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Intelligent System for Load Monitoring and Control: Sustainable Comfort, Health and Flexible Electricity Consumption

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"Experience is the teacher of all things."

—Julius Caesar

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Abstract

Load balancing is a crucial factor regarding economical and operational reliability in the present electric system. The increasing population, living standards and electrification of the economy force the electricity demand to continuously grow in most countries. On the other hand, utilities need new strategies to balance the fluctuations on the supply of electricity, due to intermittency and unpredictability, of a growing share of renewable sources. This Dissertation explores an alternative connected device strategy to balance the Demand-Response, focused on the development of a Smart Thermostat able to grant users comfort and health conditions all the time while promoting a flexible use of electricity, giving additional help to meet energy fluctuations during demand peak periods, better manage supply-demand balance, lower utility and users costs, as well as to optimize the use of demand-side resources. An efficient and scalable control algorithm was implemented to handle air conditioning tasks depending on local variables namely the probability of photovoltaic production and outdoor/indoor temperature. Such an algorithm takes advantage of the room's thermal parameters to compute the optimal start time of each air conditioning task, promoting a flexible electricity use. The algorithm makes use of a CO_2 sensor which is an effective air quality and building occupancy indicator and can be used to control the room's ventilation rate to ensure that the concentration of indoor pollutants (including SARS-Cov-2 virus) is kept below a safe value. The conducted study concludes that the end product successfully operates the air conditioner in an economical and healthy manner, while reducing energy costs while promoting a safe indoor environment.

Keywords: Smart thermostats, sustainable electricity, demand controlled ventilation, end-use efficiency, indoor air quality, sustainable buildings.

Resumo

O balanço de cargas é um fator crucial em relação à fiabilidade económica e operacional do sistema elétrico atual. O aumento da população, padrões de vida e eletrificação da economia forçam a procura por eletricidade a crescer continuamente na maioria dos países. Por outro lado, as operadores precisam de novas estratégias para equilibrar as oscilações no fornecimento de energia elétrica, devido à intermitência e imprevisibilidade, de uma parcela crescente de fontes renováveis. Esta Dissertação explora uma estratégia alternativa de dispositivos conectados para equilibrar a Procura-Resposta, focada no desenvolvimento de um Termostato Inteligente capaz de proporcionar conforto e saúde aos utilizadores em qualquer circunstância, promovendo um uso flexível de eletricidade, dando ajuda adicional para equilibrar as flutuações de energia durante períodos de pico de procura, gerir melhor o equilíbrio entre oferta e procura, reduzir os custos das operadoras e de utilizadores, bem como otimizar o uso de recursos do lado da procura. Um algoritmo escalável e eficiente de controlo foi implementado para lidar com tarefas de ar condicionado em função de variáveis locais, nomeadamente a probabilidade de produção fotovoltaica e temperatura exterior/interior. Tal algoritmo aproveita os parametros térmicos da sala para calcular o tempo de início ideal de cada tarefa do ar condicionado, promovendo um uso flexível da eletricidade. O algoritmo utiliza um sensor CO_2, que é um bom indicador de qualidade do ar e de ocupação de edifícios e pode ser usado para controlar a taxa de ventilação da sala para garantir que a concentração de poluentes internos (incluindo o vírus SARS-Cov-2) seja mantida abaixo de um valor seguro. O estudo realizado conclui que o produto final opera com sucesso o ar condicionado de uma maneira económica e saudável, enquanto reduz os custos de energia e promovendo um ambiente interno seguro.

Palavras-chave: Termostato inteligente, electricidade sustentável, ventilação controlada, eficiência de uso, qualidade de ar interior, edifícios sustentáveis.

List of Acronyms

AC air conditioner

ASHRAE American Society of Heating, Refrigerating and Air Conditioning Engineers

COP coefficient of performance

DEEC Department of Electrical and Computer Engineering

DR demand response

DSM demand side management

EPRI Electric Power Research Institute

HVAC heating, ventilation and air conditioning

IoT internet of things

IR infrared

LAN local area network

M2M machine-to-machine

MQTT message queue telemetry transport

OSHA Occupational Safety and Health Administration

PV photovoltaic

WAN wide area network

XML extensive markup language

XHR xml http request

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1 Introduction

Due to fluctuations on the supply of electricity, the need for flexible promoting electric demand has been gaining a greater relevance regarding the present grid evolution. These fluctuations are correlated with intermittency and unpredictability of renewable sources and the increasing electrification and these changes in the market environment have led to more time-of-use and flexible pricing programs across the world. Rather than investing in reserve generation and transmission & distribution capacity, as well as using the previous on-off load control switches and SCADA systems, the utilities are searching for new strategies and technologies to balance this fluctuations, better manage supply-side generation costs, as well as to optimize the use of demand-side resources. One solution is the development of interconnected smart devices to monitor and control demand. These devices represent an opportunity for utilities to engage with their customers to enable them as active grid participants, as well as to provide new choices to enhance customer satisfaction and a potential cost reduction of the energy services. Much of the activity and market uptake regarding smart connected devices has been centered on smart thermostats. The overall smart thermostat market including hardware and service is expected to grow from 585.09 million dollars in 2014 and reach 5900 millions by 2020, at a compound annual growth rate (CAGR) of 31.82% between 2015 and 2020. In the USA, the Department of Energy (DOE) states that 40 million thermostats were sold in 2015, 40% of which were smart thermostats. In Europe, however, the market penetration rate of smart thermostats is much lower, that despite recent growth this is still a nascent market. In 2017, only 2.5% European homes (mostly in Central and Northern Europe) had centrally heated houses. Having a much bigger market in this domain than Europe, the United States markets are the main focus of economic analysis in this Dissertation.

These solutions, operating side-by-side with the demand-side management (DSM) programs will reduce electricity usage throughout peak times, once power is scarce and expensive and they will facilitate the integration of intermittent renewable energy resources by balancing real-time demand and supply for electricity. Obviously, this includes many advantages to all or any sides, resulting in a win-win scenario (customer-side and utility-side).

Due to increasing population and living standards, coupled with the increasing electrification of the economy, and for sustainability reasons (e.g. electrical quality, heat pumps for space and water heating), the electricity demand has perspectives of continuing growth in most countries around the World.

In the “Internet of Things” era, smart home technology and solutions like Wi-Fi connected thermostats are giving customers the control and convenience in a way that was never experienced before. This convenience can be experienced monetarily and environmentally, avoiding the waste of energy and money, once demand is at the highest or lowest.

The acceleration of thermostat technology has stimulated electricity suppliers across the planet to market smart thermostat demand response programs. Obviously, the demand reduction and savings achieved by these devices are related to end-user behavior, the technology used and the management methods. Utilities considering smart thermostat DR programs will proactively address these variables by conducting initial planning and analysis to inform goal-setting and program design methods, rigorously evaluating vendor choices to assess factors, such as technology options, data accessibility and security, outlining client engagement and promoting methods and formulating a plan to trace and analyze data.

Having the considerations above mentioned, it is important to have a solid, autonomous and resilient infrastructure when it comes to a co-operation between technology and utilities. Such infrastructure must have multiple nodes distributed by the grid, gifted with the ability to monitor and control what is going on the grid. These nodes are the gateway to the evolution of the grid, ultimately leading to a handshake between both parts: utility and end-user, providing the consumer with lower prices and helping the main grid during stress situations.

It is proposed the design of a smart system to monitor consumptions and control schedulable loads, in the most effective and flexible way. The air conditioner (AC) is the residential appliance responsible for the most electric consumption per year (about 1450 kWh/month).

The proposed model aims to make use of a weather forecast to know if local solar energy is being produced. This can significantly reduce the operational expenses of the equipment, since the power produced is being auto-consumed. A web service was created to serve as an interface for the user to schedule AC activities. We believe that this option will have its relevance when it comes to aid the grid handling stressful situations and balance loads.

1.1 Impact

Considering the economical and operational reliability importance that load balance has over the present electric system, it is necessary to conduct more research, development and improvements over this topic. The presented solution is believed to help solving some of this concerns, namely:

- Granting an additional help to balance energy fluctuations during demand peak periods, better manage supply-demand balance, lower user and utility costs, as well as to optimize the use of demand-side resources.
- Offering an alternative method to balance the Demand-Response, granting users comfort and health conditions all the time while promoting a flexible use of electricity.

The concepts and methods described in this Thesis can be extended, in the future, to other non-critical loads (*e.g.* aggregation of HVAC loads and electric vehicle chargers). Furthermore, it will be possible the creation of a virtual power plant, taking advantage of flexible loads and energy storage, granting a more resilient grid and enhancing even more the system's operational reliability and reducing unnecessary costs.

1.2 Thesis Structure

After this **Chapter**, this Thesis is structured in the following manner:

- **2. Literature Review** - Some important theoretical concepts are briefly explained. The smart thermostats and the associated state of the art are introduced. Market leaders smart thermostat solutions are compared and used as reference to the creation of the proposed solution. This solution and it's components and features are explained in detail.
- **3. Classroom Modeling** - The theoretical model of the room and respective equations and properties are analysed. Concepts on thermal building properties are explained and the room's equivalent thermal circuit is compared to an equivalent RC circuit.
- **4. Methodology** - This chapter is intended to explain, discuss and detail how, where and when the work and experiences were developed and conducted, how data was gathered, which hardware and software were used.

- **5. System Validation and Results** - In this Chapter, three comparative experiments are conducted to test the system performance. In the first one, the whole procedure will be executed, since the scheduling on the web site to the actuation of the AC. The power consumption and temperatures variations will be reported. In the second and third study cases, the system controlled method and a more common, yet less flexible, approach will be executed and compared. Economical and performative comparisons will be pointed out.

- **6. Conclusions and Future Work** - The final Chapter is intended to concisely summarize the main research issue and emphasize why and how this research contributes to a technological evolution. Future work, in order to improve the developed system, will be addressed.

2 Literature Review

2.1 Demand Side Management

According to (Clark Gellings, The Concept of Demand-Side Management for Electric Utilities, IEEE Proc, 1985), Demand Side Management (DSM) is the planning, implementation and monitoring of those utilities activities designed to influence the client's use of electricity in ways that will produce desired and planned changes within the utility's load shape, i.e, changes in pattern and magnitude of utility's load as a function of time. Utility programs falling below the umbrella of DSM embrace the subsequent activities: load management, new uses, strategic conservation, electrification, client-side generation and adjustments in market share.

The DSM objectives can be categorized into three main types:

- Strategic:
  - Increase profits;
  - Improve relations with customers;
- Operational:
  - Reduce costs;
  - Increase flexibility of operation;
  - Give customers more options for controlling their electricity bill;
- Related with the shape of load diagram:
  - Load shifting;
  - Peak clipping;
  - Valley filling;

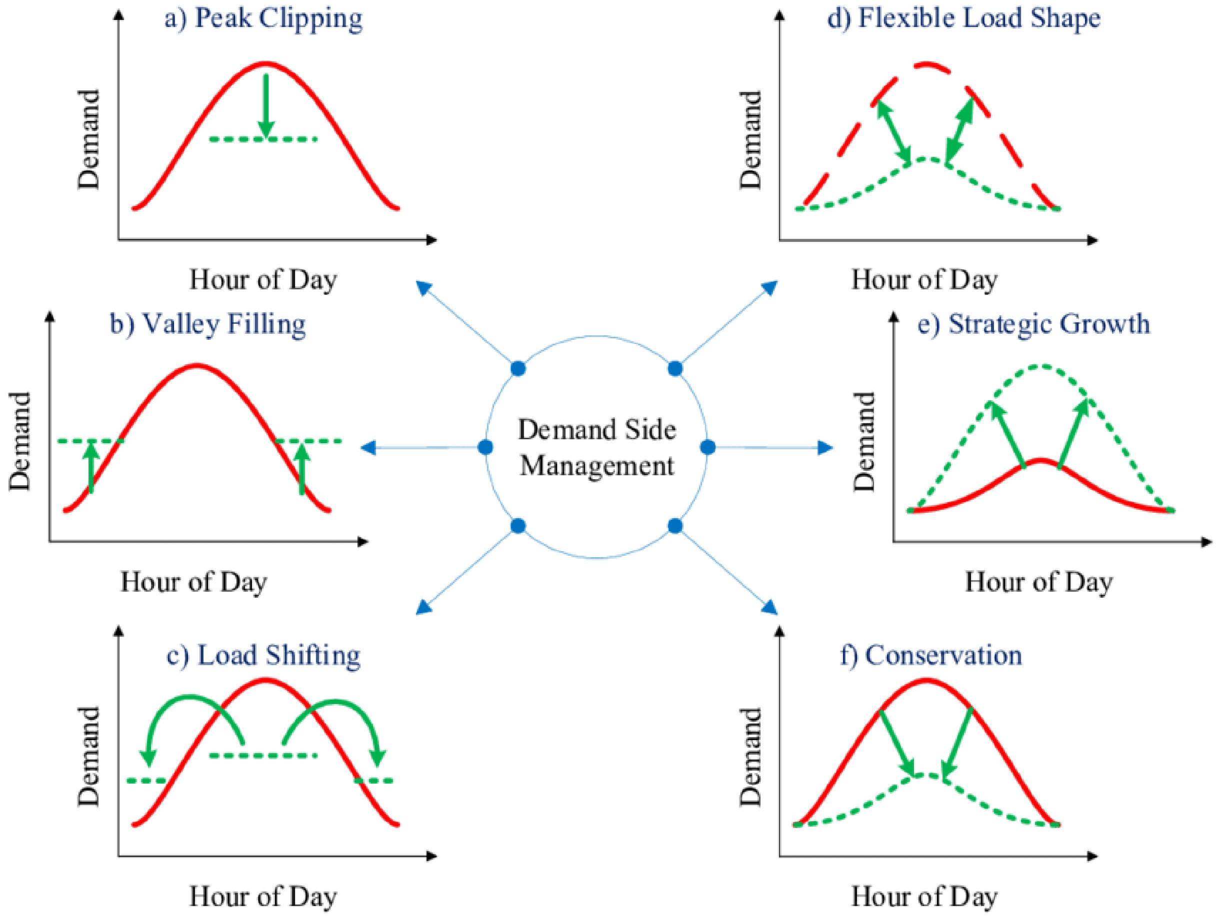

Figure 2.1: Objectives of DSM.

Figure 2.1 presents an overview of different demand-side management strategies (A. Qurat-Ul *et all*, 2019).

Electricity use can vary dramatically on short and medium time-frames, depending on variables like the need for energy services and also the availability of the intermittent renewable generation. Generally, the wholesale electricity system adjusts to the ever-changing demand by dispatching additional or reduced generation. However, throughout peak periods, the additional generation is sometimes provided by less efficient ("peaking") and more overpriced resources (normally fossil-fuels, like gas turbines). Unfortunately, the instantaneous financial and environmental costs of using these "peaking" sources isn't essentially reflected within the retail pricing system. Additionally, the ability or willingness of electricity customers to regulate the price signals by altering demand may be low, particularly over short time frames. In several markets, customers do not face real-time pricing at all, but pay rates based on average annual/seasonal prices. Energy demand management activities plan to bring the electricity demand and supply closer to a perceived optimum, and assist in giving electricity end users benefits for reducing their demand. The utility would possibly signal end-use to shed load depending on system conditions. This enables a very precise tuning of demand to ensure that it matches supply at all times, and thus scale back prices both to users and to the utility. In general, adjustments to demand can occur in various ways: through responses to price signals, behavioral changes of the customers, automated controls such as with remotely controlled air-conditioners, heat pumps, water heaters or with permanent load adjustments with energy efficient appliances.

2.2 Demand Response

Demand Response (DR) can be defined as a change in the electric usage by customers from their standard consumption pattern in response tariffs changing over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or once the system reliability is compromised. DR primarily consists in adjusting the demand for power, at a short time notice, rather than adjusting the supply. Effective demand response programs provide electricity consumers and society as a whole, with various economic and environmental benefits. Some of those benefits include:

- Avoiding the development and construction of new power plants as well as transmission and distribution networks.
- Avoiding the acquisition of overpriced energy.
- Providing greater reliability to the grid, which helps to prevent blackouts.
- Decreasing environmental impacts, allowing a larger penetration of renewable electricity generation, and by reducing the consumption of fossil fuels, which damage the environment surrounding, and decrease the carbon emissions.

