ENERGY CONSUMPTION MANAGEMENT ON IOT BASED MONITORING DEVICES. CASE STUDY: COFFEE VALUE CHAIN

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Master Thesis in Telematics Engineering

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Popayán, May 2022

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Electronics and Telecommunications Engineering
of the University of Cauca
to obtain the title of:

Master in:
Telematics Engineering

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Popayán
2022

Acknowledgments

I would like to express my deepest appreciation to my Supervisor, PhD. Juan Pablo Ruiz for his support the whole time. I would also like to extend my deepest gratitude to my Co-Advisor, PhD. Gustavo Ramirez for several contributions to the research work. I'm extremely thankful to the University of Cauca, specifically to the Telematics Engineer Group, for their financial and administrative support.

Abstract

The Internet of Things (IoT) opens opportunities to monitor, optimize, and automate processes into the Agricultural Value Chains (AVC). However, challenges remain in terms of energy consumption. In this thesis, we assessed the impact of environmental variables in AVC based on the most influential variables. We developed an adaptive sampling period method to save IoT device energy and to maintain the ideal sensing quality based on these variables, particularly for temperature and humidity monitoring. The evaluation on real scenarios (Coffee Value chain) shows that the suggested adaptive algorithm can reduce the current consumption up to 11% compared with a traditional fixed-rate approach, while preserving the accuracy of the data.

keywords: Internet of Things, Energy consumption, Agricultural value chain

Resumen

El Internet de las cosas (IoT) abre oportunidades para monitorear, optimizar y automatizar procesos en las cadenas de valor agrícolas (AVC). Sin embargo, persisten desafíos en términos de consumo de energía. En esta tesis, evaluamos el impacto de las variables ambientales en AVC en función de las variables más influyentes. Desarrollamos un método de período de muestreo adaptativo para ahorrar energía del dispositivo IoT y mantener la calidad de detección ideal en función de estas variables, particularmente para el monitoreo de temperatura y humedad. La evaluación en escenarios reales (cadena de valor del café) muestra que el algoritmo adaptativo sugerido puede reducir el consumo actual hasta en un 11% en comparación con un enfoque tradicional de tasa fija, al tiempo que preserva la precisión de los datos.

keywords: Internet de las cosas, Consumo de energia, cadena de valor agricola

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Acronyms

AR . . . . Augmented Reality

BLE . . . . Bluetooth Low Energy

BPMN . . . . Business Process Model and Notation

HVAC . . . . heating, ventilation, and air conditioning

IoT . . . . Internet of Things

IoTRMS . . . . IoT- based risk monitoring system

ISO . . . . International Organization for Standardization

LBS . . . . Location-Based Services

LOC . . . . Lab-on-a-chip

LoRa . . . . Long Range

M2H . . . . Machine-to-Human

M2M . . . . Machine-to-Machine

MAC . . . . Medium Access Control

MARE . . . . Mean absolute relative error

MBE . . . . Mean Bias Error

MCCT . . . . Minimum Cost Cross-layer Transmission model

MSE . . . . mean square error

MSWE . . . . Multi-Stage Weighted Election heuristic

NFC . . . . Near Field Communication

NSE . . . . Nash-Sutcliffe efficiency coefficient

Ps . . . . Period Sampling

QR . . . . Quick Response

R . . . . Pearson's correlation coefficient

RF . . . . Radio Frecuency

RFID . . . . Radio Frequency Identification

RH . . . . Relative Humidity

SoC . . . . System on Chip

UML . . . . Unified Modeling Language

VC . . . . Value Chain

WAS . . . . wireless agriculture system

WLCSP . . . . Wafer Level Chip Scale Package

WPT . . . . Wireless Power Transfer

WSN . . . . Wireless Sensor Networks

Chapter 1

Introduction

1.1 Problem statement

In recent years, having an effective traceability system has become an essential element in the global market, especially in the food sector companies [1]. Concerning this sector, traceability helps food safety, planning alerts and emergencies due to food issues, defending product quality, and others [2]. Traceability consists in generating concise and transparent information on each one of the production stages, transformation, and distribution of a specific product, where the set of stages that add value as the product goes through them is known as Value Chain (VC)[3]. Therefore, employing traceability, the VC of a product is reconstructed, "from farm to fork", to guarantee the product safety, the improvement of the processes, and generate greater confidence in the consumer [4].

In general, traceability systems use different technologies to record information on the VC of a product. In particular, there are systems based on technologies such as infrared, barcode, Quick Response (QR) code, Radio Frequency Identification (RFID), Near Field Communication (NFC), smart labels, or data loggers[1]. These systems work by scanning; that is, to access the information collected, it is necessary to have their respective application and reader [5]. In addition, they have been helpful in different aspects of traceability, such as inventories, product counting, among others. However, they are not sufficient with the needs required in sectors such as agriculture. Besides product management, it is necessary to guarantee specific conditions of physical variables: for example, temperature, humidity, oxygen. That indicates the conservation state of the product, or it is required to report an alert when environmental parameters are not in the desired range [6, 7, 8].

With the emergence of new technologies, such as the Internet of Things (IoT), these variables can be measured and controlled. The IoT is a technological paradigm that consists of a global network between devices, which can communicate with other objects [9]. Several kinds of research have shown that the IoT improves processes in the VCs of products in the agricultural sector [10, 11, 12, 13, 14].At the same time, the IoT opens opportunities beyond optimization and automation of processes when using the collected data. Based on this data, they can be used as inputs to intelligent systems and provide predictions and recommendations [15], which facilitates planning or decision-making by owners, managers, and heads of agricultural companies. Thus, to improve in a range of aspects, from minimizing the effort required in the different phases of the VC, enhancing the quality of the product, providing more information to the end-user, and even determining the status of the product and its market demand.

However, despite the benefits that IoT brings, there are still challenges in terms of energy consumption, transmission range, transmission and storage security, device standardization, data storage capacity, and so on [16, 14, 17], which create difficulties for the implementation in the VCs.

For example, the Colombian coffee value chains comprise different phases (preproduction, harvest and post-harvest process, marketing, threshing, export). That involves agents (suppliers, coffee growers, cooperatives, exporters). Who fulfill different functions (fertilizers supplies, planting, harvest, classification, purchase, export), and institutions (ministries of Finance, Agriculture and Commerce, National Federation of Coffee Growers, Cenicafé) dedicated to support and regulate the VC in its different phases. It entails challenges since it is required to collect and integrate the information generated in the stages of the VC.

In particular, the production and the post-harvest phase in the coffee sector is performed on mountain ranges between 1,100 and 1,700 meters above sea level [18], with great climatic variability [19], with an extension of 3.2 million hectares [20] and an average duration of 5 months from the beginning of flowering [21], n which the monitoring of variables is carried out under outdoor conditions. Like the drying and storage processes that take place over several days or weeks, constant monitoring of environmental conditions, especially humidity, is required; a decisive variable to prevent deterioration of coffee by molds and insects [22]. Such as the export stage, in which the maritime transport lasts between 4 to 28 days from the shipment to the port of destination [23], where it is unknown if the environmental conditions are necessary to ensure the quality of the product.

These phases bring along with their high levels of energy consumption in IoT devices, given the outdoor conditions, remote and duration, limit the possibility of recharging them or being connected to the grid or photovoltaic systems. That being the most used techniques, [24] are not applicable or represent a high cost, especially for small coffee growers who represent 95% of the coffee produced in Colombia [25]. Therefore, managing energy consumption is a challenge to support the efficient operation of IoT-based monitoring devices for some stages of the VC in the agricultural sector, especially the VC in the coffee sector.

Some studies have designed wireless sensors [12, 13, 26] for agricultural VCs; despite this, they do not present models related to the management of the energy consumption of their sensors. Some studies [27, 28, 29], carry out multiple configurations and evaluations of algorithms applied to IoT to achieve minimum energy cost and maximum range. However, these studies fall short of evidence in the context of the VCs; in other words, they remain only in simulations and under ideal conditions. Additionally, there are studies related to the reduction of energy consumption in the context of precision agriculture [24, 30, 31, 32, 33] focused only on improving the quality and production of crops, which corresponds to one of the first stages in the production phase of the VC. Therefore, other phases are not considered where the monitoring of environmental variables is also required. Some researches [10, 2, 34, 35] in the field of traceability has presented proposals for IoT-based logistic information systems for agricultural VCs, like previous efforts, they lack models or systems concerning the relevant parameters for efficient energy management.

Motivated by the above problem statement, this proposal formulates the following research question: **How to manage energy consumption in IoT devices for monitoring agricultural value chains?**

1.2 Objectives

1.2.1 General objective

To propose an energy consumption management system for IoT-based devices to monitor variables in agricultural value chains.

1.2.2 Specific objectives

- To structure a conceptual energy management model for value chains in terms of monitoring environmental variables.
- To develop a management system based on the conceptual model that allows managing energy consumption in IoT monitoring devices.
- To evaluate the management system proposed under the conceptual model in a case study.

1.3 Document Structure

This document has been divided into chapters described below.

- **This introductory chapter** presents the problem statement, raises the hypothesis, exposes objective general and specifics, summarises the contributions,and describes the overall structure of this thesis.
- Chapter 2 presents the **Background** of the main research topics touched in this thesis. These topics include Value chain, traceability, Internet of Things and Energy efficiency.
- Chapter 3 presents the **Related Work** that describes the researches works closer to this thesis. In addition, this chapter presents the challenges about our proposal leading to a reformulation of research question and hypothesis.
- Chapter 4 describes the **Conceptual energy Model**, that describes agricultural value chains in terms of monitoring environmental variables for focusing the management system around these variables.
- Chapter 5 describes the **Management Energy System**, that describes the steps conducted to developed system, discusses the corresponding results, and presents implementations highlights.
- Chapter 7 presents **Conclusions** and **Future work**. In this chapter is provided the main conclusion of this thesis and exposes implications.

Chapter 2

Background

2.1 Value Chain

It corresponds to a theoretical concept introduced by Porter (1985)[36] in his book called "Competitive advantage: Creating and sustaining superior performance" where he describes how the actions and activities of a company are developed. Therefore, in value chains, different links are involved in an economic process: it begins with the raw material and reaches the distribution of the product to the final consumer [37]. Through value chain analysis, a systematic representation of the activities of an organization is achieved, helping the improvement of the production process since the operation of the company can be seen in detail at each step. Cost reduction and the search for efficiency in the use of resources are usually the main objectives of the entrepreneur while looking through the value chain; in this way, it is possible to diagnose the company position concerning its competitors and obtain actions aimed at developing competitive advantages in the market.

In general, a value chain consists of three elements:

- Primary activities: directly related to the product, production, logistics, marketing and after-sales services.
- Support activities: they are complementary to the primary activities and are composed of the human resource management, purchase of goods and services, technological development and infrastructure.
- Margin: it is constituted as the difference between the total value and the total costs incurred by a company while developing the activities that generate value.

The elements consisting of the value chains are related and interact by coordinating the different activities to increase differentiation or reduce costs.From an agricultural standpoint, a value chain is defined as the itinerary or process that an agricultural, livestock, forestry, or fishing product follows through production, post-harvest stages, conservation, and transformation until it reaches the final consumer. This chain also includes the supply of inputs (financing, safety, machinery, seeds, fertilizers, among others) and essential equipment, as well as all the support services that significantly impact the development of these activities [38].

2.2 Traceability

There are different definitions of this concept according to the standards of other countries or public and private entities. However, the definition adopted by International Organization for Standardization (ISO) Standards (2001) is considered for this proposal, given its importance in management systems and quality standards. According to the ISO, traceability is defined as those pre-established and self-sufficient procedures that allow knowing the history, location, and development of a product or group of products along with the VC at a given moment, through specific tools [39]. In other words, traceability is the ability to follow a product along the value chain, from its origin to its final state as a consumer item. To do this, it is necessary to systematically associate a flow of information with a physical flow of goods. Information on the batches or groups of determined products is obtained at any time.

There are 3 types of traceability:

- Ascending traceability (backwards): it consists of knowing which products are received in the company, delimited with some traceability information (batch, expiration date / minimum durability), and who are the suppliers of those products.
- Internal traceability or traceability of processes: it means traceability within the company itself.
- Descending traceability (forward): to know which products are shipped by the company, delimited with some traceability information (batch, expiration date / minimum durability) and to know its destinations and customers.

In the agricultural sector, traceability in food allows the complete monitoring of a product on the VC. Thus, to trace its history from producer to consumer ”from farm to fork”[40]. In these terms, it is a preventive quality and safety management instrument. Traceability is a mechanism to prevent contamination and diseases that food consumption can transmit. Additionally, the information can be helpful to carry out good business administration and as feedback for future decision making, promoting continuous improvement through the production cycle, added to the satisfaction of the final consumer who can access the product information [41, 42].

2.3 Internet of Things

According to CISCO [43], IoT consists of sensor networks connected to objects and communication devices, which provide data that can be analyzed and used to initiate automated actions. The attributes of the world of things are low power consumption, automatic configuration, embedded objects. The data also generates vital intelligence for planning, management, policies, and decision-making. Essentially, the five properties that characterize the Internet of Things are the following:

- A unique identification on the Internet whereby each object and physical device connected will identify and communicate with each other.
- A unique location (static or mobile) within a network or system that gives meaning to the function and purpose of the object in its specific environment, generating intelligence to allow autonomous actions to be carried out.
- More information generated and processed by the machine that will overtake the information processed by man, and will potentially link with other systems to create what some have called "the nervous system of the planet".
- New complex security, analytics and management capabilities achievable through more powerful processing devices and software, enabling a network of connected devices and systems to cluster together and operate seamlessly with each other in a "network of networks."
- Time and location reach new levels of importance in information processing since objects connected to the Internet work to generate ambient intelligence. For example: on the heating, ventilation, and air conditioning heating, ventilation, and air conditioning (HVAC) efficiency of a building, or to study soil samples and climate change in relation to growing crops.

