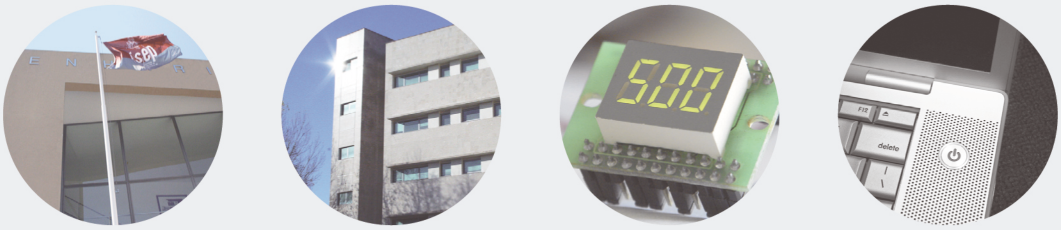
INSTITUTO SUPERIOR DE ENGENHARIA DO PORTO

MESTRADO EM ENGENHARIA ELECTROTÉCNICA - SISTEMAS ELÉCTRICOS DE ENERGIA




# ENERGY RESOURCE MANAGEMENT IN SMART BUILDINGS CONSIDERING PHOTOVOLTAIC UNCERTAINTY

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# ENERGY RESOURCE MANAGEMENT IN SMART BUILDINGS CONSIDERING PHOTOVOLTAIC UNCERTAINTY

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Mestrado em Engenharia Eletrotécnica – Sistemas Elétricos de Energia

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*"Learning is the only thing the mind never exhausts, never fears, and never regrets."*

Leonardo da Vinci

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Special thanks to all the people who along the way believed in me.

# *Resumo*

O aumento do consumo energético em edifícios residenciais tem levado a um maior foco nos métodos de eficiência energética. Deste modo, surge um sistema de gestão de energia residencial que poderá permitir controlar os recursos energéticos em pequena escala dos edifícios, levando a uma diminuição significativa dos custos energéticos através de um escalonamento eficiente. No entanto, a natureza intermitente das fontes de energia renováveis resulta num problema complexo. Para resolver este desafio, esta tese propõe um escalonamento energético baseado na otimização robusta, considerando a incerteza relacionada com a produção fotovoltaica.

A otimização robusta é um método emergente e eficaz para lidar com a incerteza e apresenta soluções ótimas considerando o pior cenário da incerteza, ou seja, encontra a melhor solução entre todos os piores cenários possíveis. Um problema de Programação Linear Binária é inicialmente formulado para minimizar os custos do escalonamento energético. De seguida, o objetivo desta tese é transformar o modelo determinístico num problema robusto equivalente para proporcionar-lhe imunidade contra a incerteza associada à produção fotovoltaica. O modelo determinístico é, assim, transformado num modelo do pior cenário possível.

Para validar a eficiência e a eficácia do modelo, a metodologia proposta foi implementada em dois cenários sendo cada um deles constituído por três casos de estudo de escalonamento de energia, para um horizonte de escalonamento a curto prazo. Os resultados da simulação demonstram que a abordagem robusta consegue, efetivamente, minimizar os custos totais de eletricidade do edifício, mitigando, simultaneamente, os obstáculos referentes à incerteza relacionada com a produção fotovoltaica. É também demonstrado que a estratégia desenvolvida permite o ajustamento do escalonamento dos recursos energéticos do edifício de acordo com o nível de robustez selecionado.

***Palavras-Chave***

Escalonamento de energia, Incerteza fotovoltaica, Otimização Robusta, Programação Linear Binária, Sistema de gestão de energia.

# *Abstract*

The increase of energy demand in residential buildings has led to a higher focus on energy efficiency methods. This way, the home energy management system arises to control small-scale energy resources on buildings allowing a significant electricity bill decrease throughout efficient scheduling. However, the intermittent and uncertain nature of renewable energy sources results in a complex problem. To solve this challenge, this thesis proposes robust optimization-based scheduling considering the uncertainty in solar generation.

Robust Optimization is a very recent and effective technique to deal with uncertainty and provides optimal solutions for the worst-case realization of the uncertain parameter, i.e., it finds the best solution among all the worst scenarios. A Mixed Binary Linear Programming problem is initially formulated to minimize the costs of the energy resource scheduling. Then, this thesis's purpose is to transform the deterministic model into a trackable robust counterpart problem to provide immunity against the photovoltaic output uncertainty. The deterministic model is transformed into the worst-case model.

To validate the model’s efficiency and effectiveness, the proposed methodology was implemented in two scenarios with three different energy scheduling case studies for a short-term scheduling horizon. The simulation results demonstrate that the robust approach can effectively minimize the electricity costs of the building while mitigating the drawbacks associated with solar uncertainty. It also proves that the proposed strategy adjusts the energy scheduling according to the selected robustness level.

***Keywords***

Energy Management System, Energy Scheduling, Mixed Binary Linear Programming, Photovoltaic Uncertainty, Robust Optimization.

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# *Acronyms*

| | | |
|---|---|---|
| AE | – | Absolute Error |
| AEV | – | All Electric Vehicles |
| AI | – | Artificial Intelligence |
| AMI | – | Advanced Metering Infrastructure |
| ANN | – | Artificial Neural Network |
| BEMS | – | Building Energy Management System |
| BESS | – | Battery Energy Storage System |
| CHP | – | Combined Heat and Power |
| DR | – | Demand Response |
| DSM | – | Demand Side Management |
| EMS | – | Energy Management System |
| EPC | – | Energy Performance Certification |
| ERSE | – | Entidade Reguladora dos Serviços Energéticos |
| ESS | – | Energy Storage System |
| EU | – | European Union |
| EV | – | Electric Vehicle |
| GB | – | Gigabyte |
| GECAD | – | Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development |
| GHG | – | GreenHouse Gas |

| | | |
|---|---|---|
| HEV | – | Hybrid Electric Vehicle |
| HVAC | – | Heating, Ventilating and Air Conditioning |
| ICT | – | Information and Communication Technology |
| IGDT | – | Information Gap Decision Theory |
| IoT | – | Internet of Things |
| kVA | – | Kilovolt-ampere |
| kW | – | Kilowatt |
| kWh | – | Kilowatt-hora |
| LP | – | Linear Programming |
| MAE | – | Mean Absolute Error |
| MBLP | – | Mixed Binary Linear Programming |
| MILP | – | Mixed Integer Linear Programming |
| NLP | – | Non-Linear Programming |
| nZEB | – | Nearly-Zero Energy Building |
| PDF | – | Probability Density Function |
| PV | – | Photovoltaic |
| RES | – | Renewable Energy Source |
| RO | – | Robust Optimization |
| SB | – | Smart Building |
| SO | – | Stochastic Optimization |
| SoC | – | State of Charge |

| | | |
|---|---|---|
| SP | – | Stochastic Programming |
| W | – | Watt |

# 1. INTRODUCTION

This chapter presents an introductory framework, the motivation of this thesis as well as its main objectives. It, then, provides a list of publications resulting from the work developed, the outline, and, finally, a brief description of the organization.

## 1.1. FRAMEWORK

With the depletion of non-renewable sources and global warming, renewable energy sources and decentralized generation are gaining broad interest; therefore, allowing the reduction of oil dependency and greenhouse gas emissions.

End-users, becoming prosumers, are now able to manage their electricity generation and their energy consumption by considering several resources such as solar photovoltaic panels, electric vehicles, and energy storage systems. These energy resources can optimize energy costs, increase the stability and reliability of systems, and change consumption patterns.

Due to the intermittent nature of renewable energy sources, forecasting techniques are also needed to predict electricity generation and, also, to manage storage systems. However, these forecasted values are not accurate due to the uncertainties associated with photovoltaic power generation.

This dissertation proposes the intelligent integration of solar photovoltaic for self-consumption and storage systems in residential buildings, considering the photovoltaic uncertainty. The development of optimization techniques and energy resources management will be crucial to increase the efficiency of energy consumption in residential buildings. It is expected to achieve a significant electricity costs reduction and contribute to rational and efficient energy use.

This work will require an energy resources management system, considering the uncertainty of the penetration of renewable-based generation in the residential building, to enable the proper building's energy resources scheduling and, therefore, optimize energy costs.

## 1.2. MOTIVATIONS

This work was developed in Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development (GECAD), as part of the project SAICT-FCT (POCI-01-0145-FEDER-029070-PTDC/EEI-EEE/29070/2017), BENEFICE: Gestão de Recursos em Edifícios para flexibilização da Potência Contratada.