Two Carnegie Mellon studies looked at the importance of demand response for the electricity industry in general terms and with specific application of real-time pricing for customers, serving 65 million consumers in the US with 180 GW of generating capacity. Further studies stated that even small shifts in peak demand can impact the customers savings and avoid costs for extra peak capacity. The same study affirms that a 1% shift in peak demand would result in savings of 3.9%, which translates to millions of dollars at the system level. An approximately 10% reduction in peak demand would result in systems savings of between 8000 to 28'000 million dollars (R. Brian, 2015).

In California it was set the goal of meeting 5% of the system's annual peak-energy demand through demand response programs. This goal was applied to "non emergency" demand response programs (non-interruptible programs). Interruptible loads (mostly large industry and large buildings) can increase even more this target (CPUC, Demand Response 2020).

2.2.1 Customer Response

Three main changes can be done by a customer in order to change his response. Each of these actions involves cost and measures taken by the customer:

- First, customers can directly reduce their electricity usage throughout critical peak periods, once prices are high without changing their consumption pattern during alternative periods. This option involves a brief loss of comfort. This response is achieved, for instance, when thermostat settings of heaters or air conditioners are temporarily changed.
- Secondly, customers may respond to high electricity prices by shifting some of their peak demand operations to off-peak periods (e.g., dishwashers, water heaters, space heating/cooling). The residential customer in this case will not experience loss of comfort or activity loss and no costs will be imposed. However, this may not be the case if an industrial client decides to reschedule some activities, since rescheduling may have extra costs to make up for lost services that are incurred.
- The third type of customer response is by using their own generation. Customers who generate their own electricity may experience zero or very little changes in their electricity usage pattern. However, from the utility perspective, electricity use patterns will change significantly, and demand can seem to be smaller.

In the future consumers may also use energy storage of the batteries of their cars, or in their homes, which can be both operated as a highly flexible load and inject electricity in the grid whenever necessary.

2.2.2 Program Classification

These programs can be classified into two main categories: Incentive-Based Programs (IBP) and Price-Based Programs (PBP) whose types are presented in **Figure 2.2** (S. Miadreza, 2015).

Price-based Programs rely on the customer's choice to voluntarily decrease or change their consumption in response to changes of electricity's price throughout a 24 hour period. On the other hand incentive-based programs are based on customer response to incentives paid by the electricity utility in times of high electricity price with the objective of influencing customers to reduce their electric consumption. Smart Grid, as a relatively new concept can help electricity utilities to meet established goals which are unattainable through today's DR methods.

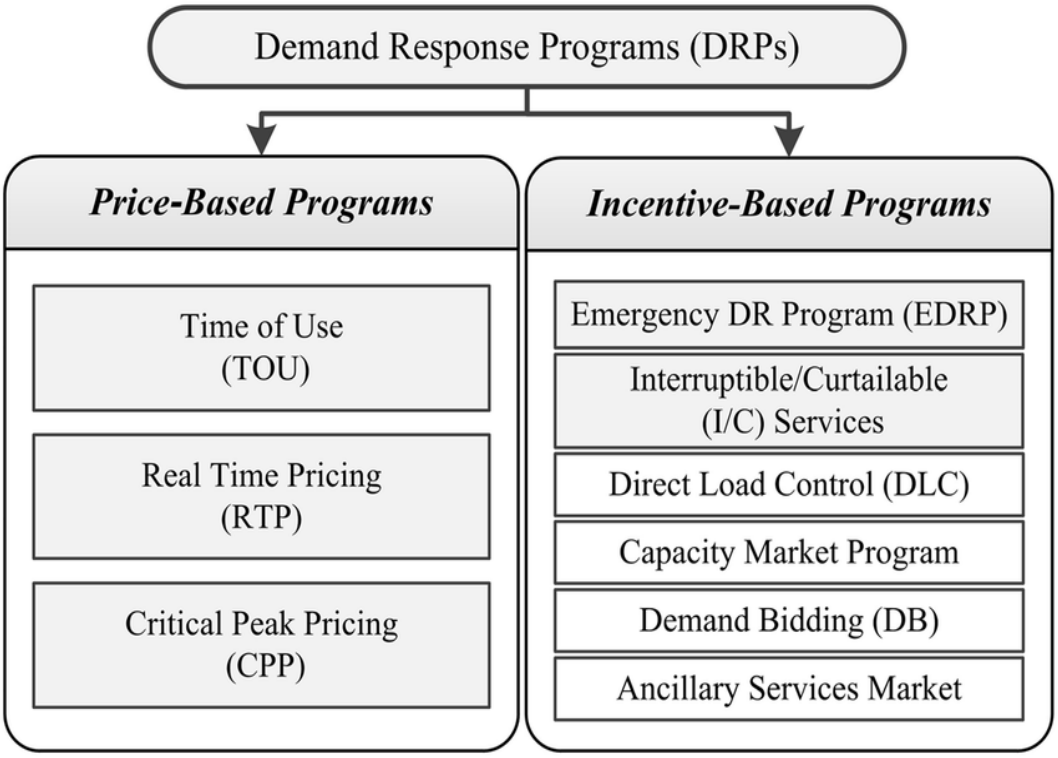

Figure 2.2: DSM program classification.

2.2.3 Demand Response Benefits

DR programs introduce benefits at multiple levels. They can be monetary, operational or performative and marketwise. The main idea is that these programs introduce a certain level of flexibility, which can be monetized. All of these allow a better relation between the utility and the customer.

- **Financial benefits**: Customers taking part in DR programs can expect savings in electricity bills, if they scale back their electricity usage throughout peak periods. Some customers might as well be able to increase their total energy consumption in the absence of having to pay more money by using off-peak equipment (as in the case of valley filling). These benefits are broadened to the utility since it reduces the demand from expensive electricity generation units. The transmission and distribution losses and costs are also larger during peak periods. Moreover, DR programs can increase the utilization of existing capacity, which in turn, ends up in avoided or deferred capacity costs.

- **Reliability and operational benefits**: By having a well-designed, strategic DR program, participants have the chance to assist the grid in reducing the risk of outages. Simultaneously and as a consequence, participants reduce their own risk of facing outages and electricity interruption. On the other hand, the utility will have additional options and resources to maintain the system reliability, thus reducing forced outages and their consequences.

- **Marketing benefits**: DR offers benefits when it comes to improving electricity market performance. Consumers can manage their consumption since they have the opportunity to have an effect in the market, particularly within the market based programs and dynamic pricing programs. This is a prime driver for utilities to offer DR programs, especially for large consumers.

2.3 Smart Grid and Applications

The Electric Power Research Institute (EPRI) defines Smart Grid as a modernization of the supply system of electricity to automatically monitor, protect and optimize the operation of its interconnected elements - from the central and distributed generator, through the high voltage network and distribution system, to energy storage and even the final customers and their loads, such as electric vehicles, appliances and other household devices.

As above mentioned, the utility can engage customers into DSM programs. Therefore, the communication between them is inherently necessary and both entities can make decisions about how and when to produce and/or consume electrical power. Alternatively, smart grid technology can influence customers to shift from a demand response event-based program to a 24/7-based demand response wherever the customer sees incentives for controlling load all the time by intelligent controllers. This way, there is a permanent and fast response to the grid's necessities. Although this back-and-forth dialogue will increase the opportunities for demand response, customers are still mostly influenced by economic incentives. Some customers are still unwilling to provide partial control of their assets to utility companies due to operational and/or comfort reasons. One of the keywords of the smart grid is connectivity. The rapid adoption of the latest technologies, particularly communications-based technologies, has provided a platform for the industry and buildings to fulfill multiple demands ranging from energy efficiency, lower costs, to improved reliability. Whether or not we have a tendency to adopt wireless technologies to read new meters or network monitoring and supervision devices, there is no dispute that connectivity is crucial to Smart Grid operation. Increasing internet penetration and connected devices are driving the connectivity market growth in areas such as:

- As the internet penetration grows with the usage of smart devices such as smartphones, so does the spread of connectivity.
- Owing to technological advancements, the appliances in residential buildings, such as washing machines, water heating, space heating, and cooling equipment, and refrigerators, are increasingly going smart. This means that they can be connected to the internet.
- Due to this, smart thermostats are progressively being adopted. This is because they enable users to regulate heating settings from other internet-connected devices, such as smartphones, which allows them remotely to control the thermostat.
- Additionally, machine-to-machine (M2M) is expected to take the home-based Internet of Things to the next level. **Figure 2.3** shows the recent impressive increase of M2M connected devices, within the framework of the Internet-of-Things (IoT) technology.
- The increasing popularity of these connected devices is expected to lead to an increased need for control, thereby driving the market growth.

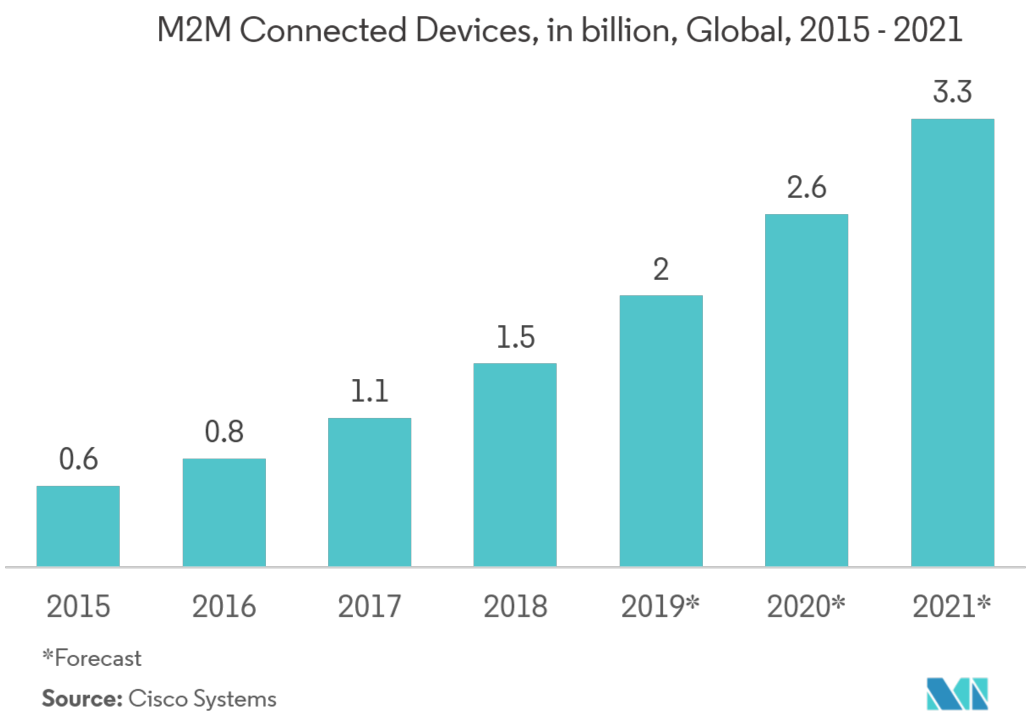

Figure 2.3: The exponential increasing of M2M connected devices.

2.4 Smart Thermostats

Smart thermostats are programmable thermostats that can be used with home automation and are responsible for controlling a building HVAC system, (heating, ventilation and air conditioning). They perform similar functions as a regular thermostat as they allow the user to control the temperature of their building throughout the day using a schedule. They also contain additional features, such as sensors (temperature, humidity, air quality such as CO_2), actuator control lines and WiFi connectivity that improve upon the performance capabilities in relation to regular thermostats, possibly reducing human errors while programming activities. The Wi-Fi connection makes it possible for the user to remotely program the thermostats, as well as provide information to the end user to the equipment operating conditions. Energy reports and warnings may also be sent to users over the internet.

Some smart features that these kind of thermostats must have include:

- Remote control: Away savings - vacation, absence, etc... and remote manual guide user interface (GUI).
- Intuitive GUI Scheduling: Enable savings from setback.
- Consumer feedback: Feedback on savings.

- Adaptive preferences: Learn consumer preferences through sensors or GUI and manage occupancy.
- 7-day schedule: This feature allows the thermostat to know what time it should start and finish its work according to parameters such as electrical tariffs and occupancy rates. In general, this point defines the periods of operation of the equipment and exceptions.
- Automated analytics: use learned preferences to optimize comfort and energy savings.
- Bi-directional communication: The device must be able to receive orders and commands from users, but it must also be able to transmit value information, (such as temperature, humidity, power consumptions, etc.) or status information (for example the state in which the system is operating).

2.4.1 Smart Thermostats Benefits

For the utility side:

Utilities have better insights on customer energy usage and typical load shapes. This information can be leveraged to more accurately predict and target customers who are likely to benefit from savings at certain times of the day. Generation and transmission of electricity throughout peak periods are very expensive. Once combined with demand response strategies, such as peak pricing and time-of-use rates while engaging customers, smart thermostats provide opportunities for utilities to regulate demand (e.g. temperature set-point as a function of electricity prices) and therefore reduce utilities own costs (both capital costs and operating costs), maintaining the system reliability.

For the customer side:

Smart thermostats can help customers to manage their energy consumption during peak periods, potentially saving them money by reducing monthly bills, and providing good quality energy services. For example, by pre-cooling or pre-heating homes during off-peak times, customers can remain comfortable during peak time events while also providing utilities a way to better handle peak-coincident load. Passive or active thermal energy can be an alternative to battery storage, holding a fraction of cost.

Smart thermostats can also be controlled remotely, send reports on energy usage habits and turn on/off depending on the room occupancy, being designed to save energy. For example, Nest has published a study indicating "customers in southern California saved an average of 1.16 kilowatt-hour per day or 11.3% of AC-related energy usage after installing a Nest Thermostat" (Nest Labs, 2014).

Thermal Storage: Smart thermostats may represent an opportunity to achieve thermal storage benefits at a comparatively low cost in existing buildings, using either the building thermal mass or dedicated active thermal storage (e.g. ice banks). Signaling the customers to tune thermostat set points, and in particular the ability to "pre-cool" or "pre-warm" before a peak period, is fundamental to enabling passive thermal storage in buildings (Carvalho. AD, 2015). Pre-cooling/pre-warming depends on the thermal mass of the building itself, which can be used to store thermal energy, taking advantage of the building materials as a thermal battery. The available storage capacity of buildings can be difficult to quantify as it depends on several building variables like insulation, solar heat gain, building occupancy patterns and customer comfort preferences. Active thermal storage systems, used in large buildings, such as ice banks, can be charged with low cost off-peak electricity or with renewable energy (e.g. solar photovoltaic generation). Smart thermostats with machine learning artificial intelligence algorithms may optimize the use of thermal storage (e.g. definition of optimal schedule and storage charge/discharge rate).

With the cost of smart thermostats presently anywhere between 100-300 dollars, this technology potentially offers similar load shifting capabilities at a fraction of the cost of electrical energy storage systems (e.g batteries). When comparing these solutions, there must be assessed the cost-effectiveness trade-offs, reliability and response time for the utility as for the customer. It's vital to notice that although buildings show to have passive thermal energy storage potential (explored in **4 Methodology Chapter**), moving a customer set point past his comfort band may lead to forfeiture in this potential and poor customer comfort.

2.4.2 Market Solutions

There are several solutions already made and available in the market. Three of the most relevant ones are analysed below: Ecobee3 Smart Thermostat, Nest Thermostat (2nd generation), formerly bought by **Google** and Honeywell Lyric Thermostat. These are the market leaders, respectively cited by ranking (Smart Thermostats Comparison, 2020). Since these are the most successful devices in this area, they were chosen to be objects of study in order to develop an enhanced and intelligent thermostat. The Table 1 makes a comparative analysis of the most desirable characteristics.

Table 2.1: Smart thermostat comparison.

	Ecobee3	Nest	Honeywell Lyric
Energy Savings	23%	20%	20%
Programmable Periods	4 days	unlimited	4 days
Learning Schedule	Yes	Yes	Yes
GUI	Innovative	Innovative	User-friendly
Energy Reports	Yes	Yes	No
Local Weather	Yes	No	Yes
Common Wire Requirement	Includes power extended kit	Yes	Yes
Remote Sensor	Yes	No	Yes
Price (USD)	250	200	170

2.4.3 Proposed Solution

This solution is being initially implemented in a classroom at the Department of Electrical and Computer Engineering at the University of Coimbra, as a way of validation. It can be extended and scaled later to other environments such as offices, commercial spaces, residential or hotel rooms, among others.

It is proposed to create an intelligent thermostat capable of managing and programming the temperature of one or more rooms. This equipment must make decisions to be made depending on the state of some input variables.

For that purpose, it is necessary to know the following variables:

- Days / hours of classes.
- Class breaks (if reheating/recooling is required).
- Indoor and outdoor room temperature.
- Indoor air quality (CO_2 is used as an air quality indicator).
- Room humidity.
- COP / EER of the high-efficiency heat pump equipment and its variation with temperature.
- Knowledge of the physical model of the room, or its self-estimation of the key parameters.