Concepts and technologies that have led to IoT, or the interconnectivity of real-world objects have been around for some time. Initially,Machine-to-Machine (M2M) and IoT communications were considered the same. However, M2M is only a subset; IoT is a phenomenon that also includes Machine-to-Human (M2H) communication. Some technological innovations such as Radio Frequency Identification (RFID), Location-Based Services (LBS), Lab-on-a-chip (LOC) sensors, Augmented Reality (AR), robotics, and telematics in vehicles, use both communications (M2M and) in the IoT as it is conceived today. From the above, applications emerge in the military and industrial supply chains that combine integrated sensory objects with communication intelligence, interchanging data over a combination of wired and wireless networks [43].

2.4 Management Power Consumption

The Internet of Things (IoT) and wireless sensor networks have developed rapidly over the years, and this has increased the demand for wireless implementations of energy efficiency [44]. The energy consumption of IoT devices depends on the integrated elements generally consisting of microcontrollers, Radio Frecuency (RF) modules, battery power, and sensors. Moreover, they can communicate wirelessly through a link and send their data to a base station or coordinating node by speaking with a gateway. Communication between IoT devices depends on the combination of various sensors, from simple (i.e., humidity, pressure, and temperature) to complex (i.e., location, tracking, micro-radar, and imaging). Although IoT devices are increasingly complex, battery manufacturing has not developed at the same rate [45]. Therefore,IoT-based devices are mainly limited by their batteries [46].

Consequently, prolonging battery life in IoT devices is a current challenge [47]. Nowadays, different techniques have been applied for energy management used in agriculture. According to the review of systems proposed in these techniques [24] they are classified into two categories, and in turn, they are classified into subcategories:

- Power reduction techniques: due to the total power consumption of a sensor node is the sum of each element in the node, (sensor, microcontroller, radio module) and each component can operate in different power states, the useful life of a device can be operated by managing the elements that comprise it in such a way that the device operation is below the sustainable operating threshold.
- Harvesting techniques: this consists of allowing the sensor nodes to obtain different types of energy, such as solar energy, Wireless Power Transfer (WPT), mechanical vibration, kinetics and wind energy from different environments. In this way, the devices are rechargeable to operate continuously for a long useful life.

These techniques show that it is possible to manage energy consumption by addressing different aspects of sensor networks. The use of wireless communication protocols or technologies relating to the best energy consumption and communication distance such as Bluetooth Low Energy (BLE), Zigbee, and LoRa. As well as energy efficiency schemes such as power reduction techniques through settings in ON/OFF times such as Duty-cycling, MAC protocols or Topology Controls, modification in radio communication parameters such as modifying transmission power or scheme modulation; as well as efficient routing schemes such as Sink mobility, Multi-path or Cluster architecture Routing [48].

Chapter 3

Related Works

This section establishes the main works that have addressed the issue related to this proposal in the framework of energy consumption management in devices based on IoT for traceability of agricultural products. The listed articles were selected from searches in the Web of Science, Scopus and Science Direct digital libraries. From the results obtained, they were organized manually in order to include only the most relevant articles for this master's degree proposal.

Table 3.1 shows the grouped words with the same meaning or synonyms used in the search criteria. Through the combination of groups using logical operators (AND, OR) supported in digital libraries, articles were obtained for further analysis. The general structure of the search queries that were applied to the information sources by integrating the words from at least 3 groups is listed below.

- (Internet of Things OR IoT OR IoT device) AND (Agriculture OR agricultural technology OR agricultural industry OR agroindustry OR agribusiness OR agriculture food OR agro-food OR agrofood OR agrifood OR agro food production OR Farm OR farming OR smart farming) AND (Traceability OR tracking OR product traceability OR food traceability).
- (Internet of Things OR IoT OR IoT device) AND (Agriculture OR agricultural technology OR agricultural industry OR agroindustry OR agribusiness OR agriculture food OR agro-food OR agrofood OR agrifood OR agro food production OR Farm OR farming OR smart farming) AND (Energy efficiency OR battery-less OR energy consumption OR power managment OR power consumption).
- (Internet of Things OR IoT OR IoT device) AND (Traceability OR tracking OR product traceability OR food traceability) AND (Energy efficiency OR battery-less OR energy consumption OR power managment OR power consumption).
- (Agriculture OR agricultural technology OR agricultural industry OR agroindustry OR agribusiness OR agriculture food OR agro-food OR agrofood OR

agrifood OR agro food production OR Farm OR farming OR smart farming) AND (Traceability OR tracking OR product traceability OR food traceability) AND (Energy efficiency OR battery-less OR energy consumption OR power managment OR power consumption)

Group 1	Internet of Things, IoT, IoT device
Group 2	Agriculture, agricultural technology, agricultural industry, agroindustry, agribusiness, agriculture food, agro-food, agrofood, agrifood, agro food production Farm, farming, smart farming
Group 3	Traceability, tracking, product traceability, food traceability
Group 4	Energy efficiency, battery-less, energy consumption, power managment, power consumption

Table 3.1: Words used in digital libraries

Despite the fact that IoT has been applied to food, it is a recent field of research [49, 47], several works have begun to generate knowledge on this subject.

3.1 IoT in food VC

In the document ”Value-centric design of the internet-of-things solution for food supply chain: Value creation, sensor portfolio and information fusion” [50], the authors propose a value-centric business-technology joint design framework. Based on it, the income-centric added-values including shelf life prediction, sales premium, precision agriculture, and reduction of assurance cost are identified and assessed. Concluding that the revolution of IoT technologies have brought out great potentials to make today’s food supply chain safer, more effective and more sustainable. However, the article does not contribute or solve some of the challenges that exist in IoT-based technologies for value chains.

In the document ”Food safety pre-warning system based on data mining for a sustainable food supply chain”[51], the researchers proposed a food safety pre-warning system, adopting association rule mining and Internet of Things technology, to timely monitor all the detection data of the whole supply chain and automatically pre-warning. The aim of pre-warning system is to help managers in food manufacturing firm to find food safety risk in advance and to give some decision support information to maintain the quality and safety of food products. However, there are no weaknesses or aspects to improve in future work related to parameters in the IoT system.

In the document ”An Internet of Things (IoT)-based risk monitoring system for managing cold supply chain risks” [52] proposes an IoT- based risk monitoring system (IoTRMS) for controlling product quality and occupational safety risks in cold chains. Real-time product monitoring and risk assessment in personal occupational safety can be then effectively established throughout the entire cold chain. In the design of IoTRMS, there are three major components for risk monitoring in cold chains, namely: wireless sensor network; cloud database services and fuzzy logic approach. However, the parameters used to manage the devices are not detailed in order to guarantee the delivery of the information, the life cycle of the device or the maximum reach.

3.2 IoT in agricultural food VC

In the paper "A reference architecture for IoT-based logistic information systems in agri-food supply chains"[35], the authors developed a reference architecture for IoT based logistic information systems in agrifood supply chains. It presents a hybrid solution that combines the IoT and cloud computing. However, a reference architecture is presented without evaluations in a real environment and does not consider the challenges in the context of agriculture.

In the document called "Conceptual Data Model for IoT in a Chain-Integrated Greenhouse Production: Case of the Tomato Production in Almeria (Spain)"[53], the researchers developed the data model of the part of the food chain in the province of Almeria (Spain), including all the data from farmer's inputs until the transport to the wholesalers and retailers; but taking into account of the whole chain where the food chain is based on IoT technology, that lets them transfer the information to the IoT platform in the cloud. However, in this article, parameters of the IoT infrastructure are not evaluated in order to extend the life cycle of the device without affecting the operation in the proposed scenario.

In the paper "Blockchain and IoT based Food Traceability for Smart Agriculture"[54], the authors proposed a trusted, self-organized, open and ecological food traceability system based on blockchain and Internet of Things (IoT) technologies, which involves all parties of a smart agriculture ecosystem, even if they may not trust each other. In addition, they use IoT devices to replace manual recording and verification as many as possible, which can reduce the human intervention to the system effectively. The authors show good results in the implementation of the system by reducing human intervention through IoT devices, however, they do not highlight the challenges that still persist in terms of the use of IoT in agriculture, just as they do not contribute to any of them.

Studies presented show that traceability through the use of the IoT generates greater efficiency in production processes, lower costs in the event of failures and better customer service. In addition, they allow monitoring environmental conditions to which the product was subjected, for this it is necessary that parameters such as energy consumption and communication range are considered in the 3 models to guarantee the sending of information, report alarms or change configurations, which greatly increases the possibilities when managing a product. This is why the proposal aims to contribute to the current needs of IoT devices for monitoring in the context of agricultural VCs.

3.3 Energy management in IoT and agricultural sector

In the paper called ”Energy efficient automated control of irrigation in agriculture by using wireless sensor networks”[31] proposes a scheme based on the collaboration of an integrated system for automated irrigation management with an advanced novel routing protocol for Wireless Sensor Networks (WSN), named ECHERP (Equalized Cluster Head Election Routing Protocol). At its core, the proposed system aims at efficiently managing water supply in cultivated fields in an automated way. The system takes into consideration the historical data and the change on the climate values to calculate the quantity of water that is needed for irrigation. In case that the change on the collected values is above a threshold, more frequent data collection is proposed to minimize the necessary quantity of water. Although techniques are applied to reduce energy consumption, these are specifically aimed at efficient irrigation management by finding the appropriate schemes for the rational use of water.

In the paper ”Power Reduction with Sleep/Wake on Redundant Data (SWORD) in a Wireless Sensor Network for Energy-Efficient Precision Agriculture”[24] the authors aim to further minimize the energy consumption of a wireless agriculture system (WAS), which includes air temperature, air humidity, and soil moisture. Two power reduction schemes are proposed to decrease the power consumption of the sensor and router nodes. The article presents good results due to the reductions in energy consumption obtained above 80%, however, it is framed in the context of precision agriculture where the proposed topology of the wireless nodes is evaluated in a reduced area of 4000 m2 under the Zigbee wireless protocol without specifying the characteristics of the crop or the topology of the test site.

In the paper ”SEES: a scalable and energy-efficient scheme for green IoT-based heterogeneous wireless nodes”[55], the researchers study the impact of energy-harvesting techniques by implementing ambient energy-harvesting relay nodes in such a way that enables a higher energy conservation and guarantees a long-lived network. SEES includes: (1) a zone-based hybrid-placement scheme, (2) a Multi-Stage Weighted Election heuristic (MSWE), and (3) a Minimum Cost Cross-layer Transmission model (MCCT). The objective is to ensure an even-random deployment of heterogeneous nodes, a scalable pre-deterministic placement of energy-harvesting nodes, a fair energy-load balancing among all the zones, and a minimum energy cost for data transmission from the bottom layer to the topmost layer. However, the results are experimental from simulations and the evaluation is based on a simplified model of the environmental energy harvesting node, therefore, it has differences when compared to tests with a real device.

In the paper ”A Real-Time Monitoring Service based on Industrial Internet of Things to manage agrifood logistics.”[56], using a technology called See Your Box, the researchers monitor changes in the cold chains and food through a logistics system in real time. In addition, it presents the results of the evaluations carried out in different stages where there is a greater emphasis on the shipment stage. However, the document does not detail the management techniques in terms of device consumption since it corresponds to a commercial device.

In this context, related works in IoT have proven to be of great help when it comes to managing energy under different fields and scenarios, however, previous works do not consider the management in terms of energy consumption in the context of agricultural VC.

3.4 Final Remarks

Table 3.2 summarizes the aspects considered in the related works, it is organized according to a horizontal classification in the context of IoT, agriculture, traceability and energy consumption.

Author	**Title**	**IoT**	**Agro**	**Traceability**	**Energy managment**
[50]	Value-centric design of the internet-of-things solution for food supply chain: Value creation, sensor portfolio and information fusion		-		-
[51]	Food safety pre-warning system based on data mining for a sustainable food supply chain		-		-
[57]	An Internet of Things (IoT)-based risk monitoring system for managing cold supply chain risks		-		-
[35]	A reference architecture for IoT-based logistic information systems in agri-food supply chains.				-
[53]	Conceptual Data Model for IoT in a Chain-Integrated Greenhouse Production: Case of the Tomato Production in Almeria (Spain)				-
[54]	Blockchain and IoT based Food Traceability for Smart Agriculture				-
[31]	Energy efficient automated control of irrigation in agriculture by using wireless sensor networks			-	Calculate
[48]	Power Reduction with Sleep/Wake on Redundant Data (SWORD) in a Wireless Sensor Network for Energy-Efficient Precision Agriculture			-	Node
[55]	SEES: a scalable and energy-efficient scheme for green IoT-based heterogeneous wireless nodes			-	Position
[56]	A Real-Time Monitoring Service based on Industrial Internet of Things to manage agrifood logistics.				Commercial

Table 3.2: Remarks on related works

There are studies in IoT dedicated to the implementation of traceability of agricultural foods, however, they do not present information about management schemes in devices related to energy consumption, as in sensor networks, different management techniques have been evaluated in the context of precision agriculture, which corresponds to a stage of the initial phases, however, it is not evaluated in other stages of the agricultural VC. Finally, in the search for the state of the art, there is only one work that involves the 4 aspects that frame this proposal (IoT, Agriculture, Traceability, energy management) which only names energy management as an existing feature in the system. Therefore, this proposal aims to provide the energy management of devices based on IoT under the context of monitoring environmental variables in traceability systems in agricultural VCs.

Chapter 4

Environmental Model

This chapter introduces a conceptual monitoring model for value chains in terms of monitoring environmental variables, it is based on literature review.

4.1 Conceptual Model

A conceptual model is a representation of a system. It uses a group of concepts that are used to help people know, understand, or simulate a subject the model represents. Conceptual model is formed after a conceptualization or generalization process[58]. Generally, Conceptual models are abstractions of things in the real world, whether physical or social.

The objective is to answer the following questions

- What is being described? (The system.)
- Who interacts with the system? (The actors.)
- What can the actors do? (The use cases.)

A widely used standard for making conceptual models is the "Business Process Model and Notation" BPMN standard (defined in [?]). That is mainly used to provide a standard notation readily understandable concept description of a study domain. BPMN diagrams to try and understand the various meanings of the terms asset pool with many experts, adopting a common language to describe processes. It is based on a flowcharting technique very similar to activity diagrams from Unified Modeling Language (UML)[59].