## 1.3. OBJECTIVES

The main objective of this work is the intelligent integration of renewable energy sources for self-consumption and energy storage systems (use of electric vehicles and batteries) in collective residential buildings, considering the uncertainty associated with photovoltaic power generation. To achieve this, the development and implementation of optimization models and energy resources management in buildings are essential to reduce electricity consumption costs and to contribute to energy efficiency in a residential building.

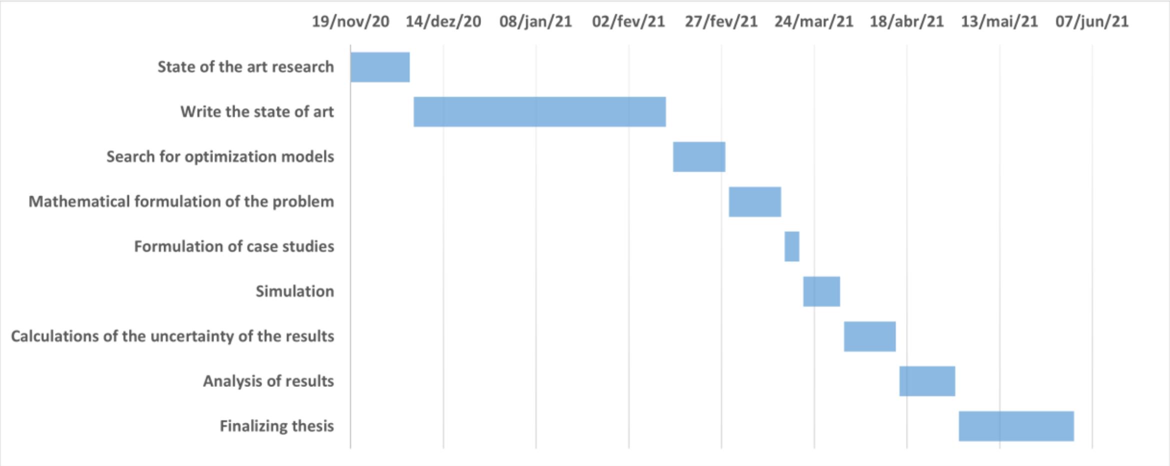
Succinctly, the initial objectives proposed for this work are the following:

- State of the art analysis;
- Definition of the mathematical formulation of the energy resource optimization problem;
- Implementation of the optimization technique;
- Development of the case study and the corresponding scenarios and simulations; and
- Analysis of results.

## 1.4. Calendarization

The calendarization of this dissertation work is presented in Table 1. It includes several tasks, such as writing the state of the art, search for optimization models, implementing the mathematical formulation of the optimization problem, simulation of the different case studies, and analysis of results. According to this table, this work will have a duration of approximately seven (7) months.

**Table 1 Dissertation Schedule.**




## 1.5. Document Organization

This thesis is composed of six (6) main chapters, which are briefly described below.

- **Chapter 1: Introduction.**

Chapter 1, Introduction, provides contextualization of the theme addressed in this dissertation, its motivation, main objectives, and a list of publications related to the project. Also, the calendarization of this work and the organization of this document are stipulated.

- **Chapter 2: State of the Art.**

Chapter 2 reviews the State of the Art, emphasizing the importance of energy management resources (photovoltaic generation, energy storage systems, electric vehicles, and forecasting techniques) in smart buildings and energy-efficient buildings.

- **Chapter 3: Problem Statement.**

Chapter 3 presents the optimization approach implemented in this thesis to deal with uncertainty and the description of the problem, as well as some assumptions.

- **Chapter 4: Intelligent Energy Management System (EMS) for Smart Building Considering PV Uncertainty.**

Chapter 4 describes the proposed methodology used in this work, with a detailed description of the mathematical formulation of the deterministic model and its transformation to a robust optimization approach.

- **Chapter 5: Case Study and Results.**

Chapter 5 defines the case study and the scenarios created for the implementation of the proposed methodology. After the numerical simulations, the results are analyzed and discussed.

- **Chapter 6: Conclusions.**

Finally, Chapter 6 exposes the main contributors and conclusions of this work, as well as the limitations found during this dissertation and a few suggestions for future work to be explored.

# 2. STATE OF THE ART

The main purpose of this chapter is to present a review of the current state of the art within the scope of energy resources in buildings, energy efficiency in buildings, smart buildings, and energy resources management in buildings.

## 2.1. ENERGY RESOURCES IN BUILDINGS

This section presents the different types of energy resources that are normally found in buildings: Photovoltaic (PV) power generation, energy storage systems (ESS), electric vehicles (EVs), and forecasting techniques for renewable generation. A brief presentation of all these concepts is provided.

### 2.1.1. PHOTOVOLTAIC POWER GENERATION

Solar energy is directly related to the sun's radiation and can produce heat, cause chemical reactions, and/or generate electricity. This type of energy is the cleanest and most abundant renewable energy source available, being an indispensable resource at a national level [1].

The concept of PV solar energy is the direct conversion of sunlight into electricity, based on the photovoltaic effect [2]. The PV solar panels are composed of PV cells consisting of semiconductor materials. When the sunlight reaches the cells, electrons are released from their atoms, thus, generating electricity. This is due to the photovoltaic effect, which corresponds to a potential difference at the extremes of a semiconductor material structure, after the absorption of sunlight [3].

Compared to traditional energy sources, PV solar energy does not cause any significant impact on the environment but rather mitigates the effects of greenhouse gas (GHG) emissions and global warming. However, PV solar energy can have a high cost for initial installation and relies on geographical conditions, especially in regions where there is a lack of solar radiation [2].

Figure 1 presents a grid-connected PV system, installed in a building, and consisting of PV panels, an inverter, an electricity meter, and the distribution network. The electricity produced by the PV panels is available in direct current and, therefore, PV systems are connected to an inverter. This inverter is installed between the panels and the building's electrical installation, allowing the conversion of direct current into alternating current [4].

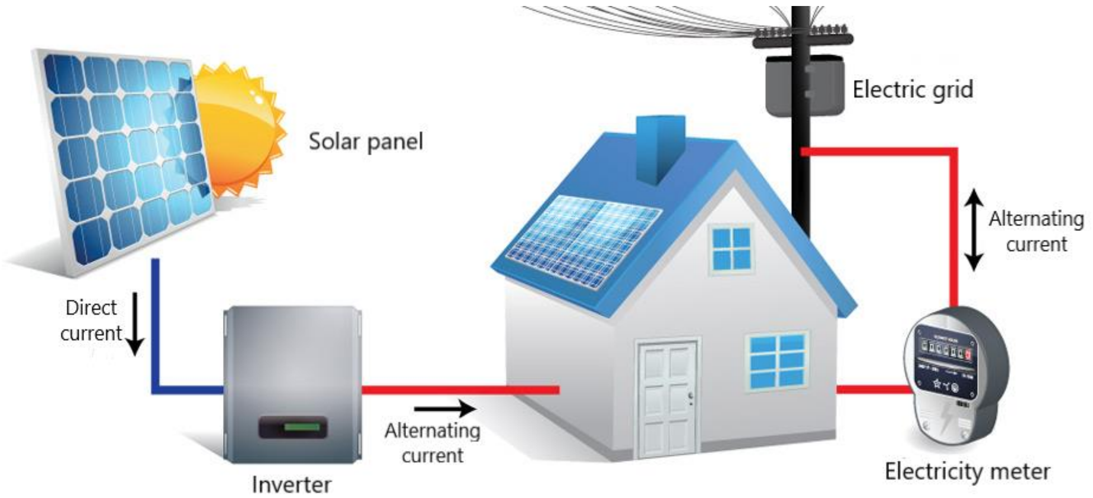



**Figure 1 Grid-connected Photovoltaic System. Adopted from [5].**

Figure 2 highlights the balance of electricity production in mainland Portugal until August 2021, in which renewable electricity generation represents 68.8% of the total electricity produced, in which solar production corresponds to 3.80% of the total.