- Local energy production supply, namely via PV panels.
- Real time building of the load diagram.
- An optional information is the weather forecast (temperature, solar radiation) for the next 24 hours.

The objective is to find a solution that provides comfort conditions and achieves optimized operation of the heating/cooling/ventilating system.

2.4.4 Desired Characteristics

The most important features and characteristics were selected and listed after the study of various features and characteristics of smart thermostats. The desirable and most important characteristics for the creation of the thermostat for our purposes are:

- **Programming schedule and Learning**: This feature allows the thermostat to know what time it should start and finish its work according to parameters such as electrical tariffs and occupancy rates. In general, this point defines the periods of operation of the equipment and exceptions such as holidays or holidays.
- **Wi-Fi and remote access**: Access to the equipment should be possible remotely if it cannot be done locally. Internet access allows to address this gap as well as bi-directional communication between user and device or else with other entities such as databases.
- **Manual versus Automatic settings**: These characteristics allow the user to choose the manual operation mode, i.e, set the desired temperature and effort of the air conditioning compressor or automatic mode (pre-defined), which is more economical.
- **Energy usage reports**: In order for the user to understand where and how he is spending more electricity and how his network is performing overall, he needs to have real measured data from his equipment. We will do this with a device already created, used to measure electrical values, which are stored in a database and made available in a web app.
- **Bi-directional communication**: The device must be able to receive orders and commands from users, but it must also be able to transmit value information, (such

as temperature, humidity, etc.) or status information (for example the state in which the system is operating - manual, automatic, etc...) if required.

- **Heating/cooling system compatibility**: The air conditioning can also be remotely controlled by an infrared command, which can be represented by an unsigned short variable.

- **Indoor air quality control for comfort and health conditions**: The smart thermostat being developed has a CO_2 sensor which allows to control optimal manner the ventilation rate. The CO_2 concentration in a room should be lower than the maximum recommended values to ensure comfort and health conditions. COVID-19 transmission is strongly affected by the virus concentration, and there is a need to ensure an optimized ventilation rate (L. Dietz *et all*, 2020).

- **Load diagram configuration**: An important and interesting feature is to configure the load diagram that the user wants to follow. The thermostat would adjust its tasks in order to try to obtain the desired diagram. The diagram can have several purposes: economic savings, helping to combat electrical stress at certain times, DSM program, etc ...

- **Climate reports and climate forecast**: Having a glance at the local weather forecast, the smart thermostat can switch between operation modes. Knowing that at certain times there will be electrical production, we can schedule tasks for those hours to optimize the consumption of renewable electricity and to reduce the energy consumed directly from the grid.

The last three items, coupled with the direct use of building characteristics (C and U values) **are innovative features** of the developed smart thermostat. Ensuring comfort and health conditions is a top priority in all institutions. Comfort conditions are essential to achieve worker satisfaction and high productivity. The recent pandemic makes this strategy of suitable ventilation absolutely essential to minimize the transmission risks.

Having known the importance of the peak shaving in high demand periods to both consumers and utility, as well as to maximize the use of renewable energies. Therefore having a flexible load diagram for the thermostat to follow would be beneficial. This can prevent a grid stress in demand peaks and users can also benefit from the DSM programs, for example the valley filling.

Regarding the climate reports and forecasts, this is also innovative in a sense that some tasks might be rescheduled depending on temperatures (space conditioning loads) and the local production. For example, if we know that in the following day it would be very sunny and a clear sky, there is a high probability of electric production from the solar panels. With such information, some tasks as the heating/cooling of rooms can be rescheduled for that electric production time.

2.4.5 Hardware Configuration

This smart thermostat hardware was built around an ESP32 - a low cost, feature-rich micro-controller unit with integrated Wi-Fi and Bluetooth connectivity, ultra-low power consumption and state-of-the-art features, such as multi-core, power modes and dynamic power scaling. This unit can work in standalone or connected mode, acting simultaneously as a wireless host, wireless client and/or a wireless bridge/mesh node. Environmental data, such as humidity and temperature, is gathered indoors with high-linearity and high-accuracy integrated digital sensors that do not require calibration. Additional data is gathered by a CO_2 sensor in order to control the ventilation rate ensuring that the **ASHRAE** and **OSHA** standards specifications are met. The hardware includes an infrared transmitter which performs fine control of Heat Pump/HVAC unit, as well as the ventilation rate. The electric values are gathered by the ESP8266-based "*Sonoff*", having included a relay for the on-off control.

Current status, commands and configuration can be accessed through the integrated Web/TCP server, or an MQTT broker (this unit can act as a MQTT publisher/subscriber, or even as a MQTT broker when working in standalone or in mesh mode). Comprehensive data logs can be stored locally (when equipped with optional flash memory) or on a remote server, within the LAN or WAN. These logs include timestamps, environmental data, power consumption and user commands, which can be used for later analysis or as inputs for learning algorithms. The system architecture is shown in **Figure 2.4**. This hardware was a courtesy of Eng. Luís Ferreira, a vital help in the development of this work.

2.4.6 Expected Outputs

The key development of this project is a low cost powerful smart thermostat, for controlling a room's temperature with multiple benefits, namely to provide health and comfort conditions. We believe that our solution will help to save energy by performing its automated and modelled functions while also balance energy fluctuations during demand peak periods,

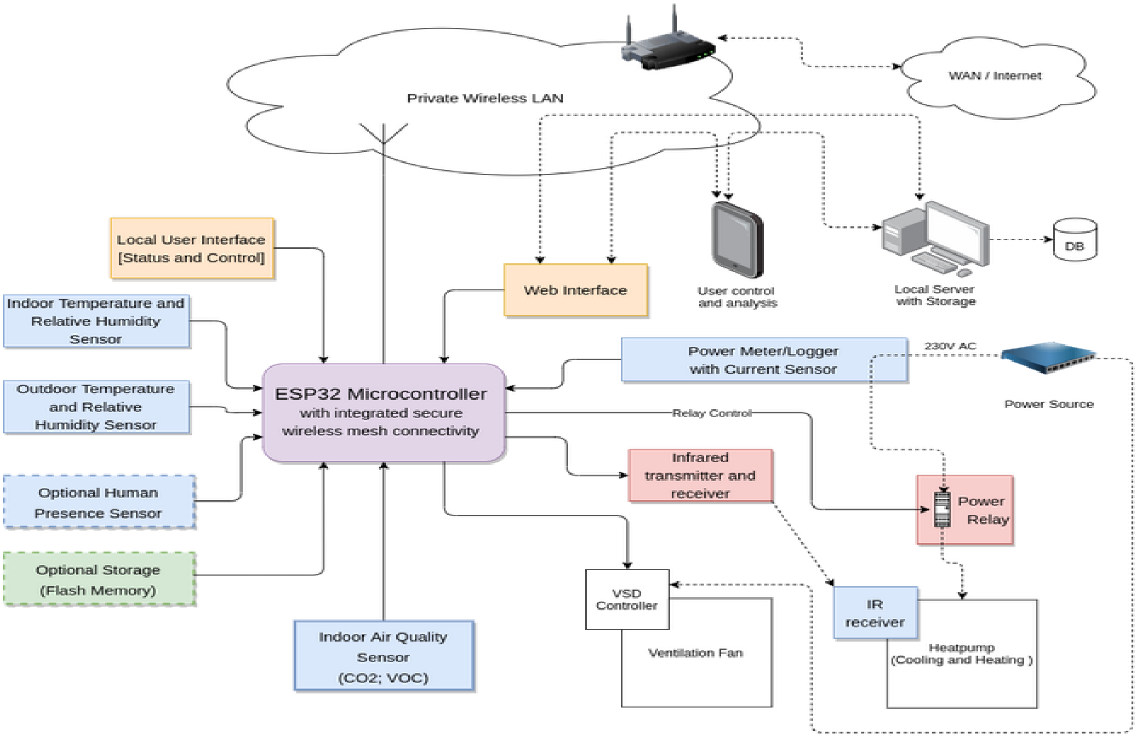

Figure 2.4: System architecture.

better manage supply-side generation costs, as well as to optimize the use of demand-side resources.

The bidirectional communication is a key value because it is possible to implement dynamic demand response programs, either by the consumer or directly by the utility. It is a large benefit because the correct signaling to the thermostat, by a third party, about the time-of-use rates, real-time pricing or critical-peak-pricing (price-bases DR programs) will be taken in consideration to the correct operation of the thermostat, if the user desires an economic approach. Such an approach is more suitable in residential buildings, where the comfort-saving trade-off is more flexible. On the other side, in non-residential buildings there are situations where trade-off is more strict, as for example, hotel rooms. In this situation, comfort is a priority and therefore, the price signaling might not have such a considerable weight. Nevertheless, there are situations where it will be taken into account. This communication channel can be used to inject a specific desired load shape diagram for the smart thermostat to follow. This channel can be used to send a stream of values that represent the time of the day and the respective desired load percentage to use or reduce. The smart thermostat will save this values and adjust its functioning to follow the data stream.

The weather forecast introduces a degree of freedom in the comfort-saving trade-off since it will not be needed to consume additional grid's energy for the equipment to function, since production is being accomplished. Moreover, there might be periods of the day where the sky can be clear and sunny, followed by cloudy periods. In such cases, the thermostat will be adjusted for the pre-heating/cooling of the rooms, while it is sunny, in a way that guarantees the customer comfort. This will directly reduce costs for the user and the utility and have other benefits listed in section above.

2.4.7 Comfort and Health Performance

Regarding the comfort and health parameters, there are standard levels of CO_2 Concentration that buildings ought to manage. In 2020 the typical CO_2 outdoor concentration is 415 ppm. Inside buildings the occupants release CO_2, due to their metabolism, therefore the concentration is higher, specially in the absence of ventilation. CO_2 concentration is a good indicator of building occupancy, and can be used to control the ventilation rate (bringing outside air into the room). When exposed to high CO_2 concentrations (e.g. greater than 5000 ppm), serious health risk can be incurred in humans. At the activity levels found in typical workplace buildings, steady-state CO_2 concentrations of about 1000 ppm level require an outdoor air ventilation rate of about 7.5 L/s/person (15 cfm/person). Thus indoor CO_2 concentrations of 1000 ppm in closed areas is an indicator that a considerable majority of visitors entering the space will be granted optimal air quality, possibly diluting human bioeffluents.

According to ASHRAE, the carbon dioxide standard levels and the recommendations in ASHRAE Standard 62-1989 to grant a decent air quality air are:

- Classrooms and conference rooms 15 cfm per occupant (person)
- Office space and restaurants 20 cfm per occupant
- Hospitals 25 cfm per occupant

where 1 cfm (ft3/min) = 1.7 m^3/h = 0.47 l/s.

Normal CO_2 Levels - The effects of CO_2 on adults at good health can be summarized to:

- Normal outdoor level: 415 ppm (this value is increasing due to climate change)
- ASHRAE and OSHA standards: 1000 ppm maximum concentration for general indoor spaces
- Acceptable levels in demanding environments like hospitals: $<$ 600 ppm

- Complaints of stiffness and odors: 600 - 1000 ppm
- General drowsiness: 1000 - 2500 ppm
- Adverse health effects may be expected: 2500 - 5000 ppm

With an appropriate CO_2 sensor, our smart thermostat is able to detect the carbon dioxide concentration in a room and activate the ventilation accordingly, granting a good air quality in the terms cited above.

2.4.8 COVID-19 and Transmission Risks

Being outdoors presents a lower risk (as much as 20 times) for COVID-19 transmission than being indoors, meaning that fresh air reduces the virus spreading. Additionally due to wind as a scatter and diluting agent.

While many of the precautions typical for halting the spread of respiratory viruses are being implemented, such as the use of facial mask and social distancing, different and less understood transmission routes ought to be considered and addressed to prevent further spread. Crowded buildings have been a concern when it comes to a rapid spread of infectious diseases and viruses (NY Times, 2020).

Enacting enhanced building HVAC operational practices may also reduce the potential for spread of COVID-19. Viruses are often related to larger particles in a range of sizes. Albeit some of these particles have been identified in sizes that could potentially penetrate high efficiency filters, ventilation and filtration remain vital in reducing the transmission potential of COVID-19. Correct filter installation and maintenance can help reduce the likelihood of airborne transmission. Higher outside air fractions and frequent air exchange rates in buildings may help to dilute the indoor contaminants, including viral particles, from air that's breathed inside the indoor environment. Higher outside air portions may be achieved by exhausting the indoor air, and possibly present airborne viral particles, by opening the HVAC damper position, allowing the air renewal. On another hand, some air conditioners make use of a ventilation system, which can extract and replace the indoor air with outdoor air (L. Dietz *et all*, 2020).

CO_2 is a good indicator of building occupancy, and can be used to control the ventilation rate to ensure that the concentration of indoor pollutants (including COVID-19 virus) is kept below a safe value. On the other hand an excessive ventilation rate leads to a large energy waste (the ventilation power grows with the cube of air flow, and also leads to increasing heating/cooling thermal losses of the building). However, health and comfort need to be ensured as a top priority.

$$P_{vent} = k(Airflow)^3 \tag{2.1}$$

Having a CO_2 sensor incorporated, our solution can detect high carbon dioxide levels and, depending on these levels, introduce new air through the ventilation system, helping to control and mitigate undesired infectious particles and ultimately lower the infectious transmissions and enhance the air quality and health. The ventilation power which grows with the cube of the flow, and the thermal losses associated with air renewal can be minimized.

2.5 Building Chosen for Model Validation

In order to test the developed system performance, a study was conducted in the Department of Electrical and Computer Engineering of the University of Coimbra. This study has as objective the measurement of the performance, savings, load diagram difference in between and after the implementation of the system, among other parameters. The department is located in a strategic place, highly exposed and suitable to solar PV electric production.

Many University campuses have been decreasing the environmental and economic impacts and costs related to electricity consumption by way of implementation of energy efficiency programs, as well as the installation of renewable and distributed energy generation. These campuse's buildings must be equipped with technologies ready to give the pliability required to extend the matching between renewable generation and electric demand. A microgrid infrastructure was implemented in the department for supporting sustainable energy systems operation, ensuring the optimized integration of renewable generation in sizable buildings. At the same time, the microgrid enables the assessment of new smart grid solutions, acting as a testbed for the research developed on flexibility options for future power systems. Smart thermostats will play a key role in the control of heating and cooling loads, namely variable speed high efficiency heat-pumps. University campuses are normally constituted by large buildings accountable for massive energy consumptions. Simultaneously, Universities face several challenges due to shortened budgets and rising energy costs. These pressures are enough motivation to fulfill energy efficiency programs and to install renewable generation technologies. (M. Pedro *et all*, 2019).

The presented infrastructure has its own solar production with enough capability to ensure a large share of the yearly electricity consumption throughout the year, slowly transforming this into a Zero Energy Building. The whole system is able to ensure a generation of 115.6 MWh per year, on average. There's a generation surplus in periods with a lower occupancy of the building, namely in the summer, leading to a small injection of the PV generation back into the grid. However, the price to pay from the grid consumed energy is well below one injected back to the grid.

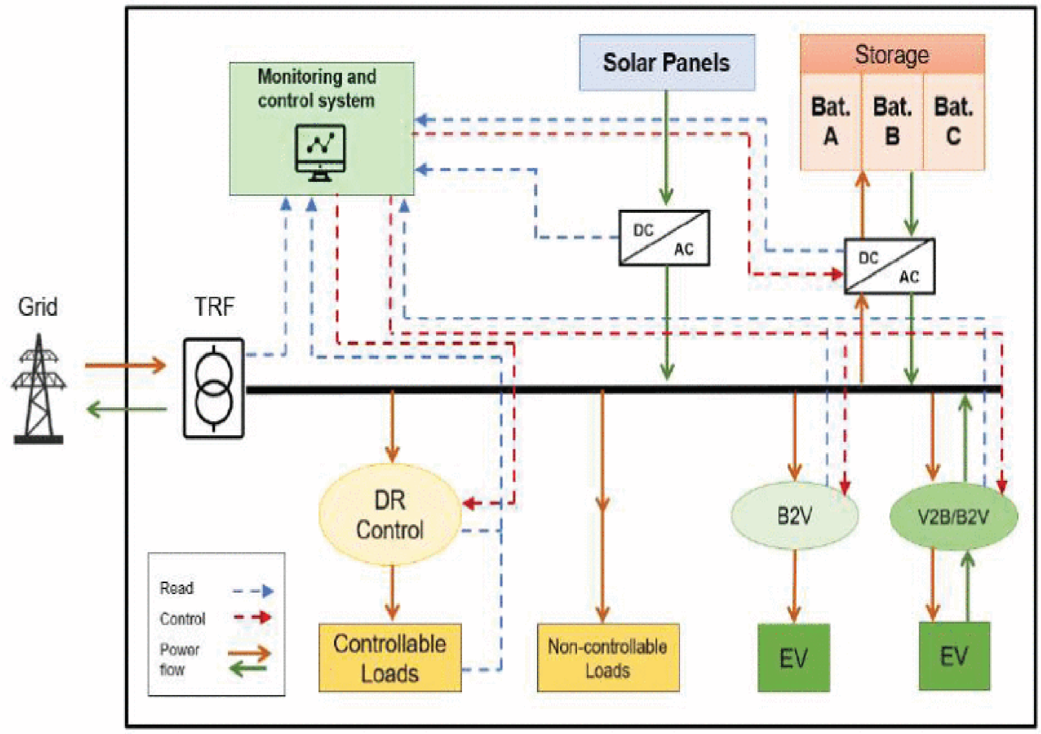

Figure 2.5: The department's microgrid diagram.