Agricultural value chains have a large number of possible adaptation options. Fig 4.1 presents a basic general model made on BPMN for providing readers a description of activities and set of stages that bring the agricultural product. From production in

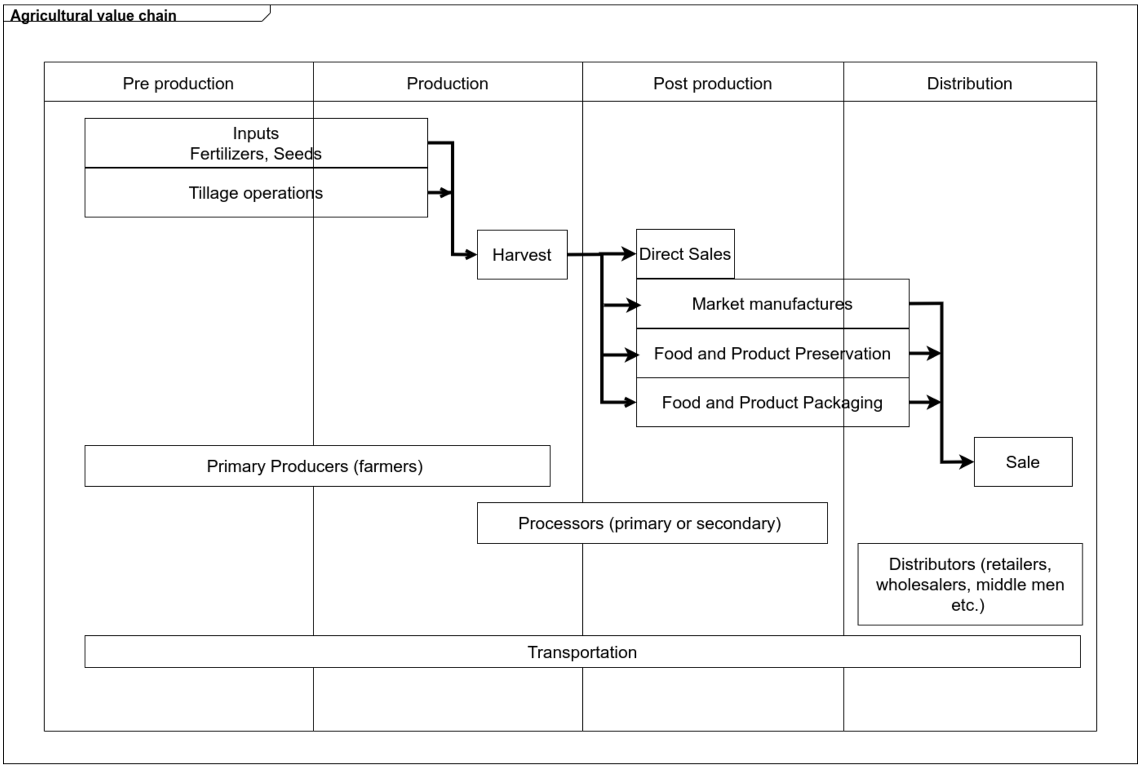

Figure 4.1: Agricultural value chain.

the field to final consumption, the value can be studied more deeply and considered a tree with many branches in each stage.

It is an approach that analyzes a production unit or process in a market chain from input suppliers to final buyers and the relationships among them, it identifies value adding activities in the chain and assign cost and added value to each of those activities.

4.2 Stages

Pre production

At this stage all inputs are prepared as seeds, agro-chemical, fertilizers and farm equipment companies are used in the production of agricultural raw materials. Furthermore, Triage operations carried out by farmers, the base actors of the value chain are also necessary.

Production

This includes triage activities until harvest is reached when raw materials such as agricultural and livestock products are ready for sale or continue to the post-production stage.

Post production

This includes food processing and manufacturing, such as beverages, breweries, wineries, and packaged food companies. These post processors companies convert raw materials into branded or unbranded food products. These products are then marketed at the retail stage for distribution and sale to consumers.

Distribution

This stage the agri-food value chain serves the consumer. the related activities are retail, distribution, sale and marketing of food products. In the last stage of the agri-food value chain, it includes all related actors in food distribution, grocery sales, and food service[60].

In addition, the remarkable point is that we are all part of value chains in one way or another as producers, consumers of goods and services, processors, retailers, finance providers. As consumers, we all eat and wear clothes, so we are linked to many value chains, chains of grain crops, roots and tubers, fruits and vegetables, legumes, oils, and textiles. These chains stretch from growers to our kitchens, eating tables, clothing, and beyond.

4.2.1 BPMN Coffee Value Chain

Supracafe[61] is company who has modeled each stage of the coffee value chain; Figure 4.2 briefly shows from crop to export stages using Business Process Model and Notation(BPMN); however, we focus only on two value chain stages highlighted in red. For Crop, the inputs at this stage are coffee seeds. This stage is associated with four roles of coffee growers at the beginning of the Crop: Germinator, Seedling, Planting, and Growth. It can take between 8 months and two years. It is the stage that takes the longest of the entire value chain. Then, the harvest stage begins, accompanied by the transport phases. Coffee beans go through transformation processes, from cherry coffee to parchment coffee and wet to dry coffee. The coffee is classified and threshed in the storage stage, turning into green coffee; This process can take between two weeks and six months. The next stages are land or ship transportation, sale, and export until roasting, where the coffee already acquires all its properties and is ready for consumption. The detailed BPMN-based coffee value chain is available at the following repository:
`https://github.com/iotagro2018/BPMN-coffee-model`.

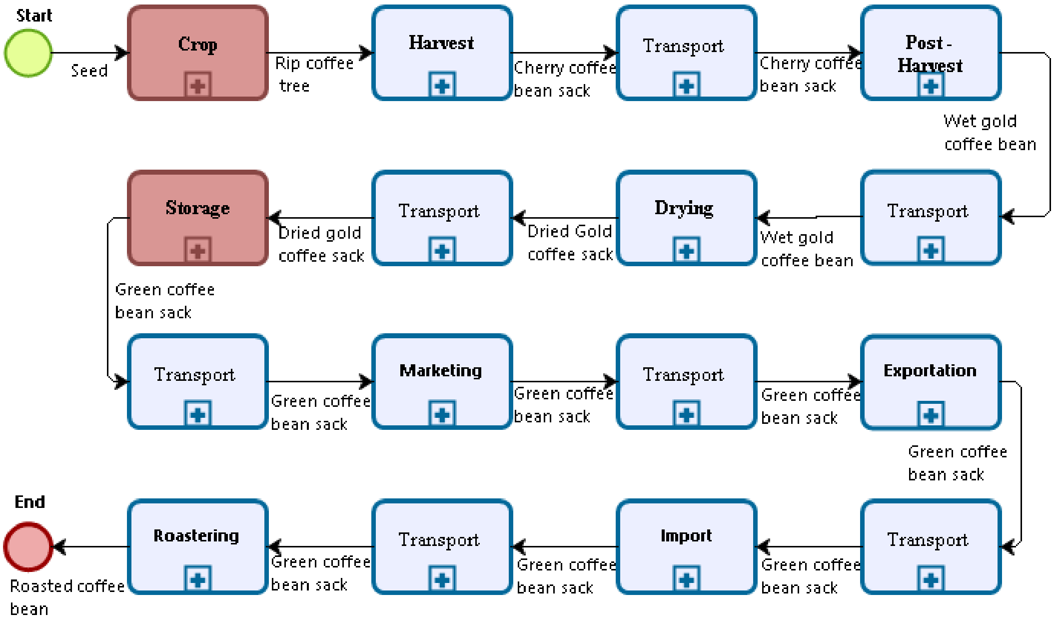

Figure 4.2: BPMN coffee value chain.

4.3 Environmental Variables

This subsection identifies a compilation of articles that assess the impact of environmental variables at agricultural value chain. From the following study, the conceptual model is structured in terms of monitoring environmental variables.

Various articles have worked on the study of environmental variables that affect agricultural products at pre production stage of the value chain, such as [62] who expose that agriculture production is directly tied to weather variables such as rainfall, temperature, humidity and wind. As well as [63] implement an agriculture greenhouse production environment measurement and control system, it offered a good growth condition based on monitoring of temperature and humidity.

Following, at production stage articles [64] identifies changes due to temperature and relative humidity in flavor, texture, shelf life, nutritional attributes, aroma, among others. once the harvest of the product occurs for different fresh fruits and vegetables. Same as [65] suggests permanent monitoring of crops in order to minimize risks in the face of dangerous levels of temperature and humidity.

Ref	Stage	Conclusion	Environment variables
[63]	Pre production	Research shows the greenhouse monitor system based on IOT technology has certain precision of monitor and control.	Temperature, Relative humidity
[64]	Production	Shelf life needs to include a retail phase and this depends on knowledge of temperatures and RH to which products are exposed. Improvements in retail display equipment may improve quality maintenance at the point of sale.	Temperature, Relative humidity
[66]	Production, Post Production	The methodology used shall enable the practitioners to understand the importance of temperature, humidity, odor and ethylene sensitivity for storage and transportation of perishables.	Temperature, humidity
[65]	Pre production, production	Big data delivered by a plethora of data sources related to these domains, has a multitude of payoffs including precision monitoring of fertilizer and fungicide levels to optimize crop yields, risk mitigation that results from monitoring when temperature and humidity levels reach dangerous levels for crops, increasing livestock production while minimizing the environmental footprint of livestock farming, ensuring high levels of welfare and health for animals, and more.	Temprature, humidity
[62]	Pre production	Agriculture production and its associated value chains are at the center of rural economies. In both developed and developing countries, agriculture production is directly tied to weather variables such as Rainfal, temperature, humidity and wind.	Rainfal, temperature, humidity and wind
[67]	Post prodution	To minimize respiration and avoid quality deterioration, perishable productsneed to be stored and transported in a controlled atmosphere environment. Among the many factors influencing the respiration process and quality degradation of fresh produce, temperature plays a dominant role	Temperature, humidity
[68]	Transport	Temperature is usually the prime parameter, but other parameters, such as relative humidity and environmental gases, may also be useful	Temperature, Humidity, enviromental gases
[69]	Distribution	The quality of such products at the place of consumption can change. This change depends on the level of temperature stressing the product, i.e., on the climate conditions. The uncertainty of the climate conditions can be responsible for uncertainty regarding the quality of the product at the place of consumption	Temperature, Humidity
[70]	post production, distribution	The study of the temperature variation of a given location not only allows verification of the compliance of the storage conditions with the imposed quality and safety standards, but also enables managers to design proper storage assignment strategies for temperature-sensitive products.	Temperature
[71]	post production, distribution	A sustainable and efficient management of food products also involves the definition of shelf life in planning warehouse operations and avoiding food loss. The shelf-life modeling of fresh foods has been largely investigated considering the effects of temperature or humidity on some quality traits	Temperature, humidity, oxigen
[72]	All Stages	The maintenance of a cold chain is a major constraint in tropical environment, and the promotion of small scale milk processing plants could be considered as one of the steps of the global strategy to improve milk quality at grass root level and to stabilize the raw milk production beside the processed milk value chain.	Temperature
[73]	All Stages	By identifying humidity as the primary enemy of quality for dried products, the importance both of initial drying and of maintaining dryness through the value chain is emphasized.	Humidity

Table 4.1: Related documents environmental variables in the agricultural value chain

In the production stage, specifically after the harvest, the environmental variables change, the wind, the radiation, and the rain disappear and the value chain focuses on to prevent product spoilage, from this point on variables such as Concentration of oxygen, light levels and gases [68, 71] are relevant because they generate the decomposition of products or materials, however variables such as temperature and humidity continue to be important.

Also several works focus on the cold chains in the transport phases which is transversely to the products in the agricultural value chains whose presents the main fruits and vegetables susceptible to chill injury variables [68].

In general, throughout the value chain it is important to emphasize that the main enemies are temperature and humidity, so it is very important that it be kept at limited levels. Evidenced in the article [73, 71]. Fig 4.3 summarizes the environmental variables that affect the stages of the value chain based on the review of previous articles.

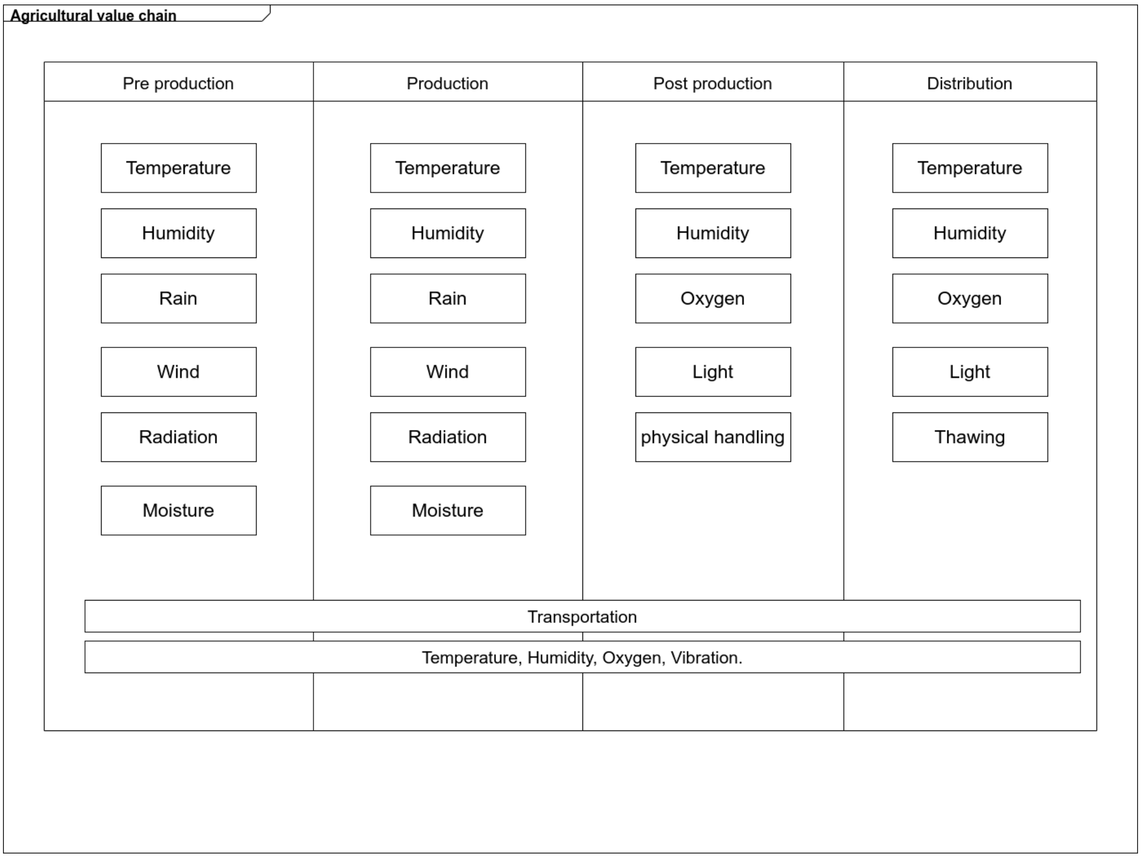

Figure 4.3: Environmental variables agricultural value chain.