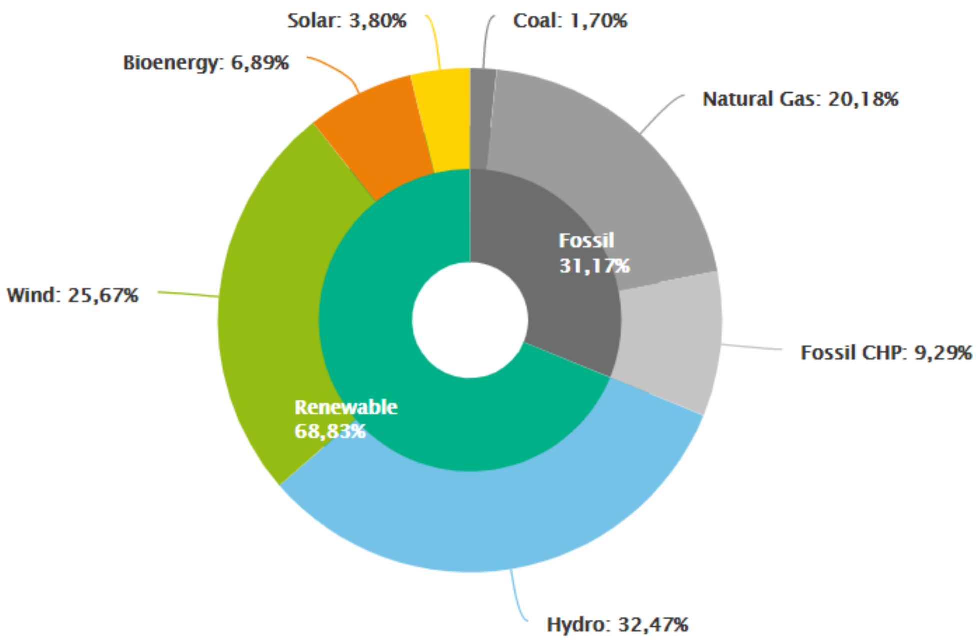



**Figure 2 Balance of electricity production of Portugal in 2021 [6].**

Figure 3 illustrates the total national energy production from each renewable source from 2012 to 2021. It is possible to observe that PV production is slightly increasing, reaching the highest values in 2021.

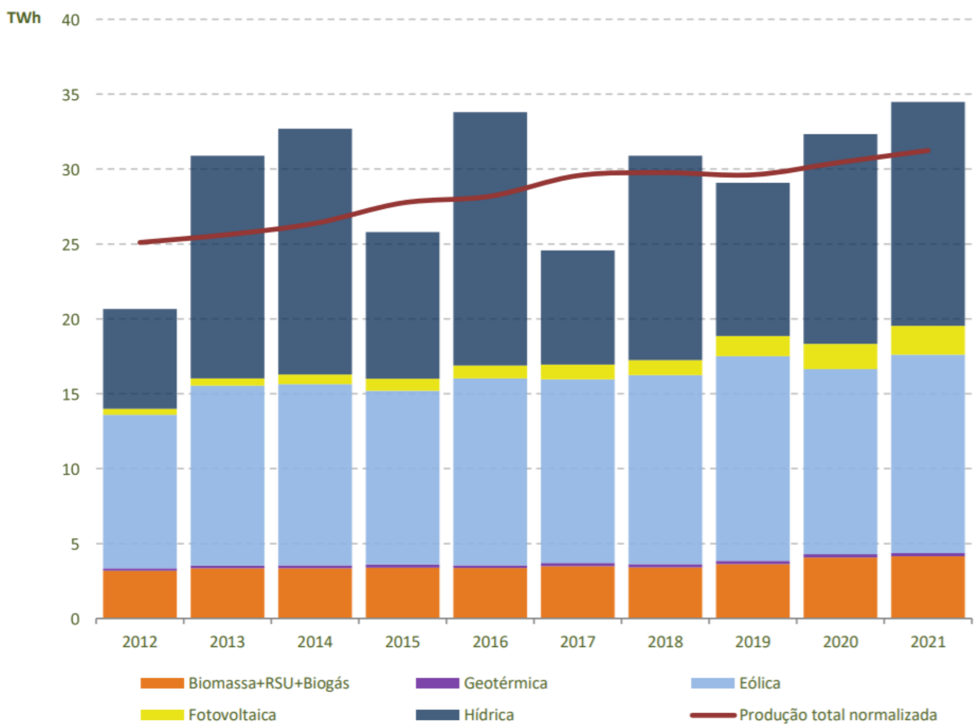



**Figure 3 Evolution of renewable electricity generation in Portugal, 2012 to 2021 [7].**

Distributed generation has been gaining broad interest from final consumers, especially the use of PV energy. The PV solar panels installation enables consumers to produce electricity in their households, allows them to use this electricity for self-consumption, and/or sell it to the grid. The consumers, by consuming and producing their own energy, become prosumers. According to Figure 4, in addition to consuming energy, prosumers also share the surplus PV energy generated with the grid and/or with other consumers in the community [8].

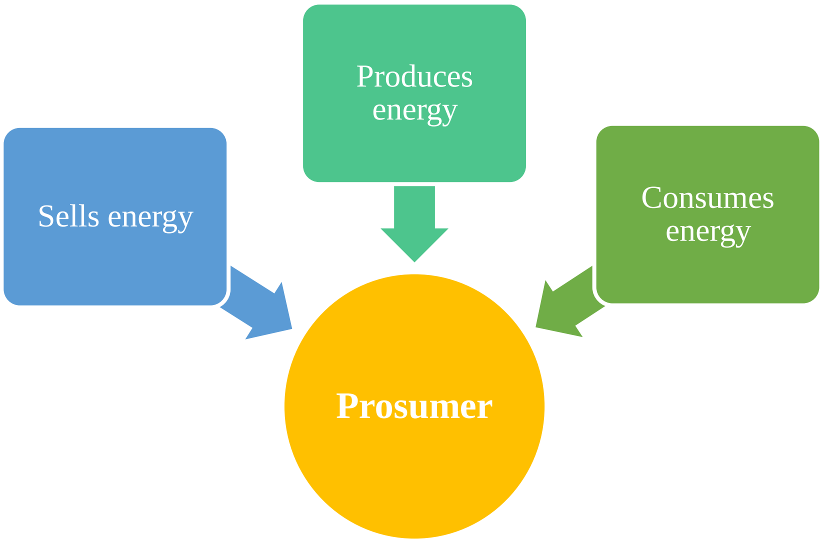



**Figure 4 The concept of prosumer [8].**

### 2.1.2. Energy Storage Systems

The Energy Storage Systems consist in transforming a certain type of energy into another type and, when necessary, can return the stored energy in a more efficient, reliable, and profitable way. Furthermore, as there is a wide variety of energy production technologies, ESS technologies also present a huge diversity [9]. Among these storage technologies, hydroelectric power is the oldest and most efficient and capable of quickly generating large amounts of energy. About 99% of the global electrical energy storage is pumped hydro storage [10]. There are also other storage technologies which are represented in Figure 5.

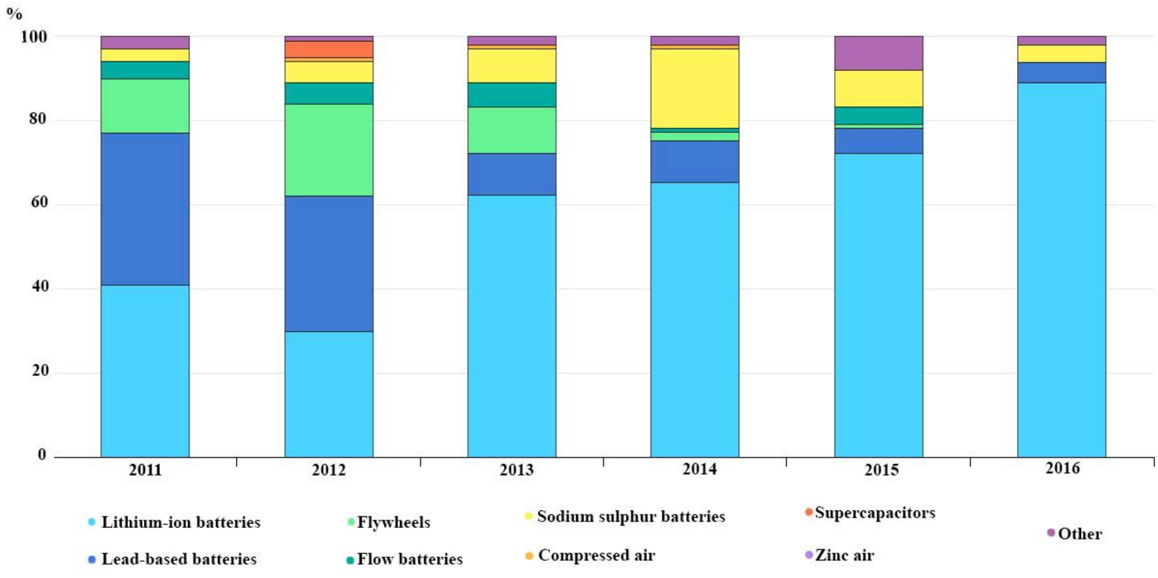



**Figure 5 Technology mix in energy storage deployments, 2011-2016 [11].**

ESS can be classified into five (5) major categories: (1) mechanical storage system; (2) chemical storage system; (3) electrical storage system; (4) electrochemical storage system; and (5) thermal storage system. Table 2 presents the energy storage categories and the storage technologies and devices associated with each one, based on [12].