3 Classroom Modeling

In order to accurately determine the optimal start time of the air conditioners operation, it is necessary to have an approximate model of the classroom. This model contains the information about the estimation of the room's **heat loss coefficient** (U) (or heat transfer coefficient) and the room's **thermal capacity value** (C). These values are intrinsic characteristics of the building, directly depending on the materials and type of structure used in its construction. The walls, roof and floor are the primary heat storage elements. The estimation of the U and C values, combined with the heating system capacity and the indoor and outdoor temperatures, allow to assess the thermal response of the building which, ultimately, leads to the determination of the pre-heating periods.

3.1 The Lumped Capacity Method

The Lumped Capacitance method is used in the analysis of a transient heating process. It is based on the assumption of a spatially uniform temperature distribution throughout the transient process. The transient is initiated whenever a system experiences changes in its operation conditions, such as internal energy generation and surface convection or conduction. Generally, convection is the responsible factor that governs the heat transfer between walls and the air. The transient temperature response is determined by formulating an overall energy balance on the object of analysis. This balance must relate the rate of heat loss at the surface to the rate of change of the internal energy.Considering a time interval from t_1 to t_2, the temperature evolution is given by **3.1** (F. P. Incropera et all, 2007).

$$\frac{T_{i2} - T_o}{T_{i1} - T_o} = e^{-\frac{U}{C}(t_2 - t_1)} \tag{3.1}$$

where,

- T_{ix} – Thermal mass equivalent temperature at time x [ºC]

- T_o – Outdoor temperature [ºC]

- C –Building thermal capacity [kJ/ºC]
- U –Building heat loss coefficient [kW/ºC]

This equations allows to compute the time required for the room to reach some temperature T_{i2}, or, conversely, to compute the temperature reached by the room at some instant t. However, this equation is only useful when the temperature is decaying in a system, in the absence of heat sources. It is required a more generic equation to model the evolution of the temperature in a system, even when this is heating.

For a heating period between t_2 and t_3 and at a supplied constant heat rate Q_p, the temperature evolution is given by **Eq. 3.2**.

$$\frac{T_{i3} - T_o}{T_{i2} - T_o} = e^{-\frac{U}{C}(t_3 - t_2)} + \frac{Q_p}{U(T_{i2} - T_o)}(1 - e^{-\frac{U}{C}(t_3 - t_2)}) \tag{3.2}$$

As it must, 3.2 reduces to 3.1 when $Q_p = 0$ and yelds $T = T_i$ at $t = 0$. When t$\rightarrow \infty$, **Eq. 3.2** reduces to ($T_{i3} - T_o$)= Q_p. As we can see, the evolution for the heating period depends directly on the building thermal capacity (C), the building heat loss coefficient (U), the thermal power of the air conditioner (Q_p) and the indoor and outdoor temperatures. The thermal power is also a function of the air conditioner and can be calculated as:

$$Q_p = COP * P_e \tag{3.3}$$

The COP is the coefficient of performance of the air conditioner and relates the electric power and the thermal power. This value is considered constant, even though this value can vary with temperature differences. Consulting the manufacturer datasheet of the equipment, we obtain the value 5 for the COP for an outdoor temperature of 7ºC. P_e is the electric power consumption of the air conditioner.

Manipulating **Eq. 3.2**, the time corresponding to the heating period can be obtained:

$$t_3 - t_2 = -\frac{C}{U} ln \left[\frac{Q_p - U(T_{i3} - T_o)}{Q_p - U(T_{i2} - T_o)} \right] \tag{3.4}$$

where t_3 is the pre-heating end time and t_2 is the pre-heat start time. At first sight, **Eq. 3.4** can seem contradictory since the time difference equals a negative quantity. However, it must be remembered that for small numbers in the argument of a *ln* function, this function returns a negative value. Thus, the overall right-hand side of **Eq. 3.4** is a positive quantity.

The U and C quantities must be obtained by assessing the temperature transfer with the outdoor environment. Having in mind that heat flows from the hot side to the cold side, the expected behaviour of a heated room is to lose heat to the outside environment. An experience must be conducted to assess this transference, whereby U and C values are calculated. Such experience will be explained in detail in the **4. Methodology Chapter**. However, in order to understand the procedure, it is necessary to have some background knowledge in materials science.

When building a room, every material selected has its own properties, regarding thermal conductivity. In fact, the quantity that measures the insulation value is called the *U'-value*, or **thermal transmittance**. The *U'-value* tells how good a material is an insulator and its units are W/m^2K. Typically, these values are given by the manufacturers. The heat loss coefficient is defined as the total space heating energy flow rate divided by the temperature difference between the inside and outside environments. Mathematically, it can be translated as:

$$\frac{Q_p}{\Delta T} = \sum_{i}^{\infty} U'_x A_x \tag{3.5}$$

In stable steady-state conditions, where there are few-to-no variations in the outside temperature and having the rate of heat produced by the air conditioner, the heat loss coefficient can be easily determined by using equations **3.5** and **3.3**. In this manner, we obtain the U quantity of our model. The room's capacitance value is calculated through the thermal time constant of the room. Considering the heat flow as current, the temperature difference as voltage and the heat storage elements as capacitors, the thermal room model can be approximated to a resistor-capacitor (RC) circuit model, as **Figure 3.1** suggests. It can be observed such similarities between **Eq. 3.1** and the typical equation that governs the voltage discharge through a capacitor in a RC circuit, having the considerations above mentioned. Therefore, from **Eq. 3.1**, and from the experience conducted, the thermal time constant can be extracted. After having the time constant and the U quantity, the thermal capacitance can be calculated:

$$\tau = \frac{C}{U} \tag{3.6}$$

Figure 3.1 shows the general equivalent electrical diagram of any room. Resistors represent the properties of the elements such as walls, floor and ceiling that prevent heat transference with adjacent rooms or environments. The capacitor represents the heat storage component.

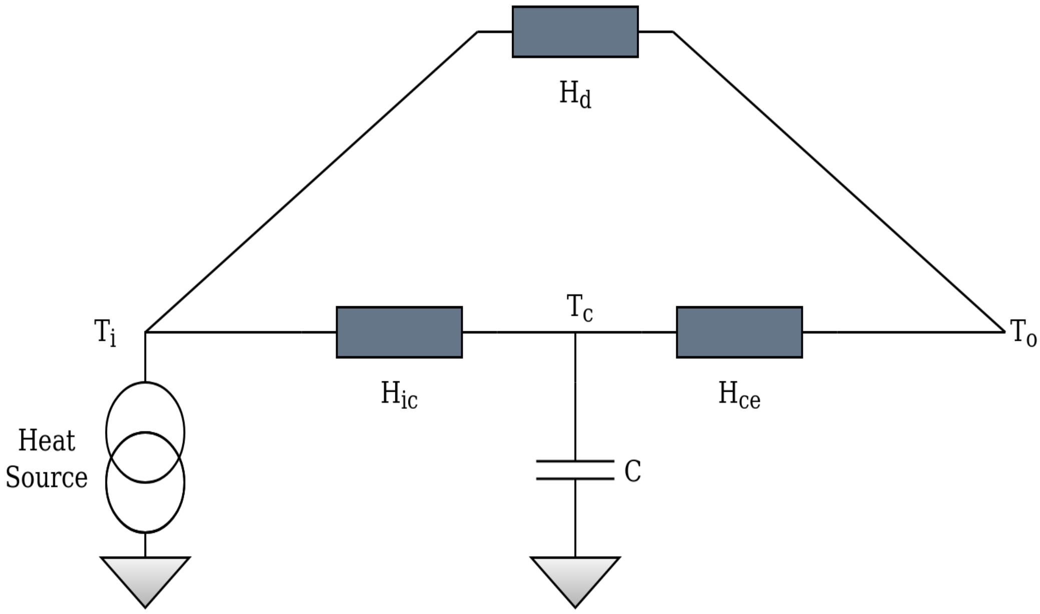

Figure 3.1: Room's equivalent electrical diagram.

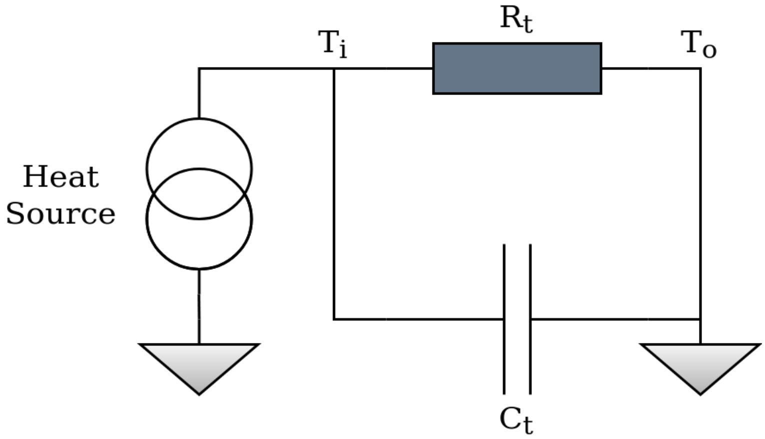

Figure 3.2: Room's simplified equivalent electrical diagram.

- T_i - Internal temperature of the room.
- T_o - External temperature of the room.
- T_c - Structure temperature.
- H_{ic} - Heat loss coefficient between the structure and the heated space.
- H_{ce} - Heat loss coefficient between the structure and the external environment.
- H_d - Direct heat loss coefficient.
- C –Internal thermal capacity of the zone related to intermittent heating.

- Heat source –The heating source of the room which, in the study case, its the air conditioner.

The simple model with a time constant can give a hint of how the room temperature dynamics will evolve given an outside temperature and the room building characteristics. The **Figure 3.1** can be further simplified into a RC circuit, where R_t is the total room's resistance and C_t is the total room's capacitance.

The more exact these values are estimated, the more precise the determination of starting times will be.

4 Methodology

This chapter is intended to explain, discuss and detail how, where and when the work and experiences were developed and conducted, how data was gathered, which hardware and software were used.

4.1 Determination of the Room's Thermal Parameters

As mentioned in the **3. Room Modeling Chapter**, the determination of the thermal parameters are an important step of the work toward an accurate determination of the starting times for the AC. In fact, the more precise the thermal parameters are, the more exact the staring times will be, leading to a flexible and optimized use of electricity.

4.1.1 The Setup

Having a general description of the experience in the previous Chapter, the environment to start the experience is now described.

A measurement unit is needed to measure the real-time electric consumption of the AC. In this experience, it was used a power monitor "Sonoff Pow R2", which is an ESP8266-based component capable of measuring electric values such as voltage, current, power, apparent and reactive power and power factor. Such a device is also capable of connecting to the Internet as well as to other devices via MQTT (Message Queue Telemetry Transport). In the laboratory, a Linux server was installed and used as a broker interface between the "Sonoff" device and the department database. The server stored the electric measurements sent via MQTT into the respective database table.

In order to measure the heat transfer between the room and the outdoor environment, it is important to avoid solar gains which would mislead the correct calculations. Thus, this experience must be done at night. Another important aspect is to choose a cloudy night where, ideally, the temperature remains almost constant outdoors, to provide an almost constant temperature heat sink. **Figure 4.1** shows the measuring system.

Figure 4.1: The AC system to measure the electric power consumption.

4.1.2 The Experience

After consulting the local weather website and selecting the night to conduct the experience (night of 11th August 2020), the target room (room T4.4) was pre-heated to the temperature of 28ºC and, according to the ***Lumped Capacity Method***, the room was maintained to this temperature for a few minutes, in order to achieve a steady-state temperature. After this condition was verified, the instantaneous electric consumption was consulted and found to be 775W. The indoor and outdoor temperatures were measured with a digital thermometer and the respective values to these quantities are, respectively, 27.7ºC and 21.2ºC. Recalling the equations **3.3** and **3.5**, the **heat loss coefficient**, U, corresponds to $\frac{5*775}{27.7-21.2} = 596.1538$ W/ºC.

A cool-down test was performed during the night, measuring the decay of the inside air temperature. To perform the outdoor and indoor temperature readings, two USB measuring units were programmed to start the sample acquisition at 00h:30m. Cutting AC power will initialize the transient process of heat transfer. The indoor and outdoor temperatures were measured overnight and the result are shown in **Figure 4.2** and **Figure 4.3**.

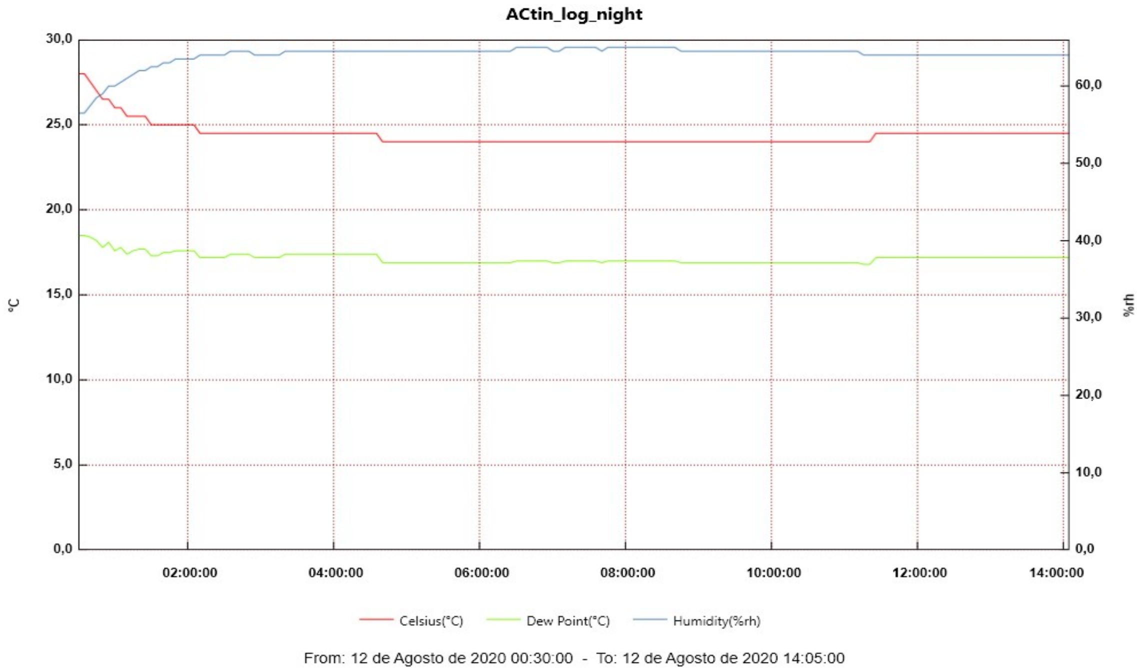

Figure 4.2: Indoor temperature evolution overnight.