Chapter 5

Management system

This section describes the device selected and the power consumption model and introduces the primary stages through an overview of the adaptive sampling period method.

5.1 Monitoring Device

Figure 5.1 shows the CSCG Tag [74]. It is an IoT solution with an internal processor 32MHz MCU w/ 512KB internal flash and audio support, which combines the features and functions needed for all 2.4 GHz IoT standards into a single System on Chip (SoC). And, it has a holder to install a coin-type battery, a programming port, and radio communication hardware; also, it has ambient light, temperature, humidity, and shock/tilt sensors. The light sensor measures the intensity of visible light. Simultaneously, humidity and temperature sensors provide high accuracy measurements with very low current consumption in an ultra-compact Wafer Level Chip Scale Package (WLCSP).

Figure 5.1: IoT monitoring Intel tag.

Figure 5.2 shows internal components, The sensor HDC2010 is placed on the bottom part of the device, which makes the HDC2010 more robust against dirt, dust, and other environmental contaminants. The capacitive-based sensor includes new integrated digital features and a heating element to dissipate condensation and moisture[75].

Temperature and humidity sensor (HDC2010):

- Relative humidity range: 0% to 100%
- Humidity accuracy: ± 2%
- Range operating temperature: –40°C to 85°C
- Functional temperature: –40°C to 125°C
- Temperature accuracy (Typ) (°C) ± 0.2

Light sensor (OPT3001):

- Precision Optical Filtering to Match Human Eye: Rejects > 99% (typ) of IR,
- Automatic Full-Scale Setting Feature Simplifies Software and Ensures Proper Configuration
- Measurements: 0.01 lux to 83 k lux

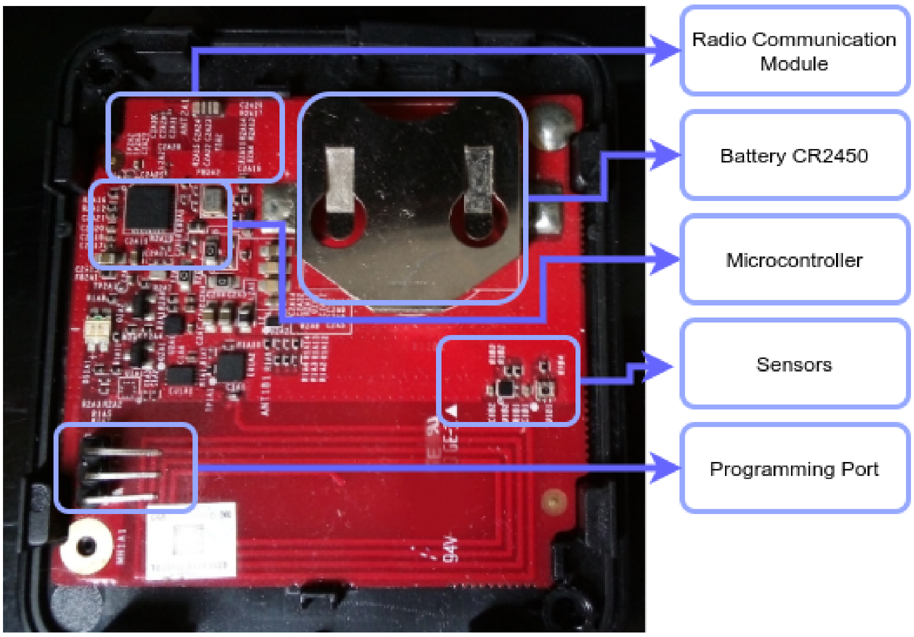

Figure 5.2: Monitoring Intel tag components.

5.1.1 Architecture

Figure 5.3 shows the device belongs to the perception layer located on the farm, the devices send the monitored variables and have communication with the higher layer (Edge Layer) which processes the data and has the ability to manage the devices if required. For this study, The CSCG label was programmed under the C language, the communication configured with the IEEE 802.15.4 [76] protocol, conceives a communication range of 10 meters with a transfer speed of 250 kbit/s. As well, the devices at the edge layer receive data from the perception layer, process them and send it to the servers for further analysis.

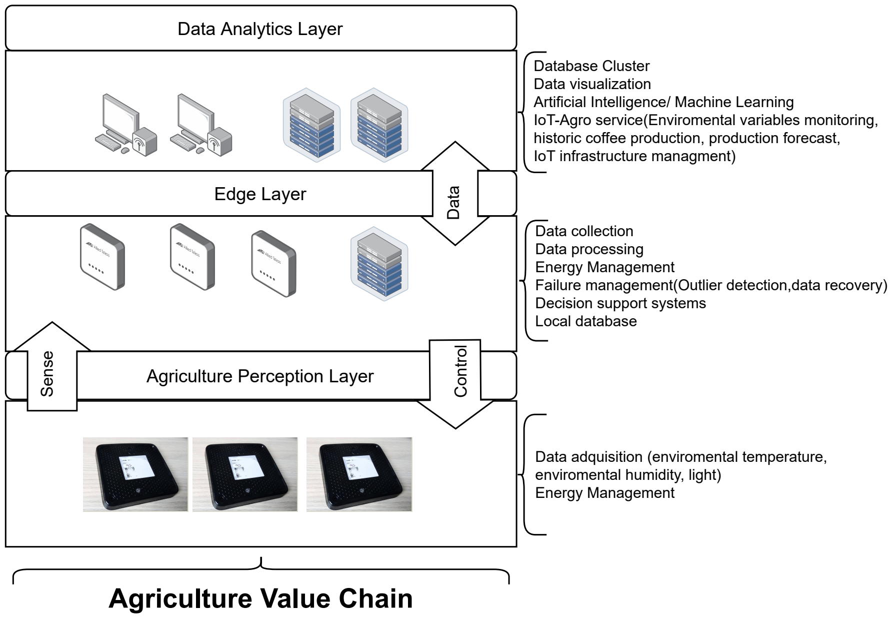

Figure 5.3: Architecture in the case study value chain.

5.1.2 Current Consumption Analysis

The CSCG tag stays most of the time in low power mode because the minimum sampling periods for environmental variables are in the order of seconds. However, some functions are activated periodically to maintain the state machine and perform sensor reading tasks, data transmission, and commands reception by wireless protocol.

For current consumption analysis, we use the Otii Arc DC Power Analyzer Data Logger device [77] set constant voltage source. Figure 5.4 shows the device's current consumption configured for data transmission every minute. The device wakes up every 30 seconds to update the state machine. Also, it shows the power-up interval where peripherals, radio communication, state machine, and configured sensors, this takes about 4 seconds.

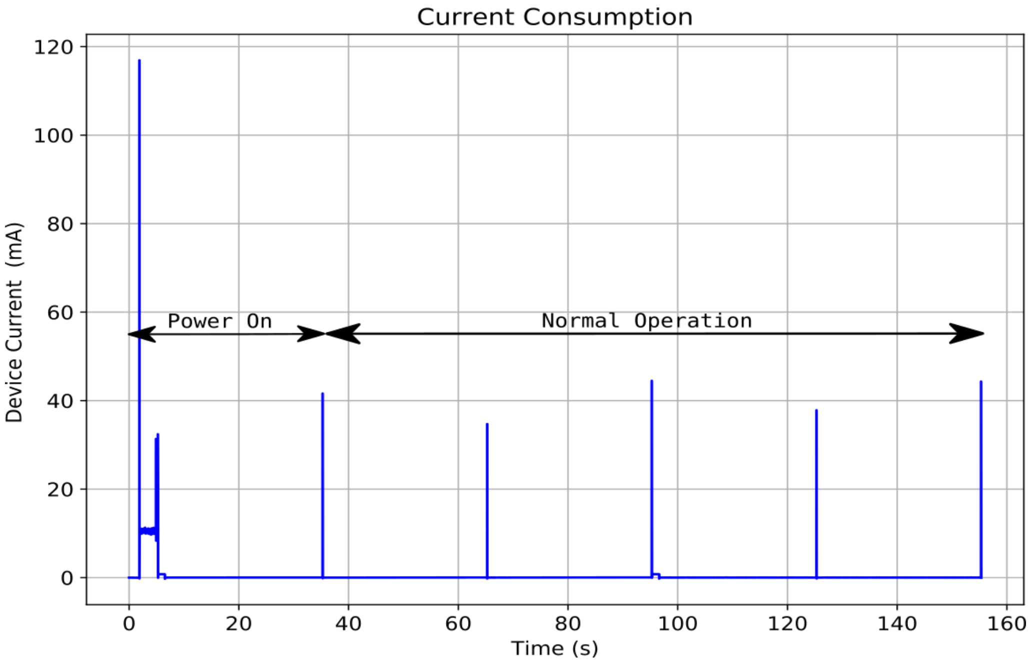

Figure 5.4: Current consumption on Intel tag.

Figure 5.6 focuses on current consumption when the device is awake; there are five stages, state machine update, sensor readout, transmission, time for reception of configuration commands, and time when the device prepares to go to sleep.

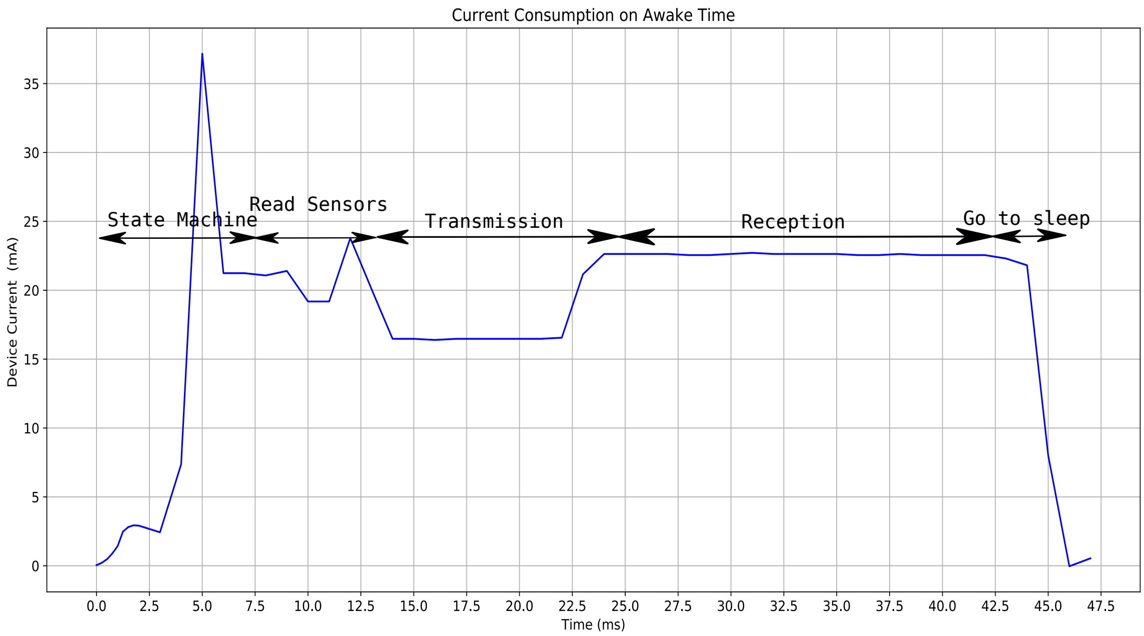

Figure 5.5: Current consumption during awake time.

From the previous information, Table 5.1 and the general equation of average current consumption on a IoT device, we established an equation in function of sampling interval.

Stage	Average Current (mA)	Duration (ms)
State machine	21	7
Reading of sensors	17	5
Transmission	22	12
Reception	24	20
Go to sleep mode	17	2

Table 5.1: Average current consumption per stage

Equation 5.1 shows the average total current consumed by an IoT device defined as the sum of the current consumption multiplied by its duration divided by the total time equation.

$$I_{avg} = \frac{I_{awake} * T_{awake} + I_{sleep} * T_{sleep}}{T_{total}} \tag{5.1}$$

Where:

- I_{avg} : average current consumption (uA)
- I_{awake} : current consumption when device is awake (uA)
- T_{awake} : awake time (ms)
- I_{sleep} : current consumption when the device is on sleep mode(uA)
- T_{sleep} : sleep time (ms)
- T_{total} : total time (ms)

Following the power consumption during active periods is:

$$I_{awake} * T_{awake} = \lambda * I_{sm} * T_{sm} * ST + I_{sn} * T_{sn} * ST + I_{tx} * T_{tx} + I_{rx} * T_{rx} + I_{sl} * T_{sl} * ST \tag{5.2}$$

Where:

- ST : times per period of time
- λ : number of times the status machine is updated per minute
- I_{sm} : current consumption when device is updating the state machine (uA)
- T_{sm} : state machine time (ms)
- I_{sn} : current consumption when device is reading sensors (uA)
- T_{sn} : reading sensors time (ms)
- I_{tx} : current consumption when device is transmitting data (uA)
- T_{tx} : transmission time (ms)

- I_{rx} : current consumption when device is on reception mode (uA)
- T_{tx} : reception time (ms)
- I_{sl} : current consumption when device is going to sleep mode (uA)
- T_{sl} : to go sleep mode time (ms)

The equation 5.2 shows ST is a variable without units that describes the number of times that each stage is executed over the total time, this means that in a period of time of 8 minutes, the reading of the sensors is performed 8 times, during this time the data is stored. When the time is up, the data from the sensors are averaged and transmitted and the reception of acknowledge and configuration commands from the central node is expected. therefore the transmission and reception only takes place once in the period of time.