**Table 2 Classification of energy storage technologies.**

| Categories | Storage technologies |
|---|---|
| **Mechanical Energy Storage** | Pumped hydroelectric storage; compressed air energy storage; flywheel energy storage. |
| **Chemical Energy Storage** | Hydrogen storage (hydrogen gas, fuel cell); biofuel. |
| **Electrical Energy Storage** | Capacitors; supercapacitors; electromagnetic energy storage. |
| **Electrochemical Energy Storage** | Different types of batteries (lead-acid, lithium-ion, sodium-sulfur). |
| **Thermal Energy Storage** | Sensible heat storage; latent heat storage; thermal absorption and adsorption systems. |

In the last years, global warming and climate change have had increasingly impactful consequences on our lives. One of the main causes of global warming is GHG emissions from electricity production using fossil fuels to meet daily energy demands. To mitigate this problem and achieve carbon neutrality, renewable energy sources (RES) have been replacing fossil fuels [13]. However, the intermittent nature of RES can cause problems of instability in the electrical grid. To smooth out these grid variations, ESS are needed, and they can maximize the introduction of renewable energy [14].

ESS are conceived to sustain unforeseen occurrences during peak and off-peak periods. The integration of ESS, with other energy sources (especially renewable), significantly reduces electricity production as well as GHG emissions. Since not all generated electricity is used, the storage of surplus energy at off-peak hours can greatly increase system reliability and sustain varying power demands at different periods of the day [15].

The high penetration of RES in the grid leads to a significant waste of electrical energy when production exceeds consumption. To avoid energy waste and provide grid flexibility, ESS can support the integration of renewable energy by balancing the power flow in the network, matching the supply with the demand, and helping distribution systems operators to satisfy demand in a reliable and sustainable way. There is great potential in the use of ESS, both from the point of view of grid operators and final consumers [14], [16]. The storage system can help balance the changing demand for electricity on a daily basis, storing energy when demand is low and releasing it when demand is high [15].

The increased installation of PV panels in residential buildings requires a replanning of the capacity of storage resources, which have been acquired to meet peak loads and system reserve requirements. Consequently, power flow direction can reverse and potentially cause issues with the quality of power, safety, and reliability which may result from local and intermittent energy generation during the day. Decentralized storage, such as batteries connected to solar installations, installed in residential buildings, plays a key role when faced with possible grid fluctuations or system failures. Thus, ESS are considered an enabling element of a future low-carbon electric grid as they allow large amounts of renewable energy on the grid [10], [17].

### 2.1.3. ELECTRIC VEHICLES

Nowadays, the conventional transportation system is incorporated with an internal combustion engine causing it to be one of the main causes of air pollution. To decrease GHG emissions and the dependence on oil in the transport sector, electric vehicles have been gaining popularity in the past few years [18]. Between 2011 and 2015, the search for electric or hybrid vehicles increased exponentially, worldwide, with more than 565,000 plug-in electric vehicles sold [19]. Figure 6 shows the evolution of EVs sales worldwide, as well as market shares, from 2010 to 2020.

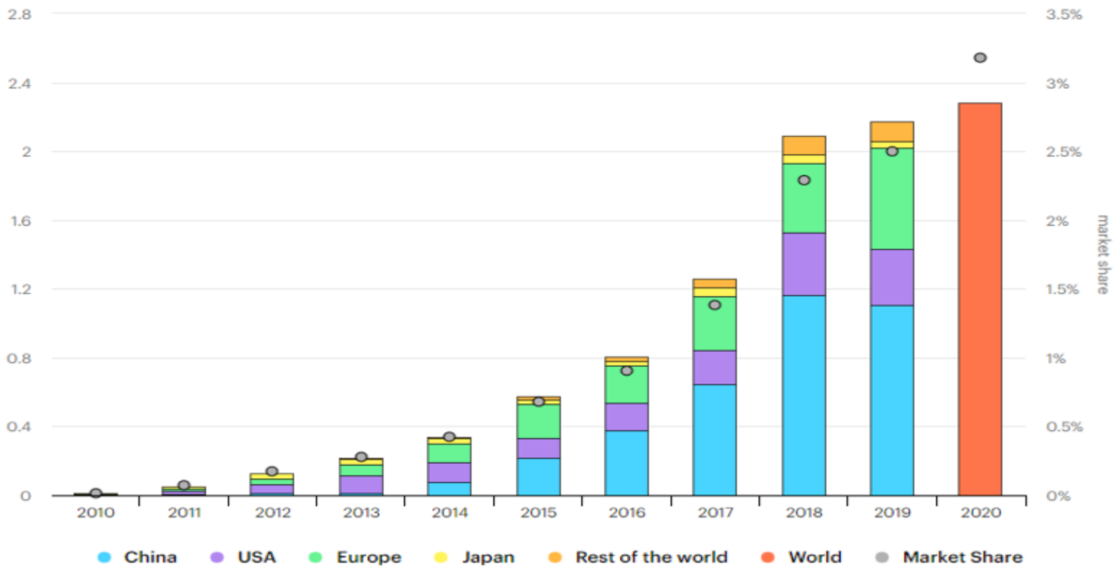



**Figure 6 Global electric car sales, 2010-2020 [20].**

EVs use batteries, ultra-condensers, and fuel cells as energy sources and do not depend on fossil fuels and, therefore, do not emit polluting gases. Depending on the type of EV, these sources can be used individually or collectively in an EV. EVs can be divided into two (2) main categories: (1) hybrid electric vehicles (HEVs); and (2) all-electric vehicles (AEVs).

Figure 7 presents the classification of these two (2) EV categories, according to [18].

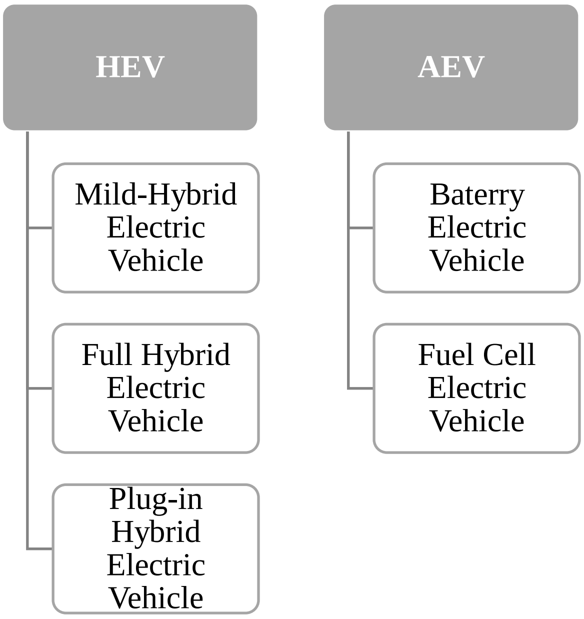



**Figure 7 Classification of Electric Vehicles [18].**

These vehicles, when connected to a charging station or outlet, store energy in the batteries which will then be used by the electric engine. The charging time of an EV depends on the storage capacity, the power the vehicle is capable of receiving, and the energy provided by the charging station [21]. Efficient charging strategies, interoperability of the charging stations, and battery costs are some challenges that need to be resolved in order to make EVs competitive in the market [18].

A significant number of EV charging stations result from a rising EV market. The charging stations can be classified into residential and non-residential categories and can promote slow or fast charging. A substantial portion of EV charging is residential and slow charging [18].

The integration of PV production and EVs in residential buildings has increased in the past few years. The EV battery can work as an ESS, discharging energy when necessary. Thus, joining the charging load of an EV to the household load can improve the self-consumption of PV production [22]. The inclusion of EVs in buildings integrated by renewable production systems can shift the loads at peak hours to off-peak hours and provide flexible energy for domestic use and transportation [23]. This way, in addition to being a means of transportation, EVs are also used as batteries for the storage of surplus energy from renewable production in buildings [24].

### 2.1.4. Renewable Generation Forecast

The growth of PV production facilities in recent years is associated with several environmental benefits and the reduction of fossil fuels. However, the intermittent nature of this renewable source can cause some technical challenges for the electric power system and can be relieved if the natural resource can be forecast accurately. Solar energy forecasting is made for short-range, i.e., up to a few hours ahead. The PV power production forecast is essential for the energy sector because it improves the stability and reliability of the electrical system, enabling operators to plan a profitable and optimized power dispatched strategy [25].

Forecasting PV power generation depends on several factors, such as the time horizons for which the forecast is made. The forecast horizon is the length of time into the future for which the PV power outputs are forecasted [26]. This forecast can be divided into three (3) categories based on time horizon, as shown in Figure 8, where the time horizon increases from top to bottom.