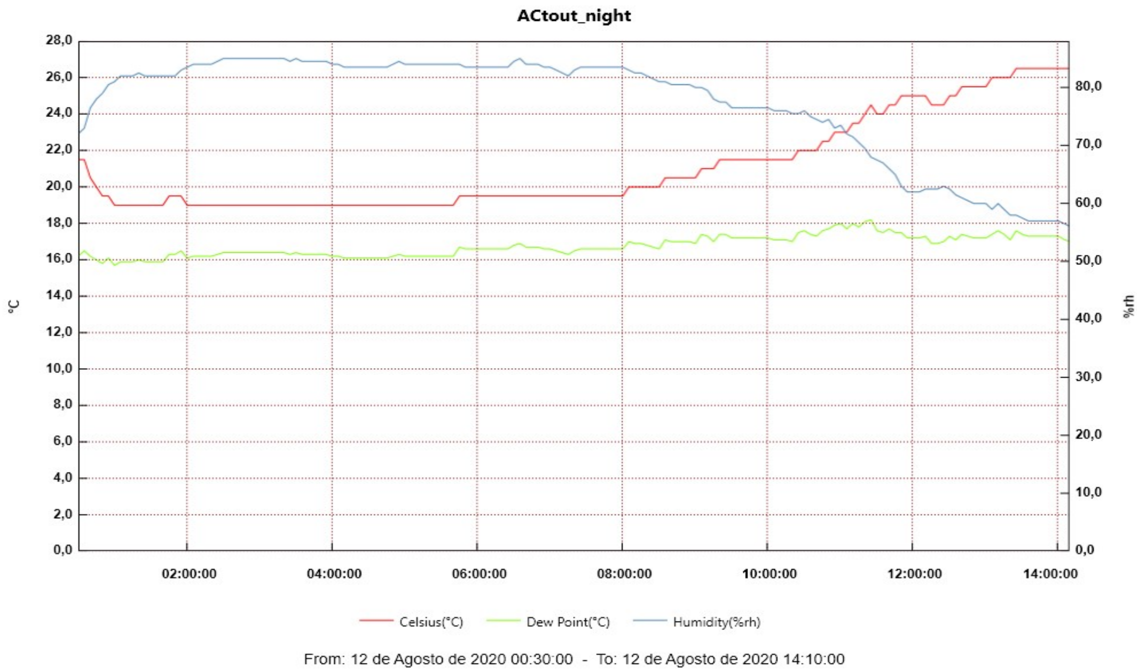

Figure 4.3: Outdoor temperature evolution overnight

4.1.3 Constants Calculation

Analysing the outdoor temperature, it can be seen that after *8h:00*, the temperature starts to increase due to solar gains. Therefore all the data will be processed from the beginning of the experiment up until *8h:00*, time at which the cool-down test was over.

The target value (thermal time constant $\tau = \frac{C}{U}$) relies on the argument of the exponential function in the right-hand side of **Eq. 3.1**. To achieve this value, it must be applied a ln function to each side of the equation. After this manipulation, a simple linear function is obtained, where its slope is the target value. After having the measured data available and manipulating **Eq. 3.1**, it was plotted a $ln(\frac{T_i - T_o}{T_{i0} - T_o})$ *versus* time (minutes after the beginning of the experiment). In **Figure 4.4**, the blue samples represent the plotted function and the red line is the respective linear regression. The red line parameters are listed at the top of the figure. Particularly, the slope of the line is $-9.74 \cdot 10^{-4}$.

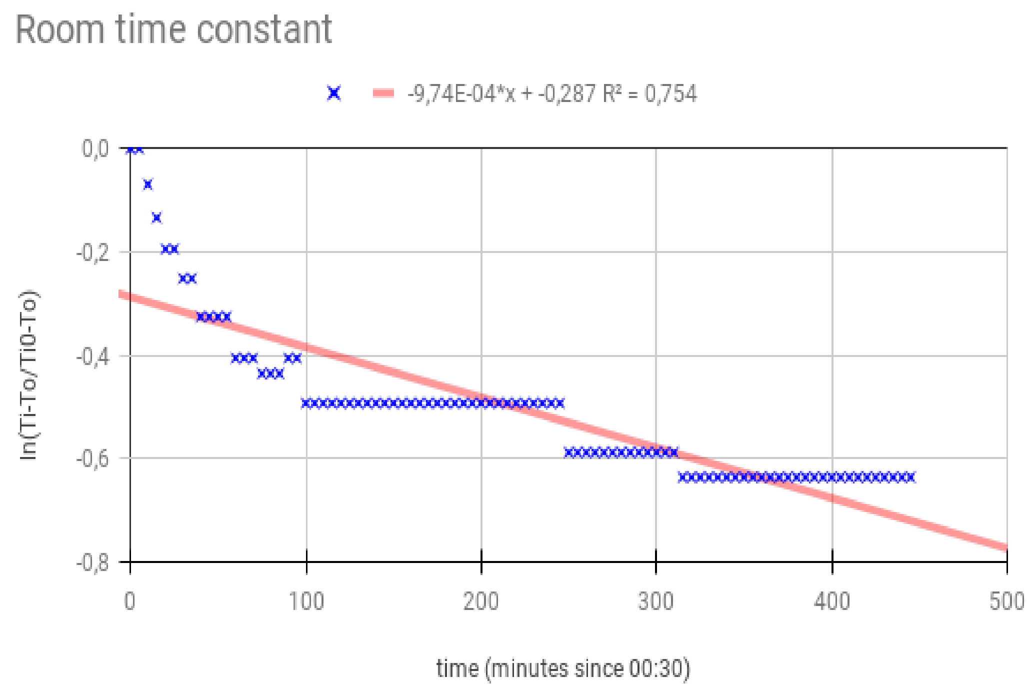

Figure 4.4: Function $ln(\frac{T_i - T_o}{T_{i0} - T_o})$ *versus* time and respective linear regression.

For this test, and using the complete cooling period, it was obtained a building time constant of $1/0.000974 = 1026.6940$ min $= 17.11$h.

According to **Eq. 3.6**, $C = \tau \cdot U = 17.11 \cdot 3600 \cdot 596 = 36.7$ MJ/ºC.

Summarily:

- $\tau = 17.11$ h

- U = 596.1538 W/ºC
- C = 36.720689 MJ/ºC
- Average AC Power P_e= 2200 W

4.2 The Monitoring and Scheduling System

One aspect of an intelligent monitoring system is the acquisition, analysis and usage of data to track the status of loads toward reaching its electrical objectives and to guide management decisions. It is important, from a user perspective, to know how much electricity they are using and how much they are paying for it. This knowledge allows user to take actions and change electric usage patterns, as suggested in DSM programs. In order to remotely access the consumption of the AC, it was created a website where it is possible, not only to view this data, but also to schedule AC operations. One benefit of this system is its accessibility. The user only needs Internet access to schedule or track the load.

4.2.1 System Specifications

The monitoring and scheduling system is hosted in the laboratory computer/server running on *Linux Ubunto 20.04*. Several services were installed to fully operate the overall system. These services include:

- node.js
  - express.js
  - mysql
  - xmlhttprequest (or XHR)
- mysql
- mosquitto

node.js its an open source server environment that allows to run JavaScript files. This framework is single-threaded, non-blocking, asynchronously programmed, memory efficient and has a high scalability potential, making it perfect for our purpose. The web server was developed under this framework.

express.js is an open-source, cross-platform, off-browser runtime environment used to develop server-side tools and applications.

mysql its a database management system which uses SQL language as an interface. This tool is used to make interactions between the server and databases.

XHR its a web browser application used to send HTTP or HTTPS requests directly to a web server and retrieve the data the web server responds to. However, as **express.js** can operate off-browser, XHR also doesn't need a browser to operate. The data is retrieved in the form of a javascript object (JSON). This method is equally used to retrieve data from the meteorological station in **Section 4.3.1**.

Mosquitto broker is an open source message broker that implements the MQTT protocol. Due to its lightness, mosquitto broker is highly suitable for use on devices that operate at a low power single board computers to full servers. MQTT provides a lightweight method of carrying out messaging using a publish/subscribe model to a certain topic.

4.2.2 Website Documentation

To produce the website front-end, it was used plain *html* markup "language" and *css* styling. Some of the web pages make use of JavaScript language to produce desired outcomes, for example electric consumption graphs. The website has $(3 + n)$ main web pages, where n represents the number of loads to monitor. The main web pages are the following:

- *Home Page* - a web page with a general description of the project.
- *Consumptions* - n web pages designed to show electric data (Voltage, Current, Power and Energy) of the load to monitor.
- *Scheduling* - a web page serving as interface, where its possible to schedule AC operations.
- *Show Tasks* - this webpage is designed to show the scheduled tasks and offers an option of deleting a task, in case the fills the scheduling form incorrectly.

The n factor in the *Consumptions* page brings the scalability side. The system was designed in a way that allows the integration of multiple measuring nodes. All the pages share a common navigation bar to help the user to switch from page to page, intuitively.

4.2.2.1 Monitoring Side

In order to display consumption graphs in the web pages, two solutions were compared: *Grafana* and *Anychart*. *Grafana* is a multi-platform and open source application for analytics, statistics and interactive visualization, generating graphs through a *SQL* query. Its plug-in system makes the software very expandable. On the other hand, *AnyChart* is a JavaScript library for cross-platform. Its main purpose is also data visualization through interactive graphs and charts. There are multiple differences in both solutions, being the main one, form a computational perspective, the way they are implemented. *Grafana* renders beautiful graphs and allows their use through a 'link', which can be hard-coded in the *html* of the web page. Unlike *Grafana*, the *Anychart* library needs JavaScript programming to build the *SQL query* and data objects 'vectors' in order to visualize data. In **Table 4.1** both solutions are compared with the purpose of assessing which solution is going to be implemented.

Table 4.1: Graph solution comparison.

	Grafana	Anychart
Method	Image render through a link	JavaScript libraries
Integration	Difficult	Easy
Aesthetics	Very good	Good
Data accessibility	Limited	Very accessible

Despite *Grafana's* generated graphs are more appealing than the opposite solution, its limited data accessibility makes this solution less useful in terms of data manipulation. Since this feature makes a huge difference in the further work, *Anychart* solution was chosen to serve the Monitoring purpose.

In the **Consumptions** main page, it is shown a canvas divided in four parts, each one containing a graph of an electric quantity (voltage, current, power and energy consumption in this case) of the load under monitoring. The user can have an idea of the consumption profile that the load is performing. These graphs are dynamically changing over time, showing a real-time monitoring. The rate of sample shifting can also be programmed. Hovering the cursor on the graphs will discriminate the sample, displaying information about the sample value and its acquisition time. At the bottom of the webpage, there is a textbox having all the latest measured values: voltage, current, apparent power, active and reactive power, power factor, energy consumed in that day and energy consumed in total. As an example, in the Power graph in **Figure 4.5**, a random sample was hovered dating the *11th August of 2020* at *21h:56*. As a matter of curiosity, this sample corresponds to the pre-heating period of the experiment night at **Section 4.1.2**.

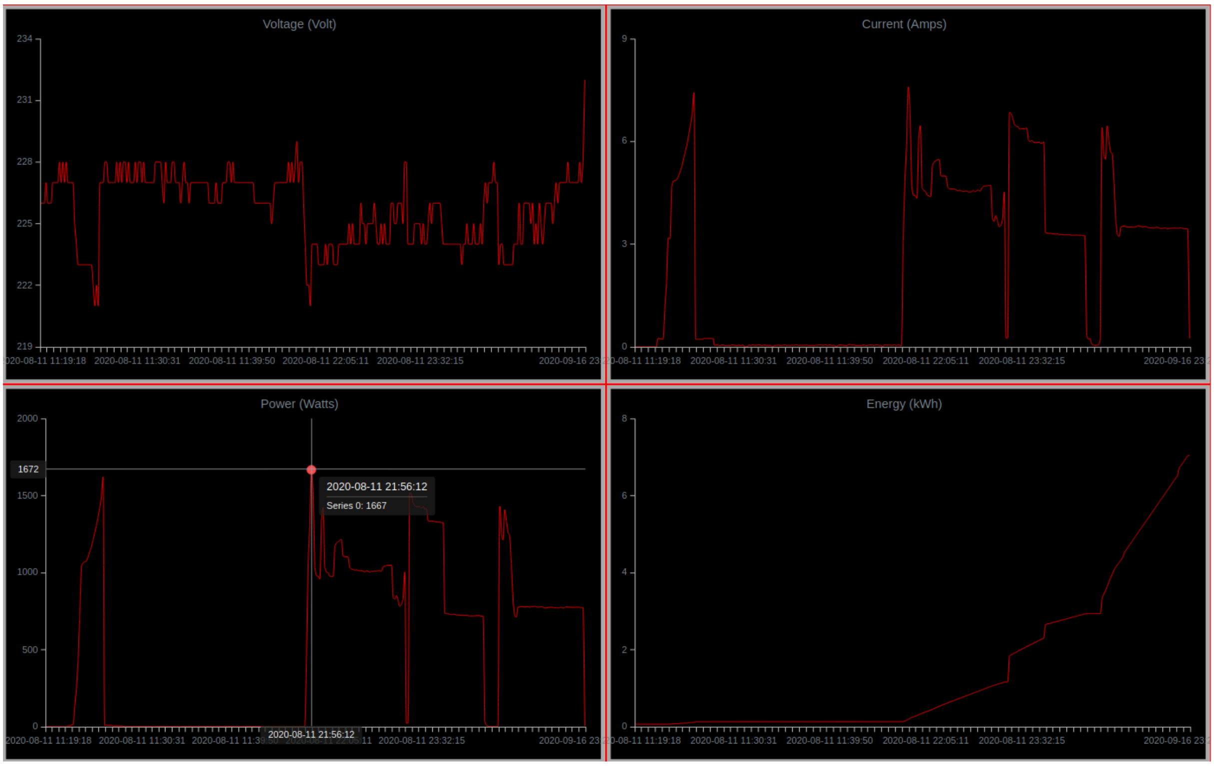

Figure 4.5: Monitoring the AC consumption

4.2.2.2 Scheduling Side

The **scheduling** web page allows the user to program an AC task by filling a form request. Once again, the remote access benefit must be addressed, since operations can be scheduled anywhere and anytime. The system imposes no constraints regarding the programmable periods, unlike usual thermostats. The scheduling can be done by any device that has Internet connection and a browser.

The form includes information about the room in which the user wants to schedule the AC task, the desired temperature, the desired day and time of the operation, an optional DSM program and a 'Repeat' flag. The flag must be 'No' if an operation is a single-event. In cases which the user might want a repeatable pattern, such as a weekly event, this flag must be switched to 'Yes'. In the 'Mode' field, the user can select a DSM program such as valley filling or peak clipping. As previously mentioned, utilities incentive the users to change their electric responses in exchange of monetary benefits. These changes can be either by reducing electric demand at peak times or increasing it at valley periods. This form request can be seen as a hypothetically interface between a "virtual" utility and the user.

The form is automatically stored into the database and waits in a queue to be processed. The form request is shown in **Figure 4.6**.

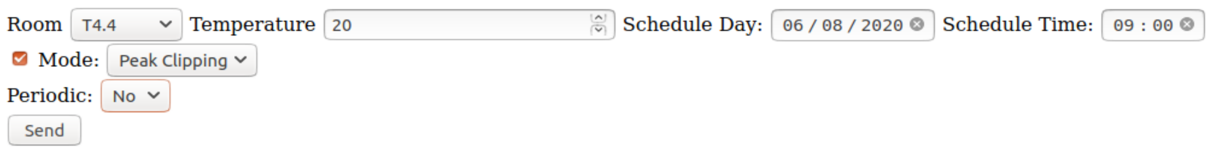

Figure 4.6: Operation scheduling form.

4.2.3 Web Service Architecture

The high level architecture of the web service is presented in **Figure 4.7**. The web service renders different *html* code, depending on the *HTTP* request. These types of requests can be *GET* type, if the user accesses the consumptions web pages. Respective load graphs will be rendered inside these pages, according to the accessed page. The other type of request is the *POST* if the user sends the filled form in the scheduling web page.