Following we define: T_{sleep}

$$T_{sleep} = (T_{total} - T_{awake}) \tag{5.3}$$

Where T_{total}: corresponds to total time in ms defined as:

$$T_{total} = 60 * 1000 * ST \tag{5.4}$$

Replacing T_{awake}

$$T_{awake} = \lambda * T_{sm} * ST + T_{sn} * ST + T_{tx} + T_{rx} + I_{sl} * T_{sl} \tag{5.5}$$

Finally, the equation of current consumption is:

$$\begin{aligned} I_{avg} = & \frac{\lambda * I_{sm} * T_{sm} * ST + I_{sn} * T_{sn} * ST + I_{tx} * T_{tx} + I_{rx} * T_{rx} + I_{sl} * T_{sl}}{60 * 1000 * ST} \\ & + \frac{(I_{sleep} * ((60000 - \lambda * T_{sm}) * ST - (T_{tx} + T_{rx})))}{60 * 1000 * ST} \end{aligned} \tag{5.6}$$

Equation 5.6 allows determining the average current consumption related to the sampling interval and the monitoring device's performance. Figure **??** shows the results for an sampling interval between 1 to 30 minutes for $\lambda = 2$.

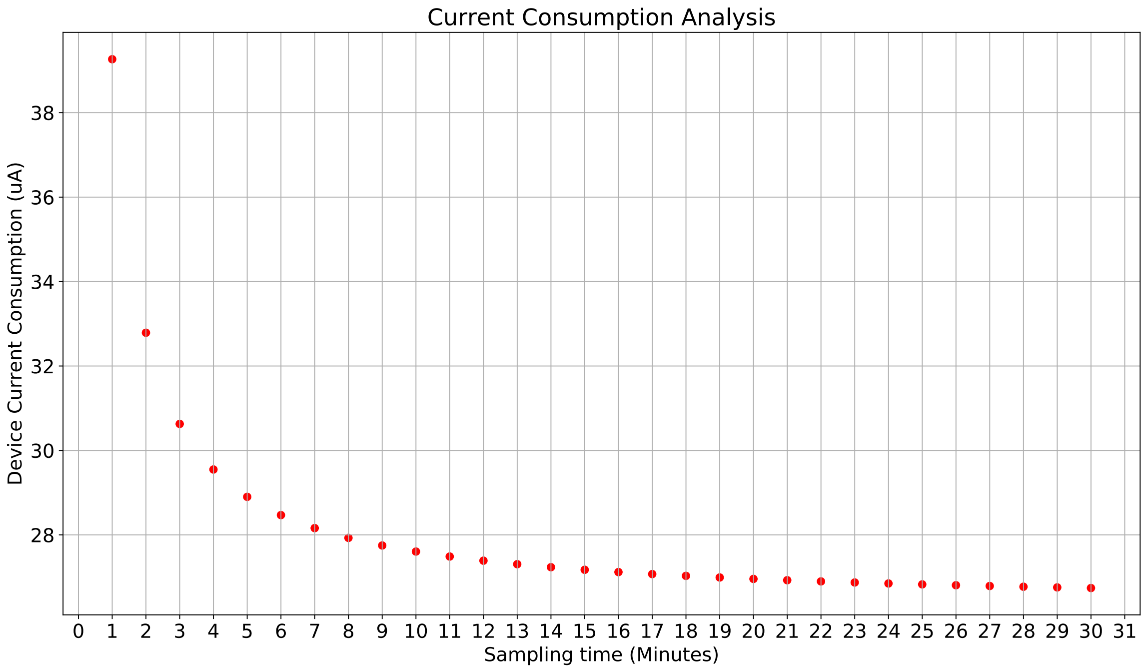

Figure 5.6: Current consumption vs sampling interval.

5.1.3 Battery life

The equation 5.7 below gives an estimate value of the life cycle.

$$EstimatedHours = \frac{Capacity(mAh)}{CurrentConsumption(mA)} * 0.7(UsableEnergy) \tag{5.7}$$

The table 5.2 shows information about different commercial battery's capacity for estimating life time of the monitoring device.

Battery	Capacity (mAh)
CR2434	320
CR2450	620
2 Batteries AAA	1200

Table 5.2: Battery's Capacity

Figure 5.7 shows the estimated days that the device lasts for different sampling intervals with different commercial batteries.

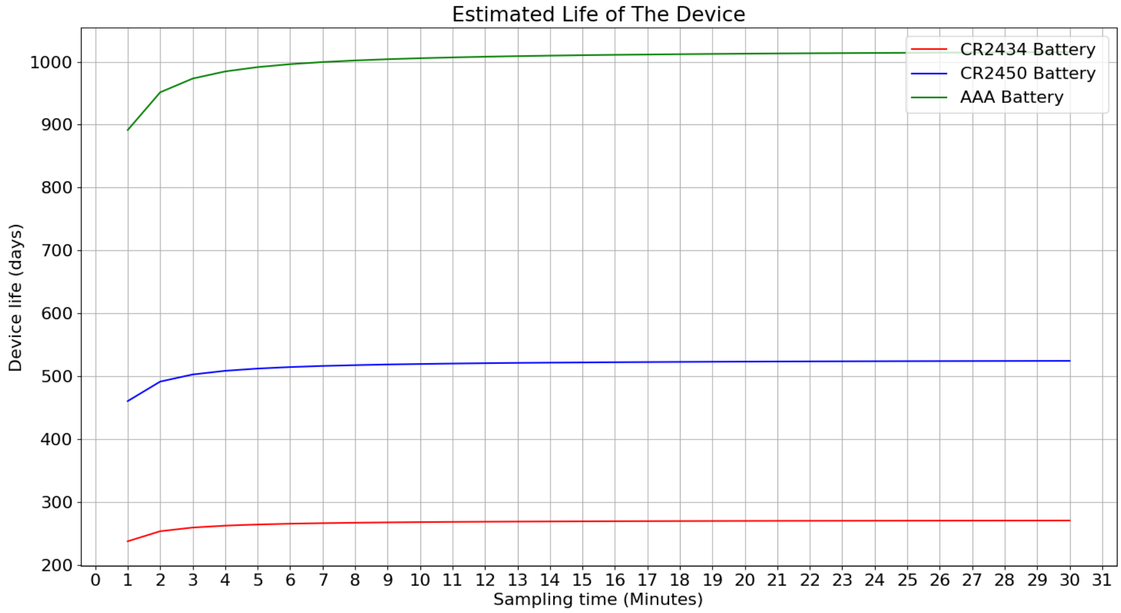

Figure 5.7: Estimated life of the device.

After developing our energy consumption model for the selected device, the following section introduces our energy consumption optimization management through an overview of the method and a brief description of the algorithm used.

5.2 System Overview

Figure 5.8 shows an overview of the method for managing optimize energy consumption in IoT monitoring systems based on adaptive sampling period. Overall, the proposed method includes three stages.

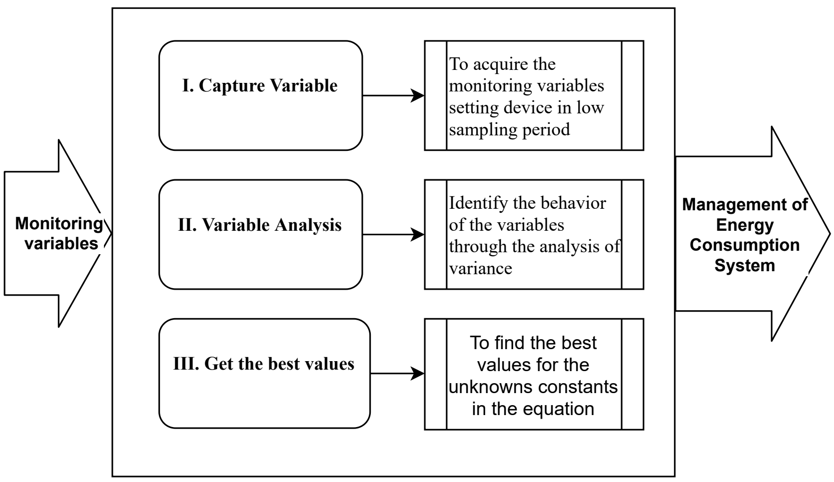

Figure 5.8: Method for management of energy consumption.

- *Stage I*: the environment variables are the input of this stage; this stage shows the behavior of the variable in the environment where it is installed; the goal is to acquire the follow-up variables with the minimum sampling period allowed. With this, it is possible to identify if a variable presents an excessive sampling because its change is not so fast or required to use a lower sampling period. The output of this stage is the monitoring variables data set.

- *Stage II*: the variable analysis receives the captured data and is responsible for analyzing the variables' behavior over time-based mainly on the variance of the data, determining the most appropriate variable to manage energy consumption. The output of this stage is the monitoring variable selected.

- *Stage III*: starts from a lineal equation as a function of the variance and two unknown constants (α, β); At this point, an iterative process is proposed that begins by defining a combination of values in a defined range, from which a pair of them is taken to test them on the dataset and obtain the evaluation metrics, the iterative process ends when all combinations of values on the dataset were tested. Finally, the pair of values that generate the minimum value of the sum of the evaluated metrics is selected. Figure 5.9 summarizes the flow of the algorithm.

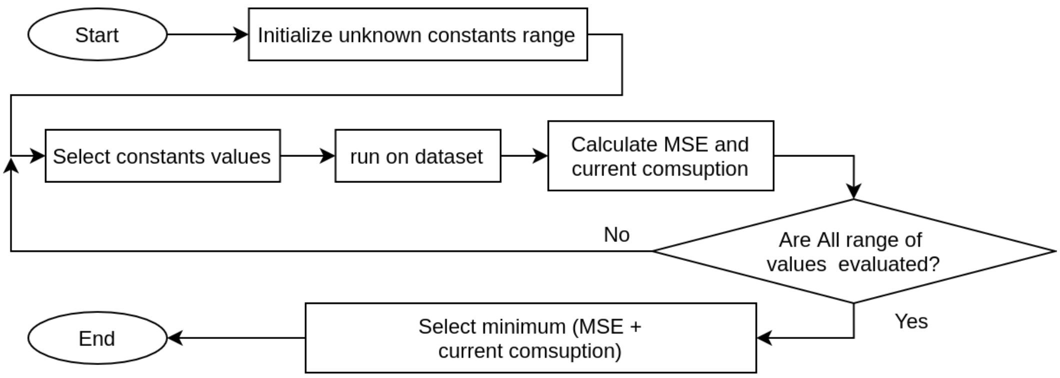

Figure 5.9: Flow chart to find the best values of the constants.

In this study, the evaluation metrics are the current consumption equation found in the subsection 5.1.2 and the mean square error (MSE) defined as:

$$MSE = \frac{1}{n} \sum_{t=1}^{n} e_t^2 \tag{5.8}$$

Where:

$$e_t^2 = (X_i - \hat{X}_i)^2$$

$$X_i \rightarrow Vector\ of\ observed\ values\ of\ the\ variable\ being\ predicted$$

$$\hat{X}_i \rightarrow Vector\ of\ predicted\ values$$

With the values of the constants of the equation, a monitoring device is programmed which manages the data transmission periods; therefore, the variables and their performance are evaluated concerning fixed sampling techniques.

5.2.1 Variables Analysis

The study case was in the crop and storage stages of the coffee value chain; with IoT monitoring devices installed in the coffee farm "Los Naranjos" we validated the model. This farm belongs to Supracafé, located in La Venta district, in the municipality of Cajibio, Cauca (21-35’08"N, 76-32’53"W).

For the crop stage, the monitoring devices were configured to the lowest sampling period (1 minute) and located at different heights in the tree. The Figure 5.10. We carried out the monitoring during March, April, June, July, August, and September 2020.

Figure 5.10: Installation devices on crop stage.

Figure 5.11 presents the variations in temperature and Relative Humidity (RH) in the selected days. The analysis considered days that presented different climatic conditions like rainy, sunny, and cloudy. The graph presents changes in temperature with minimum values of 9.42 $°C$ and a maximum value of 35.62 $°C$. In turn, there are variations in humidity with minimum values of 21.7% RH and a maximum value of 100% RH.

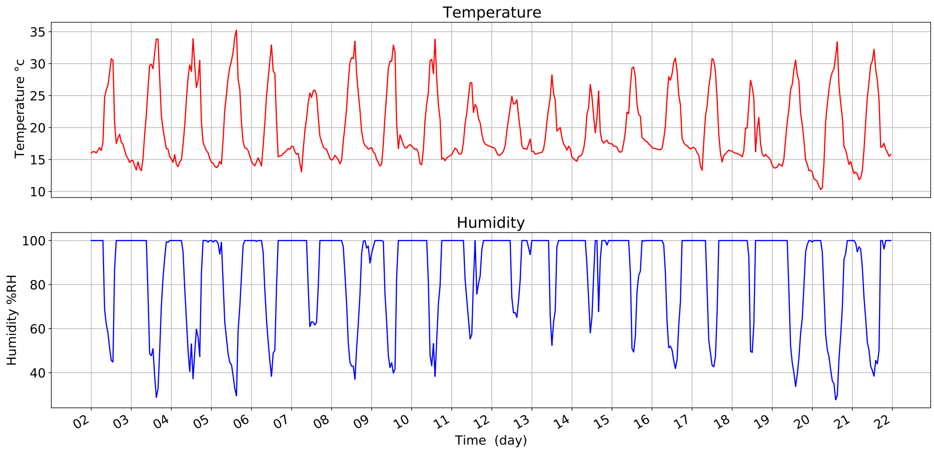

Figure 5.11: Temperature and Humidity at Coffee Farm

5.2.2 Temperature Analysis

Figure 5.12 presents the data captured (red line) and a simulation of the values when changing the sampling period to different fixed values; these values are obtained from an average of data real captured. The error presents the data sampled every minute. Similarly, an attenuation is observed in the variable's peak values concerning the original sampling period.