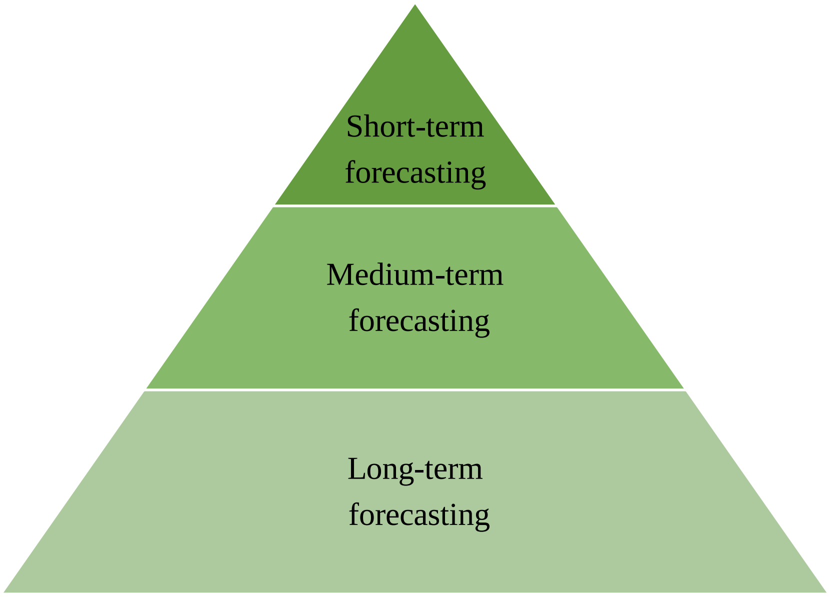



**Figure 8 Classification of PV power generation forecasting based on time horizon** [26]**.**

Short-term forecast is done for one or several hours, one (1) day, or up to (7) seven days and improves the security of the network operation. The forecasting of PV power generation for more than one (1) week to one (1) month is known as medium-term forecasting and it smooths the planning of the power system and maintenance schedule by predicting energy availability in the future. A long-term forecast is performed from one (1) month to one (1) year and it is useful for energy production, transportation, and distribution planning [26].

There are several models and techniques developed for PV power forecasting, including physical models, statistical and probabilistic models, and intelligent models based on machine learning or hybrid techniques. The forecast models based on Artificial Intelligence (AI) are often used more, than the others mentioned, due to their ability to find complex relationships without using difficult mathematics. The most common of the AI techniques is the artificial neural network (ANN) which simulates the behavior of human brain functions [25]. This method is widely used in forecasting PV energy production due to the non-linearity of the meteorological data [26].

Any forecast must be submitted to an evaluation of its accuracy, calculating its performance [27]. Measuring the accuracy of the selected forecast model is a crucial part of the forecasting process. This evaluation is made through the calculation of some metrics, such as mean absolute error, mean absolute percentage error, and the square root of the mean error [26].

## 2.2. ENERGY EFFICIENCY IN BUILDINGS

Over the past decade, energy consumption in buildings has significantly increased, also leading up to a rise for energy saving strategies. Nowadays, the building sector represents about 30% of the final energy consumption in Portugal, of which more than one-half (½) can be reduced through energy efficiency measures. Therefore, the European Union (EU) Member Countries have been promoting a set of measures aimed at encouraging the improvement of energy performance and comfort conditions of buildings. These measures conform with Directive 2010/31/EU of 19 May 2010 [28].

Directive 2010/31/EU about the energy performance of buildings aims at improving the energy performance of EU buildings, taking into consideration the different climatic and local conditions. Another objective of this directive is to establish minimum requirements and a common framework for calculating energy performance. These minimum requirements should be established by each EU Member Country, and they must be reviewed every five (5) years. These requirements should include buildings, their components, and the energy used for [29]:

- Space heating and/or cooling;
- Hot water for domestic use;

- Ventilation;
- Lighting; and
- Other technical building systems.

Regarding new buildings, the concept of Nearly-Zero Energy Buildings (nZEB) emerged, requiring that by December 31, 2020, their energy needs were almost zero (0), being supported by RES. Therefore, new buildings must fulfill minimum requirements according to the Directive [28]. For existing buildings, if they are undergoing major renovations, their energy performance should be improved in order to meet the applicable requirements [29].

Additionally, EU Member Countries should establish an energy performance certification (EPC) system. These certificates must provide potential buyers/renters with information about the energy classification of the building and include recommendations for possible improvements [29]. The implementation of an EPC system in buildings is mandatory and allows to provide information to the user about the energy performance of the building. It also provides cost reduction with energy use, enhancement of thermal comfort, and access to tax benefits [28], [30].

The EPC is emitted by a qualified specialist, and it describes the energy performance of the building on a scale of 8 categories (from A+ to F), with A+ corresponding to the most energy efficient level and F to the least efficient. Figure 9 presents the EPC adopted for buildings.

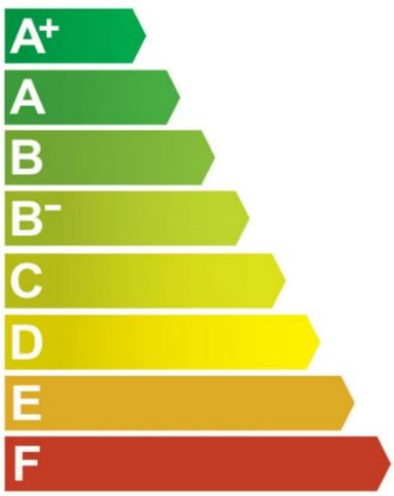



**Figure 9 Energy categories of the buildings energy certification [30].**

## 2.3. SMART BUILDINGS

Smart Buildings (SB) represent about 40% of energy consumption in the EU and 36% of GHG emissions. Consequently, they are considered the biggest energy consumers in Europe. Currently, in the European context, 35% of buildings are more than 50 years old and the renovation of existing buildings can lead to significant energy savings, reducing total energy consumption by about 5% and 6%. The Directive 2010/31/EU was also created in order to modernize the building sector and transforming them into Smart Buildings (SB) [31]. This directive introduced the concept of nZEB, which are buildings that have a high energy performance and the scarce energy, that they need, comes from RES produced on-site or in their proximity [32].

Buildings are facing a transition period, becoming highly efficient, consuming, producing, storing, and supplying energy. The concept of SB was introduced by the aforementioned Directive as being the main promoter of the future of the electric sector [33]. One of the main objectives of SB is to monitor, reduce and manage their energy consumption without compromising the comfort and safety of their occupants and energy performance [34].

SB can manage and control renewable production sources, adapt to grid conditions, communicate with other buildings, and respond actively in an efficient way to any change in the operation of the building’s technical system or the external environment, as well as to the energy needs of their occupants [33]. These are some of the basic functions of SB, represented in Figure 10.

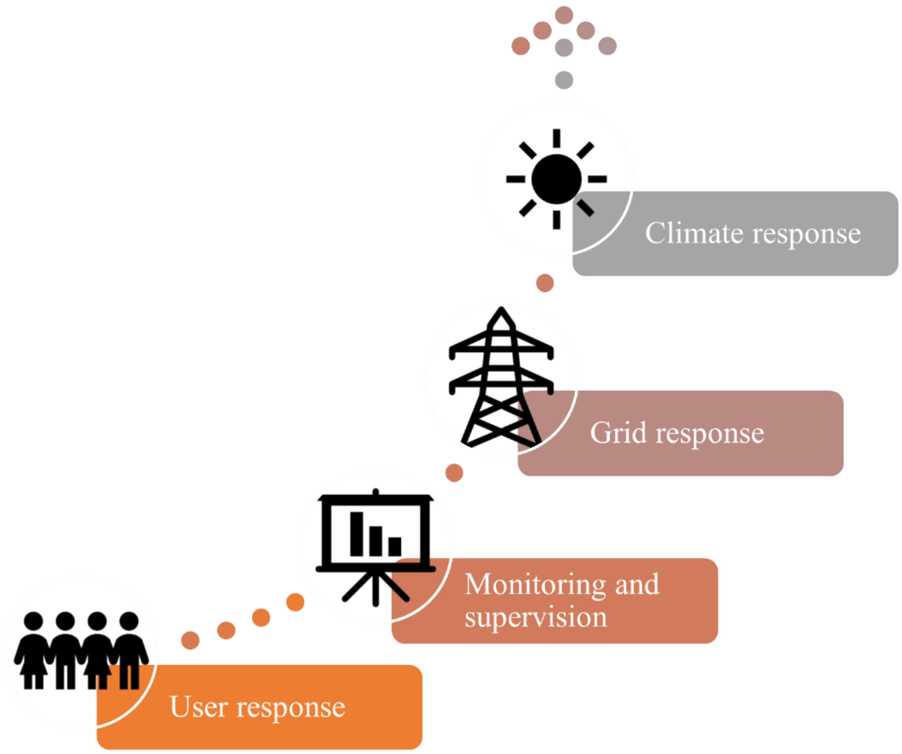



**Figure 10 Smart Buildings basic functions** [33]**.**

SB are considered to be one of the most important elements of the built environment inside a smart city, information and communication technologies (ICTs) and the Internet of Things (IoT) contributed to its development [35]. There has been an increased interest in using IoT devices to turn buildings more intelligent and efficient, such as sensors, actuators, or micro-chips. These IoT devices generate a huge amount of data that can be extracted, filtered, analyzed, and used for the evaluation of consumption profiles. Big data analytics can be used to analyze and improve energy efficiency and user experience of the buildings' occupants [34].