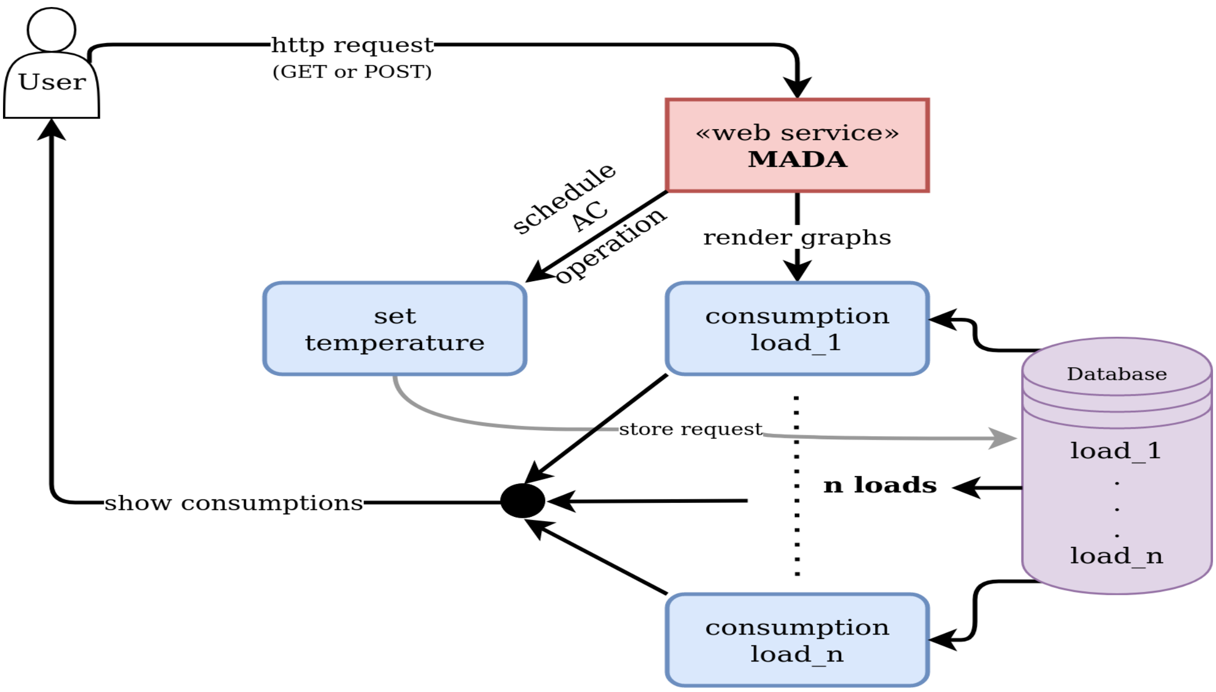

Figure 4.7: Web service architecture.

4.3 Control System

The control system is the application responsible for running the multi function operation that controls the overall system. It's the core of the developed system, having four main purposes. Firstly, the system will gather climate data forecasts through a national meteorological station which is the *Instituto Português do Mar e da Atmosfera* (IPMA). The second one is to process the temperature requests that were stored in the database through the web service in the **Scheduling Section**. The third one is to compute the timings at which the AC must start its operation, based on the room's thermal response, calculated in **Section 4.1**. Lastly, the system sends a message payload, which will activate the infrared (IR) commands to the AC according to the state of the control variables (local PV production, outside temperature, etc...) and the desired operation request (desired temperature, target room, etc...). Ideally, this application should be in execution all the time.

The control system architecture and its interaction with the web service are shown in the figure **Figure 4.8**.

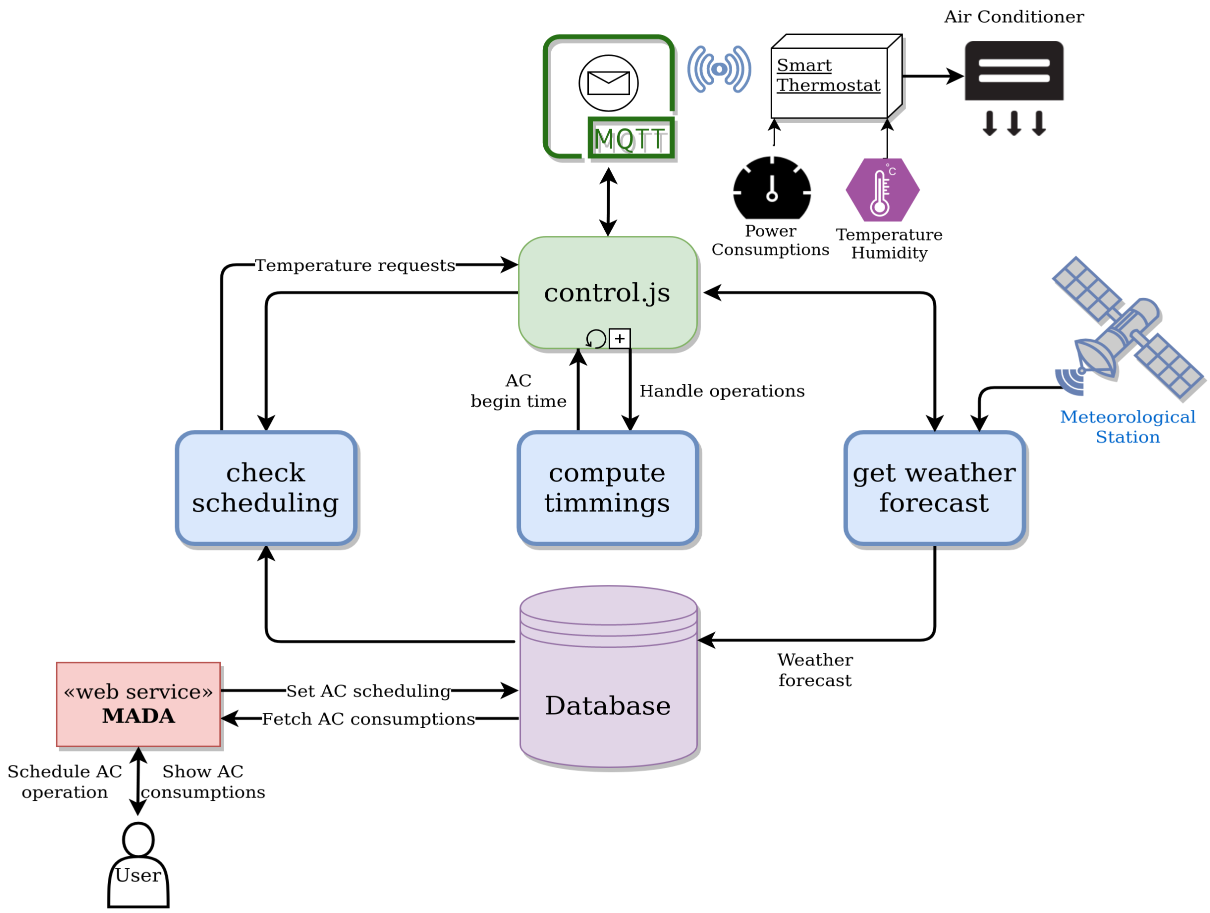

Figure 4.8: Control system diagram.

4.3.1 Weather Forecast

This functionality makes use of a **XHR** call to retrieve data from a meteorological station. This data comes as a form of an object with the properties that describe the climate: the average temperature, direction of the wind, and the state of the climate (sunny, cloudy, etc...), between others parameters.

The object contains information about the climate on a time window of three days. However, only the "today" and "tomorrow" information are processed. An iterator compares the state of the climate to find out the hours of the day where the forecast suggests the absence of clouds. This means that there is a high probability of having a PV electric production. The iterator builds an object containing the hours of the day of high PV production probability and stores it into the database. This function is periodical and runs independently once a day, since the forecast is the same at any time of the day.

It must be noted that the forecast might not be very accurate all times, depending on the meteorological station data.

4.3.2 Check Scheduling

This function was designed to process the requests that users input on the web site. The first thing the function does is to fetch all the requests for that day, from the database, ordered by time of execution. An object is created (*temp_requests* object) by an iterator which inserts all the necessary information for the AC to operate. This information includes the *room*, desired *temperature*, the desired *hour*, an optional *loadshape diagram* (in the case of future DSM programs) and a *'Done'* boolean that indicates if the request has previously been executed or not. The function activates another complementary function "*compute timings*". The output of this function is the created "*temp_requests*" object.

This function runs periodically every 10 seconds.

4.3.3 Compute Timings

Having the requests object calculated in the "*check scheduling*" function, it is necessary to determine the optimal starting time of the AC operation considering the thermal parameters of the room. The "*compute timings*" function calculates the optimal initial time for the AC to start, in order to reach the desired temperature at a certain desired time, according to **Eq. 3.4**. Respectively inputting the desired time of comfort as t_3, the room's temperature as T_{i2}, the desired temperature as T_{i3}, the outdoor temperature as T_o, the average power consumption Q_p and the room's thermal parameters U and C, the optimal starting time, t_2, for the AC is obtained. Time conversion is necessary, since this value is given in *seconds*. The function returns the previously created object ("*temp_requests*") but with the additional information of the AC optimal start time.

Since this function is activated in the "*Check Scheduling*" function, it is also periodically on a 10 seconds rate.

4.3.4 Handle Operations

After all the necessary information being gathered and processed in the "*temp_request*" object, it is required a periodic function to keep track of the system's functionality. This function regularly checks whether or not the AC should have started and acts accordingly, sending activation messages payloads via MQTT to the IR transmitter located in the room. If there is PV solar production, turbo mode is enabled.

This function has a decision-maker to analyse every temperature request. For each request that has not been 'done', if the AC is not currently working and if the request should have started, the decision-maker determines if there is a high probability of solar production, based on the **Weather Forecast** algorithm. If the weather is propitious to high PV production, the request is handled in a 'Full Power' mode, enabling the AC turbo mode and reaching the desired temperature faster. Otherwise, the request is treated in normal mode. After reaching the desired temperature at the beginning of the class, the AC operates in automatic mode for 30 minutes to ensure users comfort. After that, the AC has done its task and proceeds to turn off, waiting for the next request to arrive. In the idling case, whenever the Smart Thermostat detects high CO_2 levels above a certain threshold (1000ppm according to **ASHRAE Standard 62-1989**), the decision-maker will start the ventilation process, renewing the indoor air, promoting users health and safety. **Figure 4.9** illustrates the decision-maker flowchart.

This function is periodic at a 10 *seconds* rate, however it is only activated after the "*Compute Timings*" function runs the first time, otherwise it would not make sense since there would be no "*timings*" object.

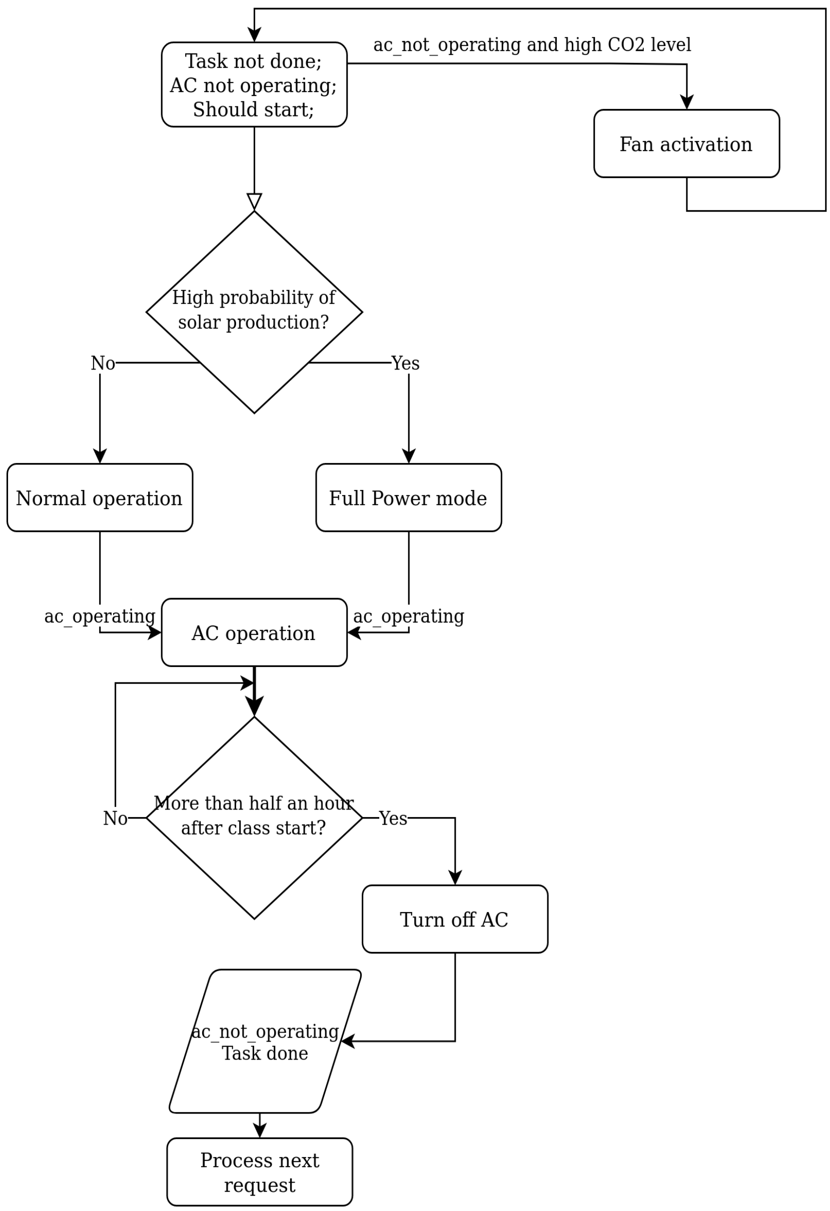

Figure 4.9: Decision maker flowchart.

4.4 Infrared Transmitter

The infrared transmitter is the component responsible for the transmission of the command that the control algorithm generates for the AC. IR transmitters use an IR LED to transmit the signal to the receiver by rapidly switching the LED on and off, creating a 24 bit binary sequence. The signal is transmitted in a carrier wave with a **38 kHz** frequency. After decoding the IR protocol used by the AC, which was found to be a *COOLIX* variant, it was possible to build a lookup table to select the desired command to send to the AC.

Table 4.2 shows the possible command patterns. Each 'x' denotes a binary digit. The *prefix* and *end* values are always the same and denote the beginning and the end of the

Table 4.2: Command pattern.

prefix	zf	ope	fan	x	curr	temp	mo	end
1011	x	xxx	xxx	x	xxxx	xxxx	xx	00

signal.

The *'mode'* option allows to choose the AC operation mode:

- 00 - cool mode
- 01 - dry mode
- 10 - auto mode
- 11 - heat mode

The *'temp'* field allows to set the desired temperature for the AC, and can have the following values:

- 0000 - 17ºC
- 0001 - 18ºC
- 0011 - 19ºC
- 0010 - 20ºC
- 0110 - 21ºC
- 0111 - 22ºC
- 0101 - 23ºC
- 0100 - 24ºC
- 1100 - 25ºC
- 1101 - 26ºC
- 1001 - 27ºC
- 1000 - 28ºC
- 1010 - 29ºC
- 1011 - 30ºC

Similarly to the *'temp'* field, the *'curr'* value tracks the current temperature for the AC to follow. This field has the fixed value of 1111 which stands for normal tracking mode.

The 'x' field switches between 0 and 1, which corresponds to swing and sleep mode if this bit has the 0 value or other modes if the bit has the value 1. Since it is not desired to put the AC in the sleep or swing mode, this value has the value of 1.

The 'fan' field corresponds to the fan velocity of the AC and can have the following values:

- 001 - Max speed.

- 010 - Medium speed.
- 100 - Minimum speed.
- 101 - Automatic speed.
- 110 - Fan with zone follow mode enabled.
- 111 - Fixed mode.

The 'ope' field, despite having three bits, only have two possible states, which are:

- 010 - Swing mode.
- 101 - Turbo and zone follow modes.

In order to have the swing mode on, the 'x' value must be '0'.

Finally, 'zf' field allows to decide whether or not the AC will have zone follow enabled. In the positive case, the 'ope' must be '101'.

There are also fixed binary sequences that map other AC modes. There are only two fixed sequence used in the algorithm, which are the 'Turbo' and 'OFF' signal, having the corresponding hexadecimal value '0xB5F5A2' and '0xB27BE0'. The 'OFF' command will obviously turn off the AC. It is important to note that turbo mode will activate the faster fan mode for a limited time period.

5 System Validation and Results

After developing the system explained in **Section 4**, a test for the validation of the system was conducted. This test consists in using the overall system to perform a desired task, since the website scheduling and programming to the control algorithm computing the optimal start time and sending the correct command to the smart thermostat to produce the desired binary IR sequence, resulting in the control of the AC. Furthermore, two comparative studies were conducted to assess the most efficient and economic method to use the air conditioner: the first one simulates the intelligent controller, pre-heating the room and making use of less expensive tariffs.The second study is a common, yet less flexible, approach in many offices and houses which is starting the AC as soon as the user enters the room, at full power, to achieve the comfort conditions as soon as possible. This approach ends up leading to larger consumptions of electricity, which adds up to a larger bill. It must be remembered that air conditioner can be an expensive load in terms of electricity usage.

