and cardiac frequency (e.g., mmWave sensors) can bring important information for the system.

Lastly, leveraging AI and machine learning models to analyze historical data could enable predictive alerts and automated recommendations for environmental management. In addition to that, comparing data from more places, such as the many weather stations in IPB, can be useful to test those AI and machine learning models.

Future work can also explore energy optimization strategies to further extend the operational life of battery-powered nodes. Techniques such as adaptive sampling, dynamic sleep intervals, and event-driven data transmission could reduce power consumption, making the system more efficient in unattended deployments.

By addressing these future directions, the system can evolve into a fully deployable, scalable, and cost-effective IoT platform for precision livestock farming, contributing to improved animal welfare, increased productivity, and the promotion of sustainable agricultural practices.

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Appendix A

Project Repository

All source code, hardware design files (including 3D models), and flow diagrams related to the development of this system are publicly available in the following GitHub repository:

`https://github.com/HenriqueOctaviano/IPB_TESE`

This repository is structured as follows:

- **/architecture**: Node-RED flows.
- **/dashboards**: Grafana dashboards Json.
- **/codes**: All codes used.
- **/hardware**: 3D models and schematics for devices.
- **/documentation**: Supporting files.

The repository serves as a companion to this thesis and aims to facilitate further development, replication, or adaptation of the proposed system in other agricultural environments.