In terms of infrastructural components, SB have different components that maintain the occupants' comfort level. Some of them include Heating, Ventilating and Air-Conditioning (HVAC) systems; electricity, gas and water smart meters; occupancy monitoring systems; and hybrid EV charging technology [34].

Figure 11 presents the main key technologies related to the functions of SB to facilitate the utilization of smart features.

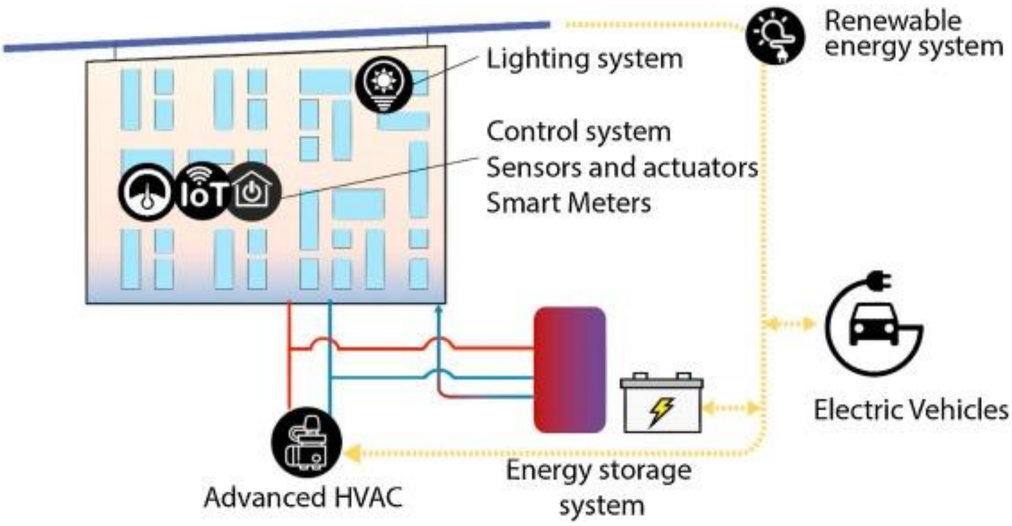



**Figure 11 Key technologies related to Smart Buildings** [33]**.**

## 2.4. BUILDING ENERGY RESOURCES MANAGEMENT

The concept of SB also includes the incorporation of technology and energy systems in buildings and with their management. Building Energy Management System (BEMS) consists of a combination of strategies and techniques required to enhance its performance, efficiency, and use of energy. The key purpose of energy management is the methodical and effective analysis of energy use, focusing on energy cost optimization relating to user characteristics, financing capability, energy needs, funding opportunities, and pollution reduction accomplished [36].

BEMS can be classified into four management strategies based on active approaches, which are represented in Figure 12.


**Figure 12 BEMS management strategies** [36]**.**

Data collection for electricity generation and consumption should be considered in a BEMS, allowing forecasting data for the period to be managed. The management system should also consider the users' needs to control their energy resources in the most optimized approach to achieve the following goals: savings in electricity bills, reducing peak consumption, and polluting emissions [37].

Associated with data forecasting, uncertainty is one of the main concerns of energy management systems as it can affect decision-making. Solar radiation and electricity market prices are the uncertainties that cause the biggest impact and that influence the operation of BEMS [38]. Based on the issues of data uncertainty, optimization has two approaches: (1) robust; and (2) stochastic optimization. [36].

In buildings, the combination of PV power production with ESS and their interaction allows a reduction in energy costs and the dependency on the use of fossil fuels [39]. Figure 13 illustrates an example of the integration of the PV system and energy storage using batteries in a residential building.

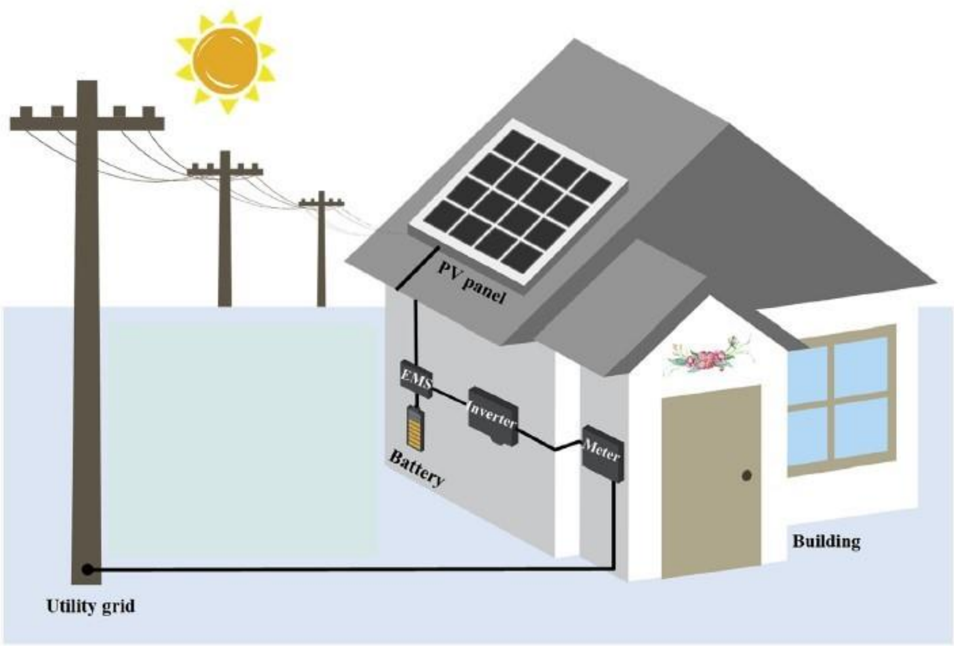



**Figure 13 Combined solar PV production system with battery storage system in a residential building** [40]**.**

The reduction of electricity costs is obtained by buying and storing electricity during periods of lower demand, when the energy prices are cheaper. Through the combination demonstrated in Figure 14, it is also possible to store surplus renewable energy production during off-peak hours and use it during peak hours, when energy is more expensive, which reduces consumer demand. The efficient battery charge and discharge scheduling are important to optimize the amount of electricity generated by PV panels and to minimize the cost of energy consumed. This requires an energy management system to define during which periods are most advantageous for electricity consumption: from the grid, from the PV production, or from the battery storage system [39].

## 2.5. Conclusions

This chapter presented a literature review about the subject matter of this thesis. The different energy resources that can be found in buildings and their management system were presented. Residential buildings are constituted of energy resources such as PV power generation, ESS, such as batteries and EVs, and the forecast of production.

Regarding energy efficiency in buildings, the EU has been promoting a set of measures to boost the improvement of energy performance and building conditions, to increase the comfort levels of its occupants.

The concept of SB enables a state of transition from existing buildings to highly efficient and effective buildings, which can produce, store, consume and supply energy.

The main purpose of an energy resource management system is the effective analysis of energy used to control the energy resources optimally, aiming at energy cost optimization considering the users' needs.

# 3. PROBLEM STATEMENT

This chapter describes the optimization approach implemented to minimize the energy costs of the residential building considering the uncertainty of the PV power generation. First, a survey about optimization models and optimization under uncertainty is made, emphasizing the Robust Optimization technique. A description of the problem and residential building is performed, along with some assumptions about the problem.

## 3.1. OPTIMIZATION MODEL

Mathematical optimization is a scientific discipline that aims to find the best decision among a set of available alternatives, in a given quantitative context. To define what is meant by a “best decision”, the concept of an objective function is required. An objective function determines the *objective value* $f(x)$ of a *decision* $x \in X$, where $x$ is feasible if $x \in X$. The concept of best decision is then defined as a feasible decision that has either the maximum or the minimum possible objective value. According to this, an optimization problem can be formulated as demonstrated in Equations (1a)-(1b) [41].

$$\text{minimize or maximize } f(x) \tag{1a}$$

$$\text{subject to } x \in X \tag{1b}$$

The characteristics of the feasible set $X$ and the objective function $f$ are used to classify optimization problems in these two categories [41]:

- Linear Programs (LP) – The objective function $f$ is linear and the set $X$ can be defined by a finite number of affine inequalities.