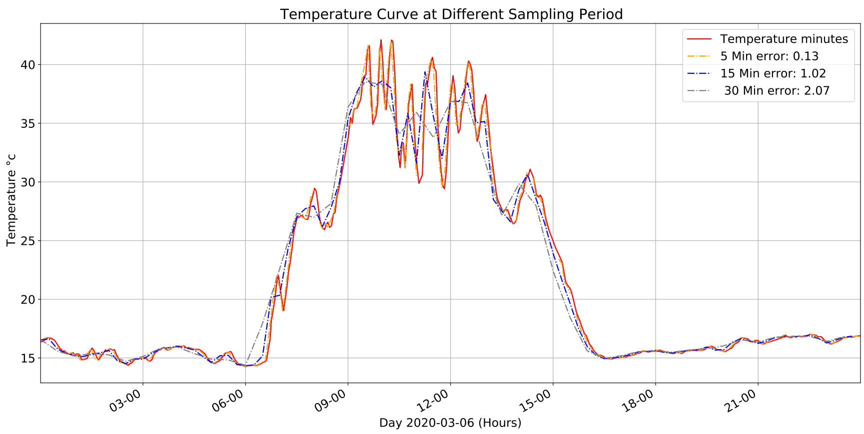

Figure 5.12: Temperature for different sampling times.

Figure 5.13 presents the calculation of the variance for the fixed sampling periods with respect to the data sampled every minute. From the previous graph it is observed that the greatest variation in the values is between 9 and 14 hours, likewise there are some minor peaks between 6 to 9 hours and 14 to 17 hours of the day, although the previous result corresponds to march 6, this behavior is similar for different days under different climatic conditions.

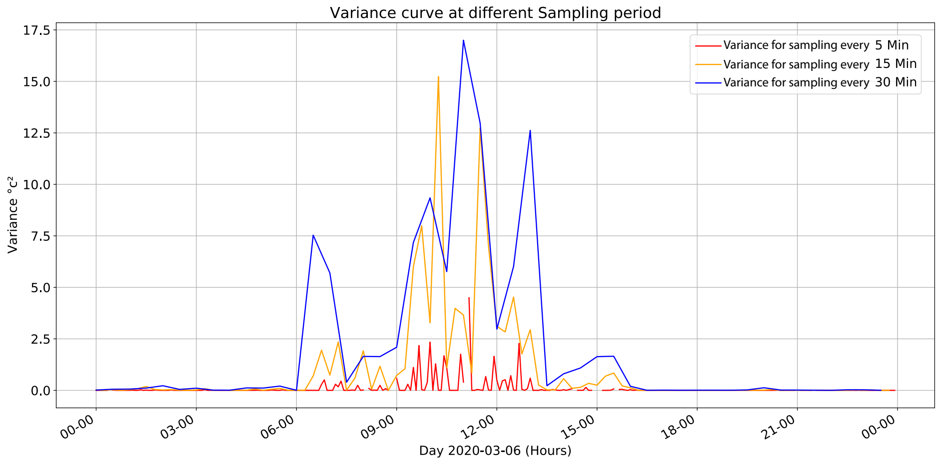

Figure 5.13: Temperature's variance for different sampling times.

Figure 5.14 shows the calculation of the absolute value of error, It is the difference between the value of the average and the value taken every minute. It can only be positive, which measures the vertical extension of the data around the mean values in 5, 15 and 30 minutes.

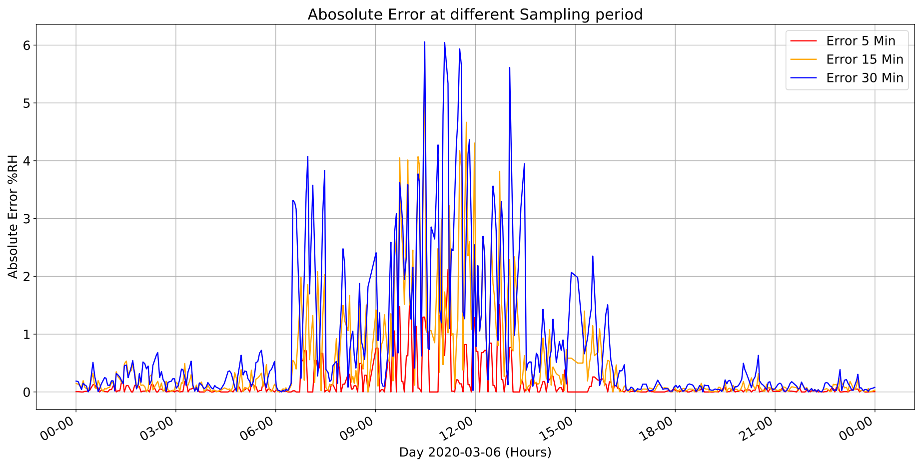

Figure 5.14: Absolute value of error for different sampling times.

5.2.3 Humidity Analysis

Figure 5.15 presents the data captured (red line), and a simulation of the humidity from the values sampled every minute when changing the sampling period to different fixed values and the error it presents concerning the data sampled every minute. Also, Figure 5.15 shows that the selected sampling period's error is more significant for those presented in the temperature graph and saturation in the percentage of humidity at night hours.

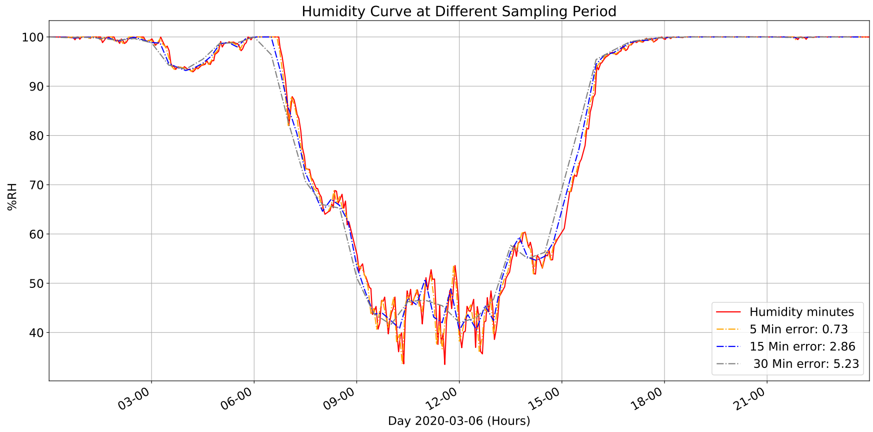

Figure 5.15: Humidity for different sampling times.

Figure 5.16 presents the calculation of the variance for the fixed sampling periods with respect to the data sampled every minute. From the previous graph, strong variations are observed between 8 and 20 hours with a maximum peak of 46 at 9.30 in the morning. However, the variations are much higher than those managed in temperature, which makes it more relevant for the management system approach.

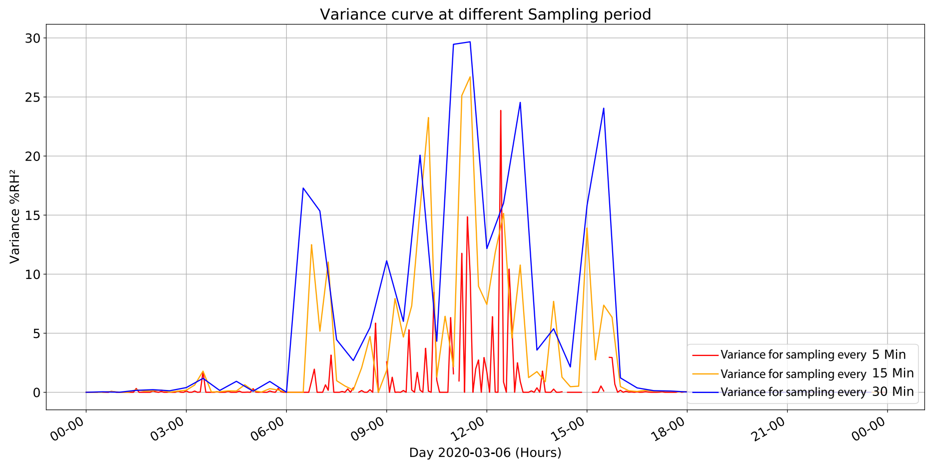

Figure 5.16: Humidity's variance for different sampling times.

Figure 5.17 shows the calculation of the absolute value of error, the error levels for humidity reach a maximal value of 12% RH for a period of 30 minutes compared to 6 degrees Celsius which is the highest value in temperature.

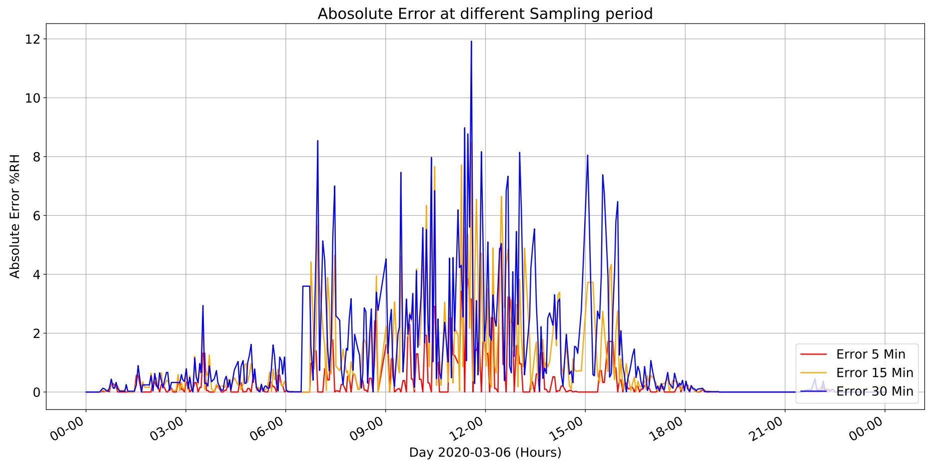

Figure 5.17: Absolute value of error for different sampling times.

The previous data corresponds to one day; therefore, we made the same analysis for the group of selected days.

Figure 5.18 shows the variance distribution to selected days, revealing a recurring variation between 7:00 and 11:30 hours with a peak of variation at 8:30, as well as a second minor peak between 13:30 and 17:00 hours. Therefore, based on the previous information, implementing an energy management system is proposed, maintaining the characteristics of carrying out sampling at a sampling period of one minute and minimizing energy consumption, which manages an inverse relationship concerning variance the absolute value of error.

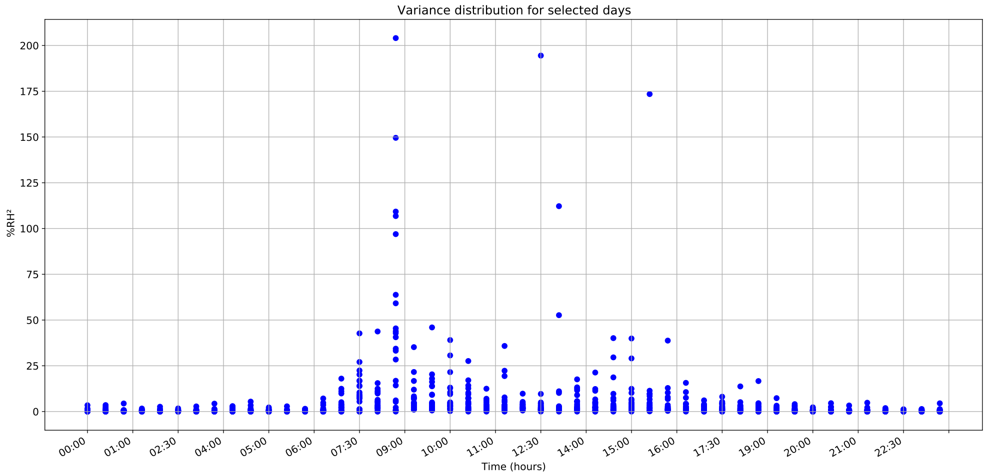

Figure 5.18: Variance behavior for all data set.

5.2.4 Best values analysis for unknown constants

Given the selected variable's variance, this section found the best values for managing the device's energy consumption from a base equation. Equation 5.9 is proposed as a base point for our adaptive algorithm as a function of the variance and with two constants to find

$$Fs = \alpha * Var(t) + \beta \tag{5.9}$$

Where:

$$Fs \rightarrow sampling\ frequency$$
$$Var(t) \rightarrow Variance\ function$$
$$\alpha, \beta \rightarrow unknowns\ constants$$

Subject to the constraints:

$5.555 \times 10^{-3} <= Fs <= 16.66 \times 10^{-3} \rightarrow$ sampling frequency range

Equation (5.9) is the base equation where the unknown variables are α and β subject to a frequency range equivalent to a sampling period between 1 min and 30 minutes. The period range is established based on the consultation of interested experts to relate changes in humidity and temperature with studies related to production estimation, disease control, storage, transportation, which require a precise estimate of the daily average maximum and minimum values of the variables selected in this study [78, 79, 80].

Therefore, based on the result of the equation, the Period Sampling (Ps) is established by the equation:

$$Ps = round\left(\frac{1}{60 * Fs}\right) \tag{5.10}$$

The equation (5.10) returns a value based on converting from frequency to time and rounding it to the nearest whole. This value is applied to the next sampling window (next 30 minutes), where the error is calculated as the energy consumption.

We selected two vectors and a day with high variance to define the α and β values. Alpha ranges from 0 to 0.1 with increments of 1×10^{-3}, and for Beta, a range from 0 to 10×10^{-3} with an increment of 0.1×10^{-3}. It generates a two-dimensional matrix for each pair of a and b values; thus, we have the error and energy consumption graph.

Figure 5.19 shows the mean square error (MSE) for different alpha and beta values. The highest error rates occur to values close to or equal to zero in alpha, related to handling fixed sampling time. Through the variation of β, it is possible to reduce the error since it forces to have lower sampling periods to the point that for values greater than 5×10^{-3}, the sampling is 1 minute corresponding to the minimum sampling period and consequently an error of zero.