5.1 System Validation Test - Case 0

After enabling all the needed services in the server, the request form was filled in the test's previous day with the following parameters:

- Room: T4.4
- Temperature: 20ºC
- Schedule Day: 08-11-2020
- Schedule Time: 08:00h
- Loadshape: None
- Periodic: No

```
[ { Room: 'T4.4',
    Temperature: 20,
    Out_temp: '15.6',
    Begin_time: 1604815550258.7253,
    time: '08:00:00',
    loadshape: 'NULL',
    done: 'NO' } ]
```

Figure 5.1: Generated timing object.

The service was left running overnight.

Through **Eq. 3.4**, the optimal start time was computed and can be found at **Figure 5.1** in the *Begin_time* field. This time structure is called Unix Epoch and represents the number of milliseconds passed since January 1st 1970. One advantage of this time structure is being timezone independent. Converting the time structure to a proper time format, it gives Nov 8th 2020 06:05:50. The *Out_temp* field is related to the outdoor temperature and *Done* field is a flag used by the algorithm to know which tasks have been performed or not. Consulting the database table created to store the air conditioning commands, in **Figure 5.2** , it is possible to see the beginning of the AC task in the first table row. In the second row it is stored the time at which the operation ended. Turbo mode was not enabled since the pre-heating period (from 06:04 to 08:00) was not cloud free and did not make use of the P4 tariff, as it will be explained further. Although the system shuts down the AC at 8:00h, the operation is stored having a small temporal delay.

timestamp	command	temperature	turbo
2020-11-08 06:04:40	heat	20	0
2020-11-08 07:57:31	off	0	0

Figure 5.2: AC commands storage.

The power and temperature evolution of the experiment, as well as the simulation of the system validation is shown in **Figure 5.3**.

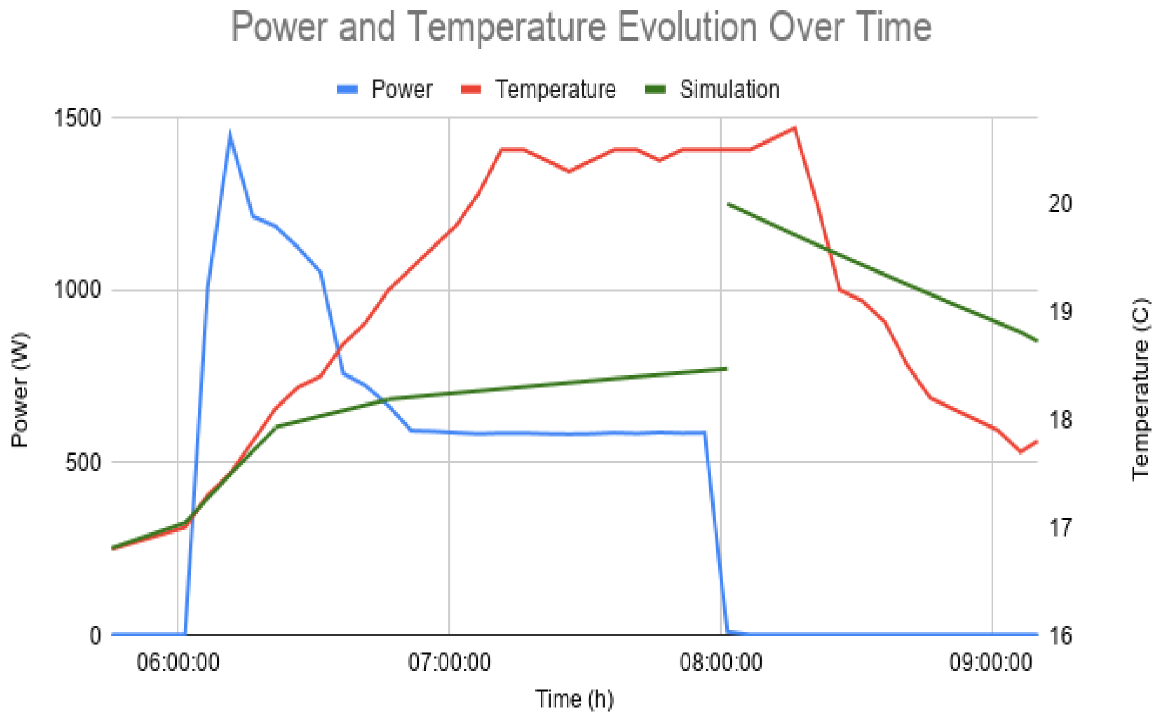

Figure 5.3: System validation power consumption and real/theoretical temperature evolution over time with pre-heating.

In this figure, it is shown the pre-heating cycle and the following discharge period where the heat transient starts to transfer heat to the outside. The room's initial temperature was 16.8ºC. The power profile starts by having a spike, almost reaching 1500W and rapidly starts dropping, as the temperature increases. Usually, devices using a motor, such as the compressor of the air conditioner, require a large amount of power to start the operation since the motor is stopped and needs a transient moment of inertia to start functioning. This moment of inertia is responsible for a power spike at the beginning of the task. Significant indoor and outdoor temperature differences may also lead to a bigger power consumption. Power consumption also increases with the difference between the desired temperature and the actual temperature of the room. The constant power consumption is reached around 45 minutes after the trial start and its value is around 550W. The temperature increases exponentially in the first half of the trial, and then linearly until reaching the desired value. There is an overshoot of 1 degree above the desired temperature and then drops again, almost remaining constant and having few variations. Near the desired end time, the system shuts down and the temperature remains constant for a few minutes until initiating the heat transfer process, decaying over a negative exponential function, similar to **Figure 4.2**. The pre-heating period was reduced owing to the fact that indoor and outdoor temperature differentials were also reduced, as well as the desired temperature was not much higher than the indoor temperature. The value of the differential value between the indoor and outdoor temperatures is crucial for the room to achieve the steady-state faster. When this value tends to 0, it means that the room and the outdoor environment are at a quasi-equilibrium state, where it has low heat transference. Whenever the Turbo mode is enabled, the power curve changes once these feature demands the air conditioner fan and compressor to rotate faster, for a limited period of time, in order to achieve the pre-set temperature in a minimum time.

The figure above also shows the theoretical temperature evolution and the temperature discharge, represented in the multi colored line. According to **Eq. 3.4**,

$$T_i = T_o + \frac{Q_p}{U} - \frac{Q_p - U(T_d - T_o)}{Ue^{-\frac{U}{C}(t_f - t)}} \tag{5.1}$$

gives the internal temperature of the room, where T_d is the desired temperature, T_o is the outdoor temperature, t_f is the ending time of the trial and t is the time variable.

Furthermore, **Eq. 3.1**,

$$T_{i2} = T_o + (T_{i1} - T_o)e^{-\frac{U}{C}t} \tag{5.2}$$

models the temperature discharge in the room, where T_{i1} is the initial temperature of the room and T_{i2} is the instantaneous temperature of the room.

Since there are three power consumption stages, the simulation needs to be modeled by a function by parts. An approximation was made within the three stages which correspond to the time periods in the following manner: $t_1 \in [6:00, 06:20[(h)$ with value $Q_1 = 1500W$, $t_2 \in [6:20, 07:00[(h)$ with value $Q_2 = 966W$ and $t_3 \in [7:00, 08:00](h)$ with value $Q_3 = 588W$. These values must be correctly inputted in **Eq. 5.1**. It's possible to see, from the previous figure, that this model predicts nearly 18,5ºC by the end of the experiment, 1,5ºC below the real observed temperature, which suggests that the room should have been heated earlier than *06h:00*. It is possible to see that the simulated and the real temperature curves are coincident at the beginning of the experiment. This suggests a good estimation of the intrinsic parameters U and C. The temperature sensor must be also placed in a representative location to give an accurate temperature measure of the room. Sensor misplacement can give a false sense of the temperature. At time $t = 08h : 00$, the temperature remains constant for a few minutes due to a hot air zone. The discharge curve, modeled by **Eq. 5.2**, has a significant negative slope, which means that the temperature in the room decreases at a high rate, which is confirmed in the real temperature evolution. Having such a large room causes a longer transient heating process and temperature may vary abruptly from several points across the room.

To model the difference between the real (T_{real}) and simulated (T_{sim}) temperature values, the error function (erf) was defined and computed as:

$$erf(t) = |T_{real} - T_{sim}| \tag{5.3}$$

The error between T_{real} and T_{sim} starts increasing exponentially from *06h:00* until *07h:00* and then it has a damped variation until *08h:00*. The function presents a discontinuity at *08h:00*, which corresponds to the same variation on **Fig. 5.3**.

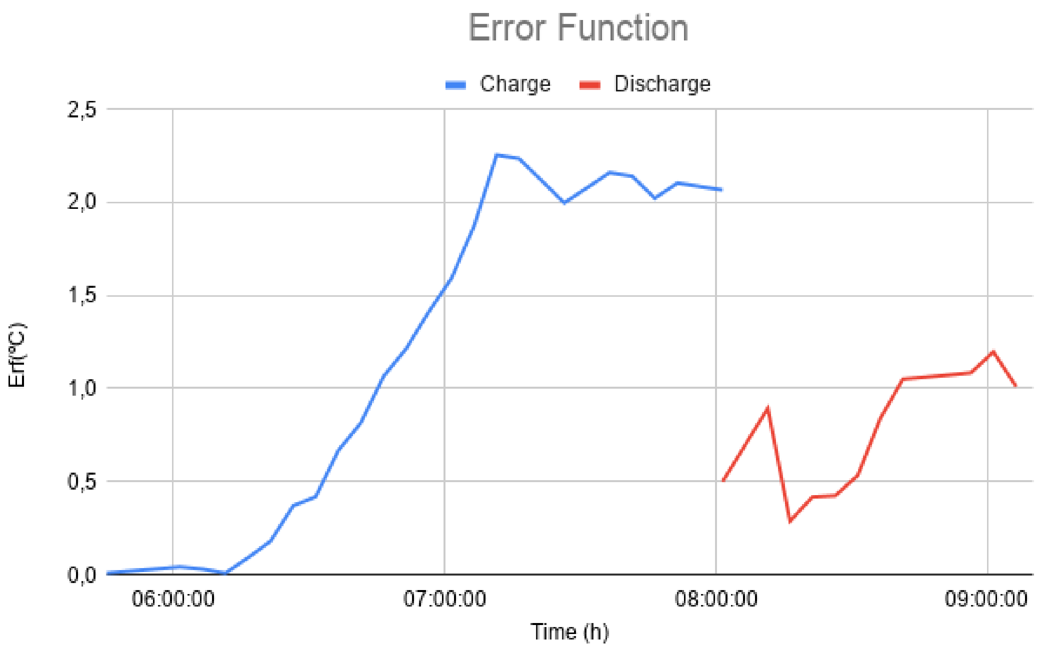

Figure 5.4: Case 0 error function.

5.2 The Smart Control Test - Case 1

To carry out the experimental phases, the trial was conducted at night to avoid interference with lectures and classes occurring in the targeted room. The AC task was scheduled on the web site and the selected parameters were:

- Desired date: 29/10/2020
- Scheduled time: 08:00h
- Desired Temperature: 25ºC

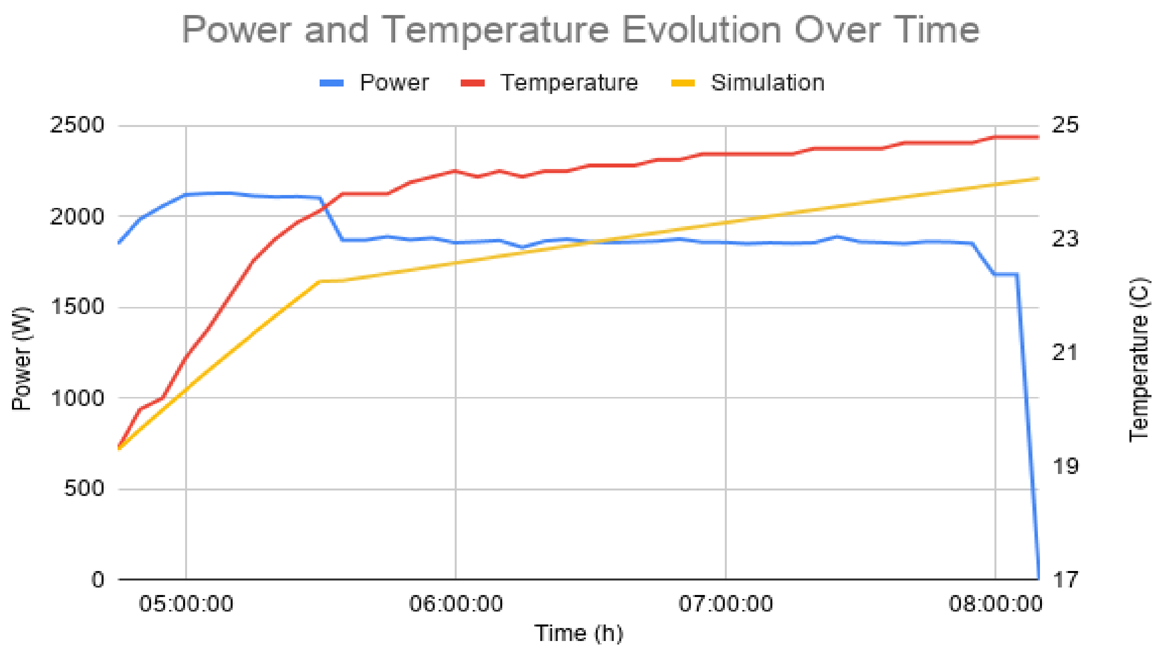

Figure 5.5: Power consumption and real/theoretical temperature evolution over time with pre-heating.

The intelligent control algorithm computed the optimal start time of the task to be around 4:45h. The initial indoor and outdoor temperature were respectively 19,3ºC and 10,0ºC. The power and temperature evolution over time are shown in **Figure 5.5**. The AC has a higher power consumption period in the first third quarter of hour of operation, which can be related to the device's compressor start and the higher indoor/outdoor and desired/actual temperature differences. Additionally, the turbo mode was activated due to operation during off-peak time tariff, which also affects the power curve. As explained previously, this feature requires a more power demand to operate, hence leading to a higher power consumption in the beginning. The temperature has a significant variation initially, which corresponds to the charge of the thermal capacity. It is possible to see that the AC is decreasing the electrical effort as the indoor temperature increases. The electrical power remains constant respectively when the temperature starts to increase almost linearly. Finally, when the temperature reaches the desired value, the control algorithm stops the AC operation and the heat starts transferring to the outside environment, thus the indoor temperature starts decreasing again. The experiment goes through two different off-peak hourly tariffs - P2 and P3 - which directly affect the overall process cost. The system reaches the desired temperature within the desired time. In the **Fig. 5.5**, due to multiple power stages, the approximation of the first stage, according to **Eq. 5.1**, has a value of $Q_p = 2200W$ while in the second stage $Q_p = 1850W$. It is possible to see that the real temperature behavior follows the expected in the simulation, although with a small error. This error is again computed and shown in **Fig. 5.6**. The error function for case 1 increases in a logarithmic way in the initial phase, reaching its maximum at *06h:00*, having a value of 1,75ºC and then decreases linearly.

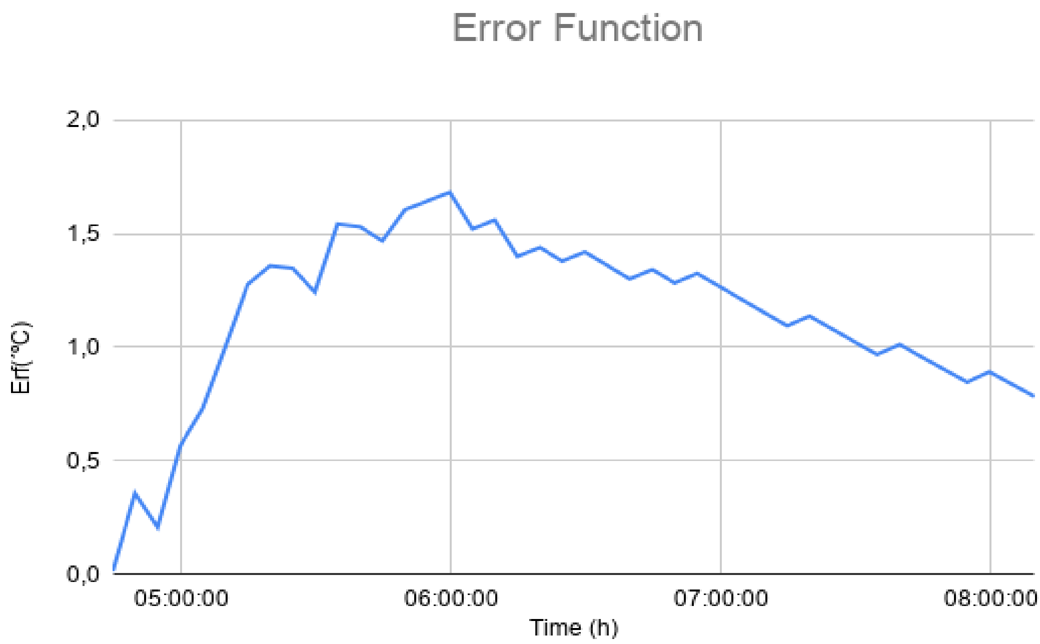

Figure 5.6: Case 1 error function.