- Non-Linear Programs (NLP) – Either the objective function $f$ or some of the constraint functions defining the feasible set $X$ are non-linear.

Mathematical optimization is commonly applied to problems related to residential energy resources management, i.e., the scheduling of home appliances. LP is the simplest approach of mathematical optimization, where the objective and constraints are connected functions. They can be solved in polynomial time but may not be sufficiently accurate in describing the household energy system [42].

In LP, the objective is always to maximize or minimize some linear function of the decision variables. Decision variables are values that are determined in some optimal way. The LP problem can be formulated as follows, where the number of constraints is denoted by $m$ and $n$ indicates the number of decision variables.

$$\text{minimize or maximize } Z = c_1x_1 + c_2x_2 + \ldots + c_nx_n \tag{2a}$$

subject to

$$a_{m1}x_1 + c_{m2}x_2 + \ldots + c_{mn}x_n \{\leq, =, \geq\} b_m \tag{2b}$$

$$x_1, x_2, \ldots x_n \geq 0 \tag{2c}$$

Equation (2a) is entitled as the objective function $Z$. Moreover, there are constraints associated with the objective function. They consist of either equality or an inequality related with some linear combination of the decision variables, as shown in (2b). It is also necessary to establish that all the decision variables are nonnegative, as in (2c).

The solution of the problem $(x_1, x_2, \ldots x_n)$ consists of a proposal of specific values for the decision values. A solution is considered optimal if it achieves the desired maximum or minimum value [43].

Mixed-Integer Linear Programming (MILP) is a mathematical approach that includes integer variables and, although non-linear, it allows discontinuities in modeling for additional flexibility, such as binary variables [42].

MILP problems consist of one linear objective function and linear constraints. The decision variables can either be defined as continuous or integer variables. It can be formulated as in Equations (3a)-(3d), considering the objective function $g(x, y)$ [44].

$$\min g(x, y) \tag{3a}$$

subject to

$$Ax + Ey = b \tag{3b}$$

$$0 \leq x \tag{3c}$$

$$\alpha \leq y \leq \beta \tag{3d}$$

Continuous variables are considered $x_i$, whereas $y_i$ are the integer variables. The bounds over $y$ must be finite, either positive or negative. An optimal integer solution is an integer solution maximizing or minimizing $g(x, y)$ [45].

In the buildings' energy management systems domain, MILP is often used. MILP models describe the building energy systems quite well and solve the optimization problems at an appropriate time [44].

A Mixed Binary Linear Program (MBLP) can be expressed as in Equations (4a)-(4c).

$$\min Z = c^T x \tag{4a}$$

subject to

$$Ax \geq b \tag{4b}$$

$$x_i \in \{0,1\}, \qquad i \in I \tag{4c}$$

The set $I$ indicates the set of indices of variables in the optimization problem which are required to be binary, typically represent so-called either/or decisions. The concept of MBLP derives from the fact that relaxing the binary requirements (4c) results in an LP, which denotes an optimization problem with affine constraints and a linear objective function [41]. This thesis adopts this approach.

In [46], an MBLP is proposed to optimize the charge and discharge scheduling of EVs, in which the binary decision variables represent the charging and discharging of EVs in each period. The methodology of this work is intended to manage the energy resources of the residential building, such as PV generation, battery energy storage system (BESS), EVs, external electricity supply, and information about the consumption load profile. Regarding the mathematical formulation, the objective is to minimize the peak load power demand of a residential building with intensive EV usage. The results show that the energy management resources could be profitable for residential buildings, providing a decrease in electricity consumption peaks and optimizing the charging/discharging of EVs with interesting financial results. Reference [47] presents an EMS capable of forecasting PV power generation and optimizing power flows between PV systems, EV battery, and grid. A MILP framework was developed to minimize charging costs while increasing PV self-consumption and, consequently, enhance the sustainability of the vehicle fleet and reduce grid constraints. The results show that the EMS significantly reduced total cost while reducing energy exchange with the grid and increasing self-consumption. Also, energy demand was assured, and the consumers' comfort level was maintained.

## 3.2. OPTIMIZATION UNDER UNCERTAINTY

The uncertainty modelling techniques to deal with uncertainty in optimization problems are presented in this chapter. Also, the limitations of Stochastic Programming and the benefits of implementing Robust Optimization to handle uncertainty are provided.

### 3.2.1. UNCERTAINTY MODELLING TECHNIQUES

Power system scheduling can be performed for short, medium, and long-term horizons and the need for accurate decision-making for these periods is crucial. Among all power system challenges, the rise of total installed RES with intermittent nature causes the complex planning of power systems [48]. The majority of decisions taken by decision-makers in the energy sector are based on a considerable amount of data uncertainty [49].

In power systems, the uncertain parameters can be classified into two categories [49]:

- Technical parameters: can be divided into two classes, namely: (1) topological parameters (line and generator outage); and (2) operational parameters (demand or generation);

- Economical parameters: can be divided into two classes, namely: (1) macroeconomic parameters (concentrates on the entire power system industry); and (2) microeconomic parameters (aggregators, domestic or industrial consumers' decisions).

The intermittent nature of RES causes the complex planning of power systems, and it is associated with uncertainties because it depends on climate conditions. However, as renewable energy penetration rises, there will also be an increase in the uncertainty associated with power systems. Hence, uncertainty modeling is essential [48].

In decision-making, different techniques have been developed to deal with uncertainties. As shown in Figure 14, the existing uncertainty modeling techniques cover an extensive range such as probabilistic approaches, possibilistic approaches, hybrid possibilistic-probabilistic approach, information gap decision theory (IGDT), and robust optimization [50].

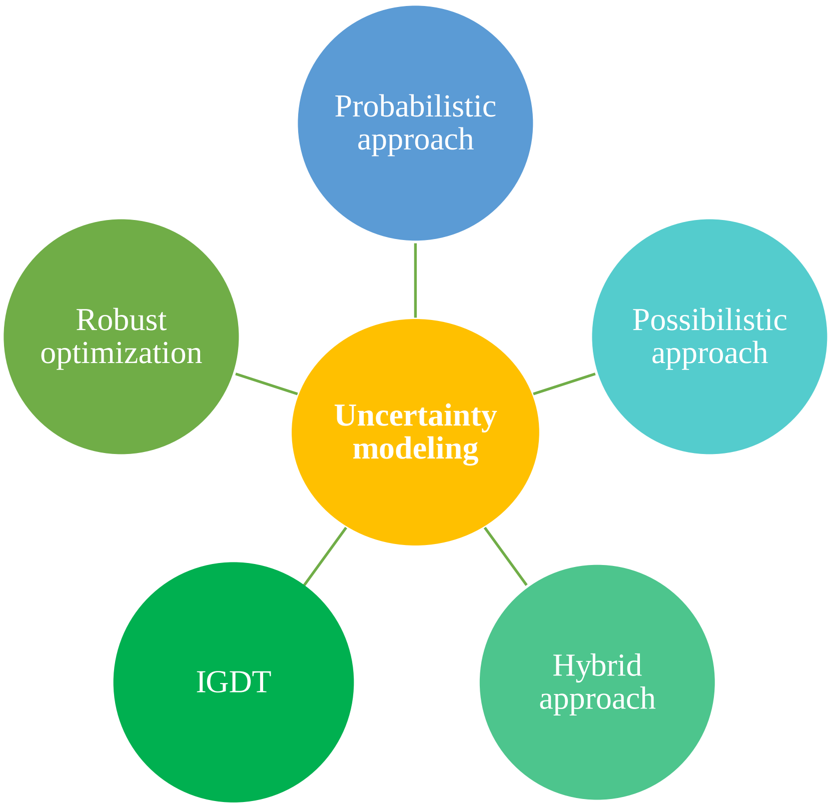



**Figure 14 Uncertainty modeling methods.**

The main objective of these modeling techniques is to evaluate the impact of certain input parameters on the system output parameters. The main difference between these methods, though, is the use of multiple approaches applied to describe the uncertainty of input parameters [51].

### 3.2.2. Comparison between Stochastic Optimization and Robust Optimization

In optimization problems, uncertainty has aroused researchers' interest since the beginning of mathematical programming. In an optimization problem, uncertainty refers to the fact that some or all of the problem's parameters are unknown at the time it must be solved [52].

There are two techniques used to deal with data uncertainty: (1) Stochastic Optimization (SO); and (2) Robust Optimization (RO) [53].