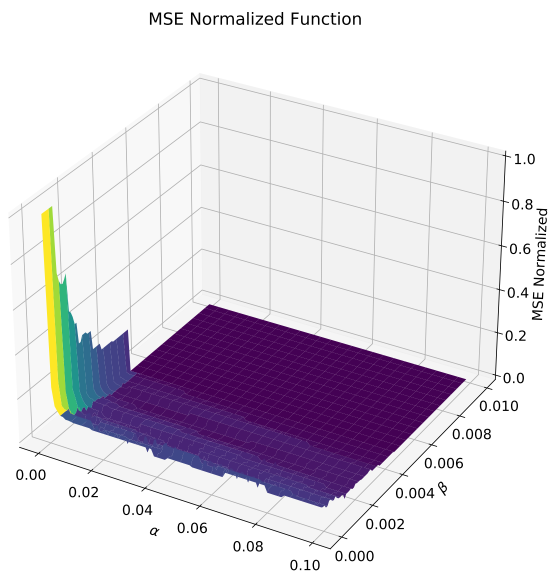

Figure 5.19: Normalized MSE for different α *and* β.

Figure 5.20 shows the current consumption for different values of alpha and beta where a direct relationship is observed for the parameters alpha, beta, and energy consumption; if fixed sampling intervals are selected ($\alpha = 0$), the lower current consumption values are obtained.

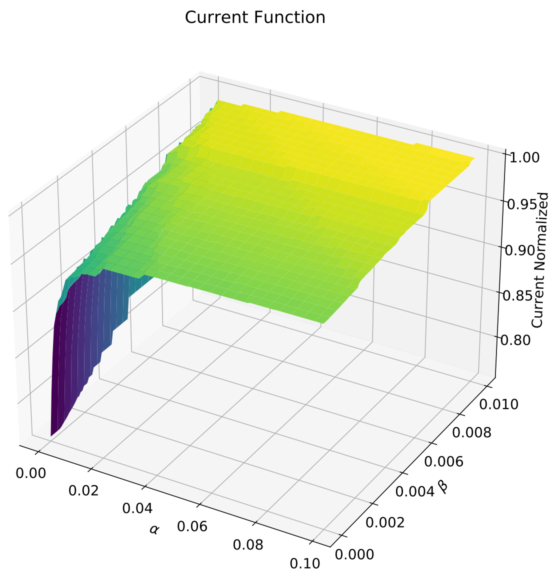

Figure 5.20: Normalized current consumption for different α *and* β.

For simplification purposes, we selected $\beta = 0$ based on the previous graph due it represents the lowest current consumption curve. The equation is simplified to find a suitable alpha value because both the error and the current consumption are acceptable minimums. From the elimination of β, the normalized curves of error and current consumption are in Figure 5.21.

Figure 5.21 shows the error(blue line), the current consumption (red line), and the sum of error and current consumption (green line) in the function of α. Error and energy consumption are normalized because the contribution is proportional to the sum function. Due to high error values, the sum function shows a maximum alpha close to zero; and a stable value due to the current function. Likewise, we determined the value to reach the minimum value, which corresponds to the lowest consumption under a low error and low current consumption (black vertical line).

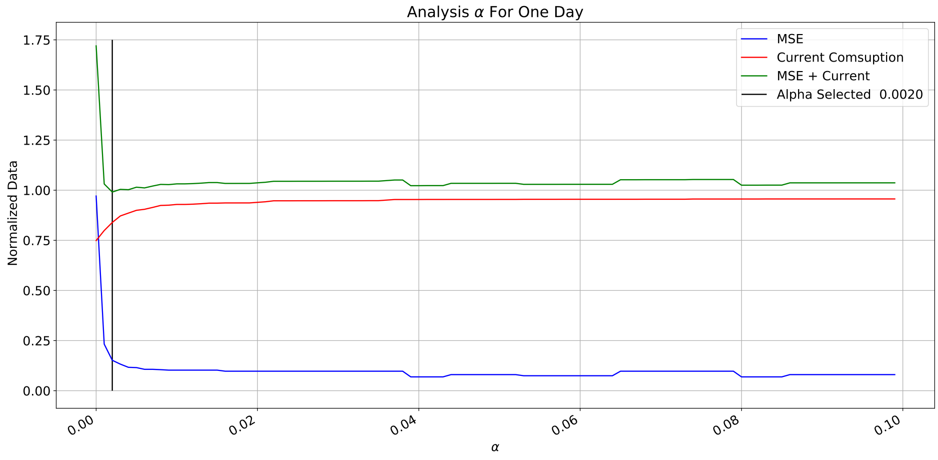

Figure 5.21: Analysis of α for one day.

We carried out the previous analysis for all the selected days. Figure 5.22 shows the MSE and current consumption; they had similar behavior, especially for the MSE; the current and MSE of Figure 5.22 are normalized, which generates the general function as shown in Figure 5.23, where the best α is selected for each day(black lines). As a result, a distribution of points shows a value of alpha between 2×10^{-3} and 12×10^{-3}. We took the mean value represented in the red line for the general equation.

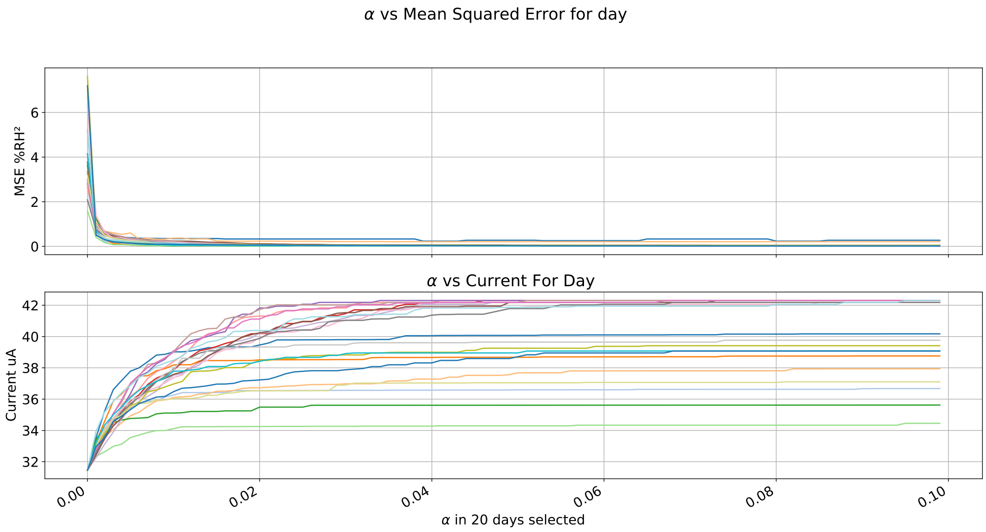

Figure 5.22: Analysis of α vs Mean squared error and current.

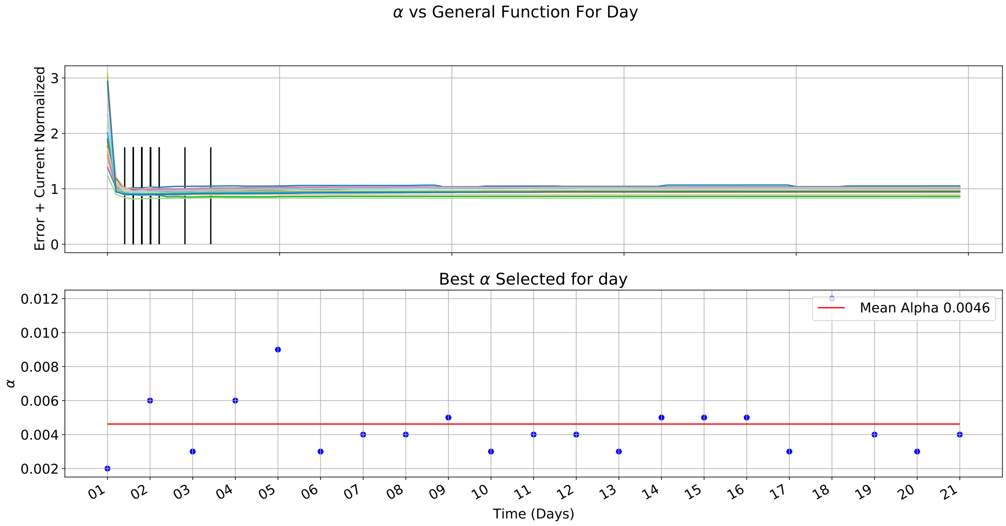

Figure 5.23: Analysis of best α for day and mean α.

Therefore, the equation is:

$$Fs = 4.6 \times 10^{-3} * Var(t) \tag{5.11}$$

$$Ps = round\left(\frac{1}{60 * (4.6 \times 10^{-3} * Var(t))}\right) \tag{5.12}$$

Finally, we have the next equation:

$$Ps = round\left(\frac{3.623}{Var(t)}\right) \tag{5.13}$$

The equation 5.13 defines the transmission period of the averaged variables; it takes as a starting point the variance calculated in a 30-minute window and determines the sending period. Ps can be between transmission every minute or a single one in 30 minutes. Since the variance calculation does not involve complex operations, as well as the equation found, can be programmed in the firmware of the IoT devices, the equation does not represent a significant additional time.

Chapter 6

Evaluation

This chapter evaluates the management system proposed in a case study.

For evaluating the equation, we installed two devices, one with the lowest sampling period (1 min) and the other with the equation's execution as a function of the humidity variance. Figures 6.1 and 6.2 show the results and demonstrate that our adaptive sampling method is working correctly (These measurements correspond to one day only apart from the whole data-set).

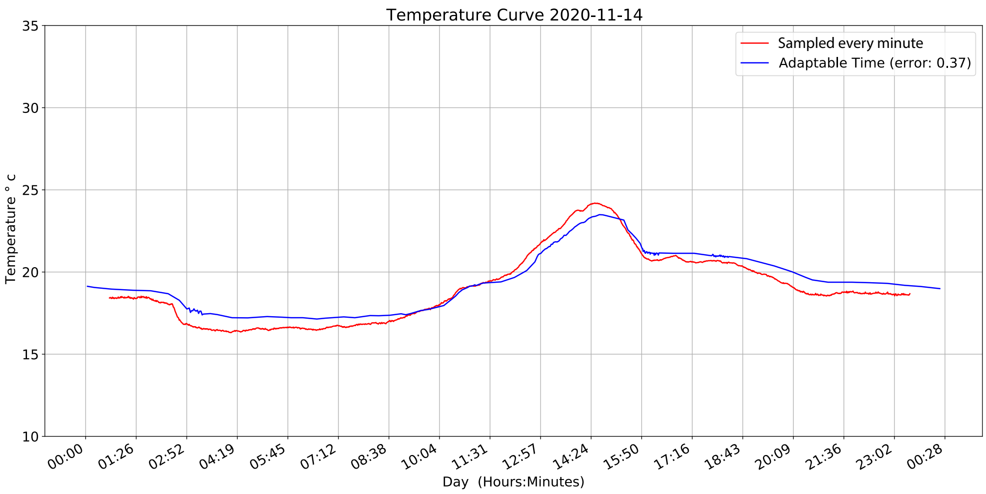

Figure 6.1: Temperature curve.

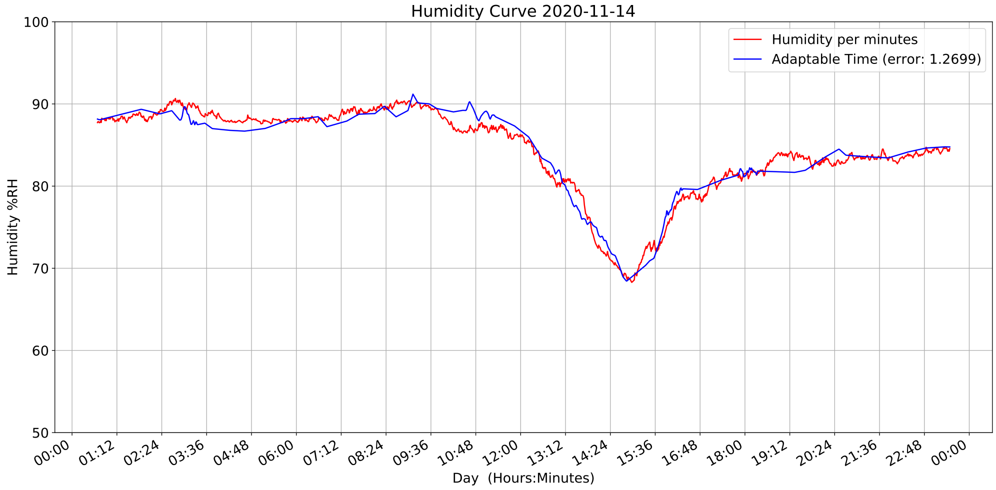

Figure 6.2: Humidity curve.

As shown in Figure 6.3, the IoT device sampling time is 30 minutes at the starting point. The variance equation says humidity is changing, and the measure is updated 12 minutes after the first measurement window.

Figure 6.3 shows the sampling intervals during measurements. If the calculated variance increases, the sampling interval becomes smaller. In other words, if there is a significant change in humidity, the IoT monitoring device measures the variables more often. This result proves that our code works fine, and our method can control the sampling period according to the variable behavior.

We select a 30 minutes window because sensors have certain noises, and the humidity measurements, especially humidity measurements, are not negligible. Since our adaptive sampling method can be susceptible to the input values, noises can result in wrong sampling period adjustment, resulting in a loss of energy.

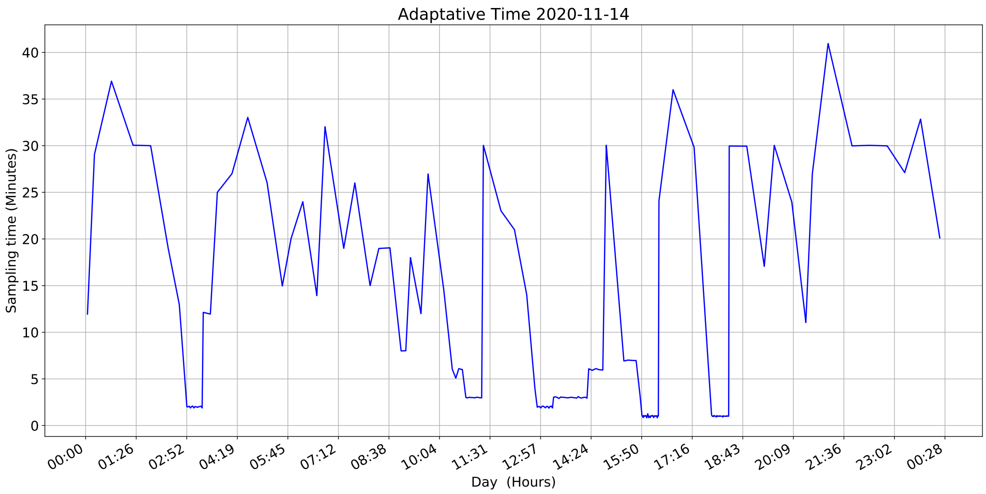

Figure 6.3: Analysis of adaptable time.