Outdoor temperature fluctuated around 10ºC and 11ºC, which is not a significant difference. The targeted room has a huge air volume, which increases the heating process duration. Additionally, present gaps near the windows and door lead to air leakage and infiltration, causing significant heat loss.

5.3 Less Efficient Approach - Case 2

This test should try to replicate one of the most common uses of an air conditioner. The goal in this test is to heat up the room at full power, as soon as the user enters the room, until user comfort and satisfaction is achieved and compare the temperature evolution and power consumption with the first study in order to verify which one is the most economical method to use.

The initial conditions were similar to the conditions in which the first experience was subject to:

- Indoor temperature: 19,4ºC
- Outdoor temperature: 12,1ºC
- Desired user temperature: 25ºC

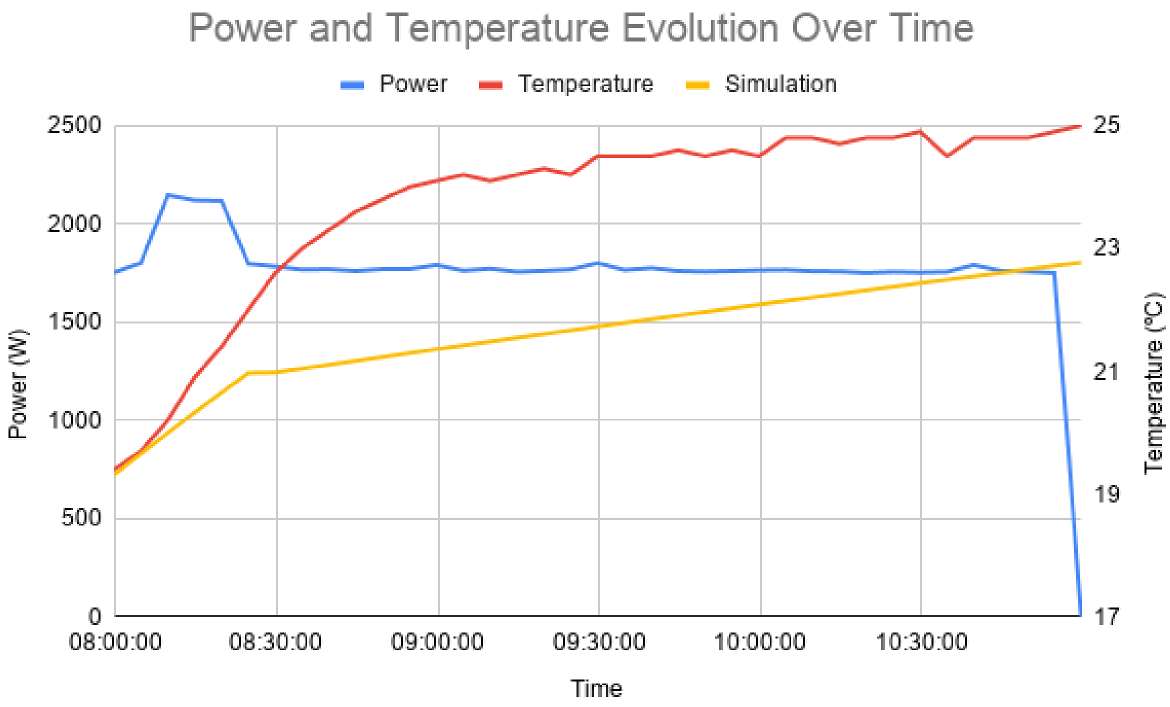

Figure 5.7: Power consumption and temperature evolution over time without pre-heating.

In the initial phase of the process, the AC requires a bigger electric consumption to start the thermal inertia, within the first half hour of the experiment. After this phase, it is observed a nearly constant power consumption and a linear temperature evolution, until the experience ends. This experiment was conducted during the hourly peak tariffs, coincidentally with the beginning of the classes.

Once again, the simulation of the indoor temperature evolution was plotted. The real temperature of the room behaves similarly to the simulation, since its start by increasing the temperature exponentially in the initial trial phase, then followed by a linear increase. The linear phase happened half an hour after the prediction in the simulation.

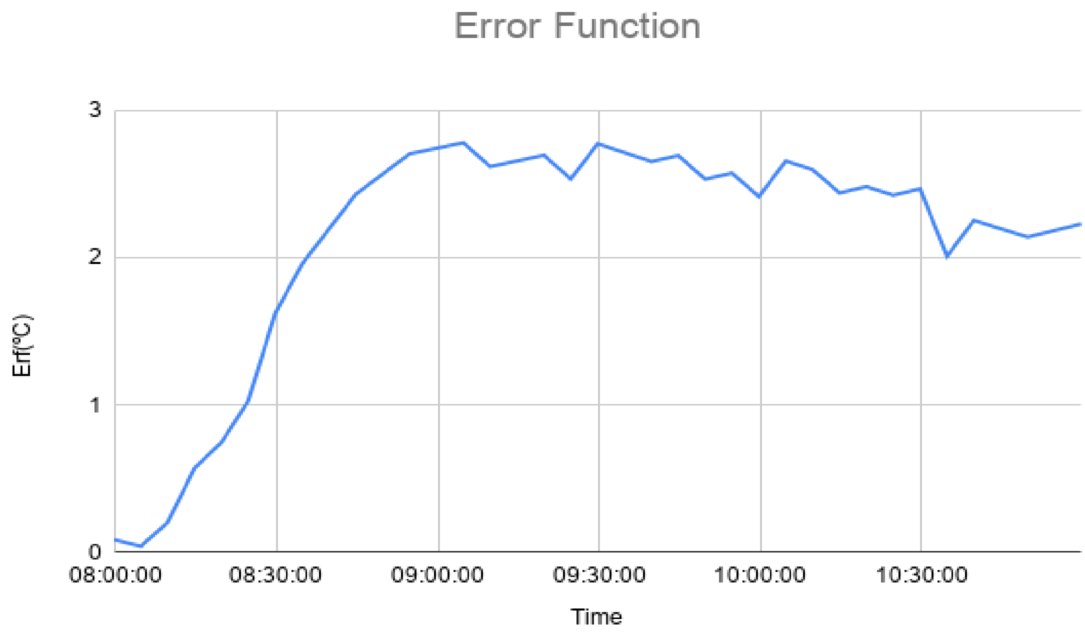

Figure 5.8: Case 2 error function.

Figure 5.8 shows the error function of case 2, having a maximum value of 2,77ºC.

In the following section, the three tests are compared from an operational point of view. Expenses of Case 2 and Case 2 are calculated within the respective time periods.

Analysing the three error functions cases and the three real and simulated curves, it is possible to see that the error $|T_{real} - T_{sim}|$ tends to a value of 0, meaning that in a steady-state, the real and simulation values are equal.

5.4 Tests Comparison

Compared to the Case 2, the Case 1 presents longer power consumption in the initial phase of the operation, taking a longer time to reach the steady power consumption. It is important to notice that in both cases, it takes approximately the same amount of time to complete the task. The constant power consumption is around 1870W in the first case while the second one is around 1760W. The smart controlled method also has a more linear behavior, presenting less temperature variations. In terms of comfort, in Case 1, the room is nearly at the desired temperature when the class starts. On the other hand, in Case 2, only almost one hour later the users achieve the same temperature in Case 1. As a conclusion, and comparing the three test cases, it is observed a larger power consumption when the air conditioner is required to operate at a greater temperature, which is an expected result. The power consumption also increases with the indoor and outdoor temperature differences (ΔT_{io}) as it is needed more effort to balance bigger temperature fluctuations. Another factor that contributes to the increasing power demand is the difference between the desired temperature and the actual temperature of the room (ΔT_{di}). Turbo mode also requires more power consumption. These results are summarized in **Table 5.1**.

Table 5.1: Three cases comparison table.

	Case 0	Case 1	Case 2
Desired Temp (ºC)	20	25	25
ΔT_{io} (ºC)	0.8	9.3	7.3
ΔT_{di} (ºC)	3.2	5.7	5.6
Constant Power (W)	600	1870	1760

In *Case 0*, the power consumption in the constant phase is around 600W, which is a third of the other cases. This value is meaningful from an economical perspective, since savings can be expected to be also a third of the *Case* 1 and 2. This low power consumption suggests that the room has entered in a steady-state, having an uniform temperature across the room. This steady-state was faster achieved than other cases due to a reduced temperature differential, ΔT, and a lower desired temperature. The highest power consumption corresponds to the *Case* 1, where bigger differential temperatures (both ΔT_{io} and ΔT_{di}) were registered.

5.4.1 Economical Perspective - Case 1 and Case 2 Comparison

Economically, there are significant differences regarding *Case 1* and *Case 2*. The money expenditure of the heating process depends on which time of the day and the year season the electric consumption is done. The department makes use of a tetra-hourly tariff, divided in periods from P1 to P4, where P1 corresponds to the peak hour. Conversely, P4 is associated with off-peak hours. **Table 5.2** shows the association of each hour to its corresponding tariff.

Table 5.2: Period corresponding tariffs.

	P1	P2	P3	P4
€/kWh	0.077646	0.07137	0.064721	0.05788

The time periods depend on the year season (summer or winter). The tests were done during the summer hour, having the division that follows on **Table 5.3**.

Table 5.3: Time Periods.

	Hour
P4	02:00 - 06:00
P3	00:00 - 02:00
	06:00 - 08:00
	22:00 - 00:00
P2	08:00 - 10:30
	13:00 - 19:30
	21:00 - 22:00
P1	10:30 - 13:00
	19:30 - 21:00

To compare the electric prices of the two methods for the AC, it is needed to divide the operation time according to **Table 5.3**. After this time division, and knowing the hourly price-per-kilowatt (€/kWh), it is possible to compute the electric expenses of the AC, which follows in **Table 5.4**.

Table 5.4: Two method costs.

Operational Costs(€)	
Smart Control Approach	Less Efficient Approach
0,204	0,384

According to **Table 5.4**, heating up the classroom at full power as soon as the users enter the room costs approximately **1,88** times more than using the smart controller. The estimated savings of choosing the smart controller over the less efficient approach operations were approximately **0,18€**. Hypothetically, if the AC is used everyday of a year for three hours, this saving acts as a compound value, which at the end of the year extends the savings up to **65,70€**. This saving was calculated for a room with an air conditioning operation similar to a residence. In the case of a large building such as an University campus, hospital or industry, the savings will be much larger, reducing significantly the yearly electric bill. Despite the smart control algorithm has shown to consume a little bit more power, this approach ends up by saving a larger amount of money. Using the smart controller to schedule a task to equivalent hours in both cases, the intelligent control algorithm will start operating in previous periods, benefiting even more from the tariff.

6 Conclusion and Future Work

The increasing living standards, as well as the electrification of the economy, force the global electricity demand to continuously grow in most countries around the World. Utilities have been struggling to balance the fluctuations on the supply of electricity, due to the mentioned concerns and also the intermittency and unpredictability of a growing share of renewable sources.

Having in mind these concerns it is necessary to seek new ways to balance non-critical loads. Alternative solutions like smart connected thermostats introduce different ways and approaches to make a flexible use of electricity, being advantageous to both the user and the utility. The acceleration development of new technologies has stimulated utilities to market new demand-response programs, where both client and utility can benefit if they agree to implement these programs.

As a way of solving these problems, this Dissertation proposes a low-cost, innovative and powerful smart thermostat with an intuitive web-browser guide user interface, capable of monitoring and control multiple loads across the building. Particularly, the smart thermostat is able to control the temperature of a target room, through an infrared transmitter, according to user input specifications, making use of an intelligent control algorithm that takes advantage of renewable production sources, namely the building solar PV production. The algorithm computes the optimal starting time for the air conditioner operation considering the thermal resistance and capacitance of the classroom. This feature allows the user/entity to benefit from the hourly tariffs, being able to achieve large savings, compared to the most conventional on-off method. In a large building such as an University campus or an hospital, the savings value will become much more substantial. From this project also resulted in the creation of a web service serving as an interface to schedule air conditioning operations and monitoring multiple loads across the building. Monitoring helps the user understand how loads behave and what patterns do they follow. This supervision is essential to help the consumer to have an idea of what costs to expect from the air conditioner operation.

Extending this monitoring to other non-critical loads give a more accurate perspective of the monthly electric bill, possibly influencing users to take other measures.

The main purpose of the work was fulfilled since the experiment conducted in **Section 5.2** successfully controlled the desired temperature in a more economic way than the general use of an air conditioner. Another important aspect was the creation of an online system which allows users to program the air conditioner over the internet from anywhere. Economical factors are generally an user top preference. Consumers make decisions by allocating their income across all possible goods in order to obtain the greatest satisfaction at the lowest price. Knowing the benefits of such smart devices can influence customers to acquire these products as a way of mid-to-long term investment.

The power consumption of the air conditioner can be controlled by changing the velocity of the fan, which changes the velocity of the compressor and ultimately changes the consumption curve. Features such as the turbo mode also change this profile for a limited amount of time. This study shows that air conditioner power demand profiles not only increases with indoor and outdoor temperature differences ΔT_{io}, but also with difference between the actual room temperature and the desired set temperature ΔT_{di}.

Innovation was achieved since none of the studied smart thermostats had extra features such as automatically compute optimal start times for the air conditioner operation using building intrinsic characteristics. The operation is optimized since the settings dynamically change, depending on the local climate, the probability of solar photovoltaic production and hourly tariffs to maximize comfort and minimize costs and operation time. The control algorithm was made in a way that supports future DSM programs proposed by utilities, possibly introducing dynamic tariffs.

The real and simulated temperature evolution have similar behaviors having, however, a small variable error as a function of time, which suggests a good estimation of the U and C quantities. Despite having this small discrepancy, the steady-state error value $|T_{real} - T_{sim}|$ tends to 0, meaning that T_{real} and T_{sim} approximate each other as time increases.

The optimization of pre-heating times has its own limitations regarding the room dimensions and the heating power. The target room has a large air volume, which interferes with the heating operation, prolonging its duration. For such a large room air quantity, it is preferable a more potent equipment, ensuring a greater heating power. Another limitation is the highly dependency on Internet connection. This parameter must be always ensured to grant correct operation.

The ventilation mode of the air conditioner is a support feature to air renewal, granting users proper health conditions, if CO_2 concentrations are above a threshold. This operation mode must not be activated after the pre-heating period, before occupation, since the air renewal will remove the heated air to the outside environment. Desirably, there should be installed a proper ventilator connected to the CO_2 sensor. These concerns are left to future work.

Future extension of the concepts described in this thesis to other non-critical loads such as HVAC and electric vehicle chargers will allow the creation of a virtual power plant, taking advantage of flexible loads and energy storage, granting a more resilient grid and enhancing the system's operational reliability. For other non-critical loads different from the air conditioner, each load requires its own smart controller, therefore there is a need to do further research over intelligent optimization algorithms.

As a last reflection, this work offers an alternative and innovative method to grant additional help balancing energy fluctuations during peak periods, better manage supply-demand balance, lower user and utility costs as well as to optimize the use of demand-side resources, all while granting users comfort and health conditions all the time and promoting a flexible use of electricity. The model of the classroom was validated, leading to a successful calculation of optimal pre-heating periods allowing the room to be heated to a desired temperature within the desired time.

6.1 Future Work

Every system presents its own shortcomings. These gaps can be filled with more research and development in order to strengthen, complete and make the product even more resilient. Many different adaptations, tests, and experiments have been left for the future due to lack of time, since the real experiments and tests end up being time consuming and could not be performed at any time due to lectures and classes in the target room. Future work concerns the addition of new features to the smart thermostat such as:

- Creation of a lookup table for the Thermal Power (Q_p) variable as a function of an indoor/outdoor temperature differential (ΔT) and desired temperature, in order to further optimize the optimal starting time of the air conditioning task.

- Installing a ventilator in the room to optimally control the indoor air quality, controlled by the CO_2 sensor in the smart thermostat.

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