6.1 Performance Evaluation

For the evaluation of the performance of environmental parameters, we used statistical metrics.

- mean square error (MSE): define previously in 5.8 and parameter base in this study. It can take any positive value with zero indicating a perfect lack of error
- Mean absolute relative error (MARE): is defined as the ratio of the absolute error of the measurement to the actual measurement. The relative error indicates how good measurement is relative to the size of the object being measured. If x is the actual value of a quantity, x0 is the quantity's measured value, and δx is the absolute error. The relative error is measured $(\delta x)/x$
- Mean Bias Error (MBE): this measures the extent to which the estimated value deviates from the observed value. It can take any value, with negative values indicating systematic under-estimation and positive values, over-estimation, and zero indicating a perfect lack of bias.
- Pearson's correlation coefficient (R) represents a linear dependence between two variables is widely used and easily interpreted, taking a value between $-1 \rightarrow 1$ with one indicating a perfect positive linear correlation [81].
- Nash-Sutcliffe efficiency coefficient (NSE): is a normalized indicator of model efficiency corresponding to the estimate's statistical agreement or skill relative to the experimental measurements. It takes a value ranging from $-\infty \rightarrow 1.0$,

with one being a perfect fit and negative values meaning that the station offers a better estimate.

Table 6.1 presents the results for the different metrics evaluated for energy system management. The temperature sensor presents better results than the humidity sensor because the first one has better accuracy (± 0.2 $°C$) than (± 2 % RH) humidity variable register. It was mainly reflected in the MSE, which yielded results close to the sensor's accuracy, although a uniform environment for both devices.

Regarding MARE, the evaluation presents good results because, for this parameter, it considers the size or magnitude of the measured variable; therefore, given that the humidity values are more significant than the temperature, the result yielded a smaller value. Concerning MBE related to a measurement error that remains constant in magnitude for all observations, it shows that temperature and humidity present values close to zero, indicating a pleasing lack of bias. For R, both variables have values close to 1; it indicates that a linear equation perfectly describes the relationship between the variables sampled every minute and adaptive sampling. Subsequently, the NSE represents that the sampling with the adaptive function has a model with good predictive skill.

Above all, the current consumption with adaptative sampling was equivalent to a fixed sampling of 8 minutes, which, based on Figure 5.6 shows almost the flat part of the curve of the estimated life of the device, this means the % decrease is very close to the maximal % decrease allowed.

Statistic	Adaptative Time	Range	Ideal Value
MSE Temperature	0.369 $°C^2$	$0 \to \infty °C^2$	0.0 $°C^2$
MSE Humidity	1.28 $\%RH^2$	$0 \to \infty \%RH^2$	0.0 $\%RH^2$
MARE Temperature	0.028	$0 \to \infty$	0.0
MARE humidity	0.011	$0 \to \infty$	0.0
MBE Temperature	0.345	$-\infty \to \infty$	0.0
MBE humidity	0.0015	$-\infty \to \infty$	0.0
R Temperature	0.979	$-1.0 \to 1.0$	1.0
R Humidity	0.977	$-1.0 \to 1.0$	1.0
NSE temperature	0.917	$-\infty \to 1.0$	1.0
NSE humidity	0.954	$-\infty \to 1.0$	1.0
Power Consumption	34.92uA	$34.47uA \to 39.27uA$	34.47 uA
% Power Consumption Decrease	11.04%	$0\% \to 12.2\%$	12.2%

Table 6.1: Statistics used for evaluation energy system management.

Figure 6.4 illustrates the results obtained under different climatic conditions. A more significant variation in temperature and humidity is on sunny days; the devices adjust to a sampling period of one minute longer than rainy days. The above allows us to evaluate the behavior of the α parameter and the proposed management system from a lower level of variation in temperature and humidity and more extended sampling periods. We conducted this experiment on conditions presented on different outdoor days where climate variability is more significant than warehouses or transport vehicles.

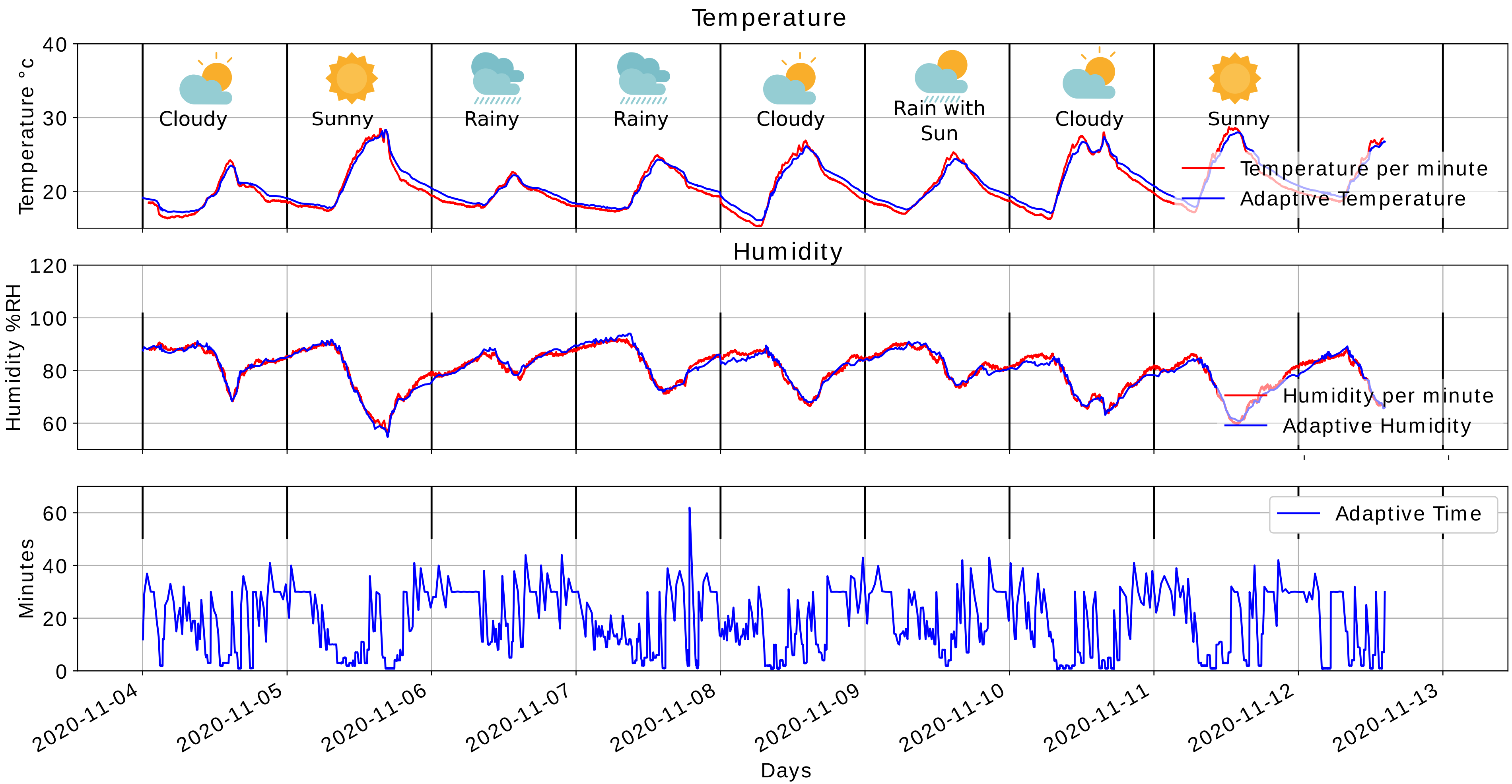

Figure 6.4: Result for different conditions of the day.

Finally, table 6.2 presents the different metrics evaluated for days under different climatic conditions. The results are the approach of the worse scenario, where the system is implemented. The metrics do not present a significant difference concerning the analysis of the selected day that presented great variation. The energy savings compared to the analysis of one day decreased by 0.16%.

Statics	Adaptative Time	Range	Ideal Value
MSE Temperature	0.476 $°C^2$	$0 \to \infty °C^2$	0.0 $°C^2$
MSE Humidity	2.33 $\%RH^2$	$0 \to \infty \%RH^2$	0.0 $\%RH^2$
MARE Temperature	0.030	$0 \to \infty$	0.0
MARE humidity	0.015	$0 \to \infty$	0.0
MBE Temperature	0.302	$-\infty \to \infty$	0.0
MBE humidity	-0.25	$-\infty \to \infty$	0.0
R Temperature	0.983	$-1.0 \to 1.0$	1.0
R Humidity	0.981	$-1.0 \to 1.0$	1.0
NSE temperature	0.9498	$-\infty \to 1.0$	1.0
NSE humidity	0.959	$-\infty \to 1.0$	1.0
Power Consumption	34.99 uA	$34.47uA \to 39.27uA$	34.47 uA
% Power Consumption Decrease	10.88%	$0\% \to 12.2\%$	12.2%

Table 6.2: Resume Statics for days with different conditions.

6.2 Discussion

In this section, we discuss the performance of energy consumption management compared to other results obtained in other proposed models. In summary, the evaluation of adaptive solutions is mainly compared with fixed sampling schemes, where consumption savings and data quality are primarily taken into account. In [82] selects a suitable sampling frequency during the acquisition process according to the signal frequency's spectral content. This paper got energy savings between 44% and 72% and MSE values between 1.3E-04 and 1.5E-02 for three evaluated signals. As well as in [83] performs a frequency analysis through a fast Fourier transform mainly. They found that the algorithm can reduce the number of acquired samples up to 79% concerning the fixed sampling frequency. At the same time, generally, the () shows a preserving the accuracy of the data. In [84] shows a model based on the sensing-driven cluster, correlation-based sampler selection and model derivation and adaptive data collection, and model-based prediction called ASAP. This was compared introducing two variants of ASAP: local approach and central approach under a set of experiments study the performance concerning messaging cost, energy consumption perspective, and the quality of the collected data. In [85] different aspects were evaluated, which it is highlighted their methods conserved the energy by 29%, 47%, and 25%, respectively. The last paper has a close proposal since one of the proposed algorithms considers the variance, however, the proposed similarity algorithm is different from the strategy proposed in our article.

Our proposal evaluated different metrics by capturing real data, evidencing good results in terms of data quality such as MSE, , and Pearson correlation. However, it's important highlight the effect of variables such as the devices' accuracy and sensitivity used. Regarding energy-saving terms, on average, it was a 10.88% significantly low value compared to other related works; however, it corresponds to a value of 89% within the possible range of possible reduction for the IoT device.

Chapter 7

Conclusion and Future Work

7.1 Conclusions

We proposed the adaptive sampling period method to keep the IoT device power consumption to a minimum and maintain the outstanding sensing quality based on the MSE of variables, especially for humidity monitoring. We found a specific variance pattern in the everyday humidity and temperature measurements in which humidity is more significant than temperature. It let us reduce transmission, which is a big part of energy consumption on IoT devices. We decided that an adaptive sampling method is appropriate to achieve our goal and develop the technique to adapt the sampling interval of devices based on the variables' variance, which is a dispersion measure between values in environmental variables.

We simulated the method with Python taking into account a minute-by-minute measured dataset. The outcome proves that an adaptive sampling method decreases transmissions significantly while providing quite acceptable quality measurements. Finally, we tested our method with real sensors used in the IoT-Agro project, demonstrating the effectiveness and flexibility.

In a real scenario, we evaluated the proposed management systems indoors and outdoors; we located two devices, one with sampling every minute and the other with the adaptive system. For temperature evaluation, the mean square error (MSE) was 0.369 $°C^2$, a value close to 0.2 $°C$ the accuracy of the sensor; in Pearson's correlation, the results were above 0.97, in mean absolute relative error (MARE) presented values lower than 0.028.

For humidity, we got an error more significant than expected. Despite generating conditions similar to the two devices, the sensor's accuracy means that two sensors do not deliver the same value under the same conditions. Therefore, the mean square error (MSE) was 1.39% RH, a value lower than 2% RH to the sensor's accuracy. In terms of Pearson's correlation, the results gave values above 0.97, in the mean absolute relative error (MARE) presented values lower than 0.03. With the advantages of adaptive sampling, we achieved an equivalent to an 8-minute sampling in terms of current consumption. The lowest admissible sampling corresponds to a minute in the hours where there is a more significant variation.

With the proposed management system, a reduction of 11.04% is achieved; the result is significant because the maximum possible percentage is 12.2%, equivalent to performing sampling every 30 minutes all the time. The reduction percentage was 90% for the selected day and 89.18% for the selected group of days with different weather conditions concerning the total percentage decrease allowed.

Our adaptive sampling method determines the next sampling period based on the variance of the previous measurements. Thus, if there is considerable noise, it will not affect the result, and since the method has a 30 minutes window is not very sensitive to the slight change of the measurements; therefore, we can handle the noise. In this document, we got the best values for α *and* β by simulations with the humidity variable. However, α *and* β are user parameters that the target variable can be determined.

7.2 Future Work

From work carried out, opportunities open up to continue improving the proposed energy management system; some current challenges are: To obtain feedback from the system through a forecasting service to fine-tune the selected α parameter. Evaluate the system in other scenarios such as in a mesh mode network (communication through hops). To work in a controlled environment to generate equal conditions for the sensors, get good evaluations of developed systems, and perform system evaluations for extended periods to detect faults.

Appendix B

Repository

the code and the data used in this thesis can be found in the following link

`https://github.com/Carlosrod298/AdaptiveSampling.git`

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