One of the key modeling characteristics of SO is representing uncertainty, in which Stochastic Programming (SP) will represent future events as scenarios, and RO models, uncertainty in terms of uncertainty sets [54]. Optimization under uncertainty depends on information accessible on the uncertain problem components. There are worst-case approaches, such as RO, based on the assumption that only the ranges of the uncertain parameters are known, without distributional information. On the other hand, SO is associated with models where uncertainty can be captured by a probability distribution [55].

Stochastic Programming is the first method developed to deal with uncertainty in mathematical programming-based optimization and it is a probabilistic approach [52]. SP emerged in the 1950s intending to introduce uncertainty into linear programs. [56] The probability distribution of uncertain data has to be known or estimated. [53]

Due to some limitations of SO and several advantages of RO, its popularity in optimization has increased [57]. Robust Optimization also incorporates an uncertainty model into a mathematical program and it was established in the 1990s [52]. It is a very popular uncertainty modeling method due to its computation tractability for many classes of uncertainty sets, consisting of a very recent and active research field that has been mainly developed in the last years [53]. It is a novel approach to solving optimization problems involving uncertainty, especially where there is a lack of information about the nature of uncertainty [49]. Since the additional difficulty of including uncertainty can be limited in many situations, robust optimization is practical for implementing in home energy management systems [42].

RO problems are formulated with an uncertainty set $U$ as in (5a)-(5b). It is possible to consider the constraint functions individually and they must be satisfied for all $u$. The objective function is fixed and not subject to uncertainty [58].

$$\text{Minimize } f(x) \tag{5a}$$

Subject to

$$max\, f_i(x,u) \le 0 \tag{5b}$$

The need in engineering to design for a "worst-case" scenario prompted the development of RO, defined by the uncertainty set $U$. It then developed into a method for performing SO without specifying the underlying probability distribution [54].

The uncertainty set is an important part of RO and it consists of a set of values for the uncertain parameters that are considered in the robust problem, denoted by $U$ [53]. In other words, they are used to describe the uncertainty of input parameters. Using the RO technique, the obtained decisions continue optimal for the worst-case realization of the uncertain parameter within a given set [51]. So, RO focuses on minimizing the impact of the worst-case scenario [42].

The RO concept is based on the following three statements [53]:

I. All decision variables $x$ represent "here and now" decisions: they should get specific numerical values as a result of solving the problem before the actual data "reveals itself".

II. The decision-maker is responsible for the consequences of the decisions to be made when, and only when, the actual data is within the prespecified uncertainty set $U$.

III. The constraints of the uncertain problem in question cannot be violated when the data is in a prespecified uncertainty set $U$.

Figure 15 presents the differences between the SO and RO approaches. It shows that RO just requires information about the upper and lower bounds of uncertainty while SO needs to generate scenarios to guarantee a solution [57].

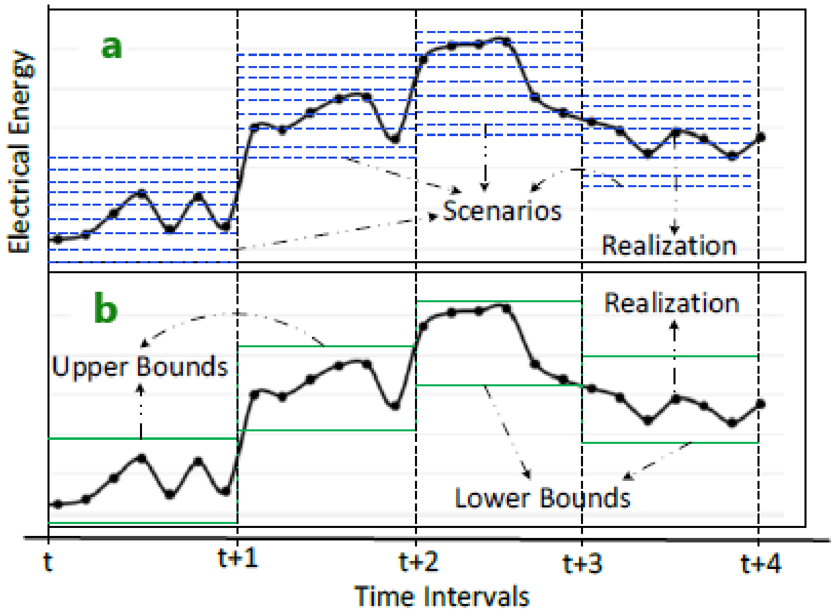



**Figure 15 Uncertainty representation in (a) Stochastic Optimization and (b) Robust Optimization [57].**

Based on [57], the advantages of RO and limitations of SO can be summarized in Table 3.

**Table 3 Limitations of Stochastic Optimization and benefits of Robust Optimization.**

| Stochastic Optimization | Robust Optimization |
|---|---|
| Provides probabilistic guarantee to the feasibility of the solution. | Immunizes a solution against all possible realizations of the uncertain parameters within a deterministic uncertainty set. |
| To assure the quality of the solution, many scenarios are required, resulting in a computational burden. | Puts the problem parameters in a deterministic uncertainty set that includes the worst-case scenario and the model remains computationally tractable. |
| Requires information about uncertainties to construct accurate Probability Density Functions (PDF). | Do not assume probability distributions and describes uncertainties by sets (upper and lower bounds). |
| The approach adopted for scenario generation affects the accuracy of the solution. | Only needs information about the upper and lower bounds. |

According to the previous information, the Robust Optimization technique is chosen to deal with the uncertainty of PV power generation output in this thesis.

Several studies, about the RO problem under uncertainty, have been stated in the recent literature. Reference [59] proposes an adjustable robust optimization model to participate in day-ahead energy markets, considering uncertainty in energy prices, PV generation, and load. The results show that the robust formulation achieves a cost reduction of 5.7% in comparison with the deterministic solution. A robust approach is developed in [60] to deal with the uncertainty of PV power output regarding the load scheduling of a smart home. Further, the robust formulation is transformed into an equivalent quadratic programming problem. The simulation results confirm the validity and advantage of the proposed technique. [61] suggests a robust optimization model considering the randomness of electric and thermal loads and solar power generation, as also the coordination of several energy sources, such as electric grid, battery, and combined heat and power (CHP). The results demonstrate the effectiveness of the CHP unit and battery in mitigating the influence of uncertainties in the scheduling operation of the building's energy resources.

## 3.3. PROBLEM DESCRIPTION

The problem consists in optimizing the energy scheduling and energy costs in a residential building using an energy resource management system, considering the uncertainty of PV generation.

Each consumer’s total power cost is determined by the amount of energy consumed from the load demand of the apartment, the charging consumption of the EV and the injected power from the PV generation system.

There is an electricity tariff associated to the every building’s consumer and there are three types: (1) simple; (2) bi-hourly; and (3) tri-hourly tariffs. In this case, the consumers have a bi-hourly tariff, where the energy price is lower in normal off-peak hours (night and weekends) and is higher in periods of greater consumption (peak hours).

Commonly, each apartment has its own contracted power and electric vehicles are plugged in and charged as soon as they arrive in the building, without any charging schedule. As a result of these scenarios, customers’ electricity bills are increased. For that reason, scheduling the charging time of EVs would lower the energy bill. This thesis' approach considers the following conditions to decrease the electricity bill:

- Centralize the EVs' charging/discharging schedule;
- Centralize the EVs battery discharge process during peak hours;
- Use of a Battery Energy Storage System.

To solve the energy resources management of the residential building, a new player emerges: the energy building manager entity, which is an aggregator. The aggregator is responsible for managing all the building's energy resources to minimize total electricity costs. It is also considered that all the building's occupants agree to participate in the new player's management. Thus, the building is seen as a whole, rather than as a group of autonomous electricity units.

## 3.4. RESIDENTIAL BUILDING DESCRIPTION

The residential building considered in this thesis is composed of six (6) apartments, with a contracted power of 6.9 kVA.

Each apartment is connected to a PV panel, and it is considered that the PV generation is the same for all the apartments. The maximum installed PV power for each apartment is 0.5 kW.

Electricity has different prices depending on the time at which it is consumed. The hourly periods are how electricity consumption is distributed throughout the twenty-four (24) hours of each day and the seven (7) days of the week. So, in addition to the hourly periods, the energy tariff can correspond to a weekly or daily cycle. In the daily cycle, the hourly periods are the same every day of the year and in the weekly cycle, the hourly periods differ between weekdays and weekends [62]. For this study, the Portuguese bi-hourly tariff and daily cycle were used.

The dataset of PV power generation, energy consumption of each apartment, and common services used in this thesis correspond to a complete year (2019) and are measured in fifteen (15) minute intervals for all the twenty-four (24) hours of the day, resulting in ninety-six (96) periods. However, in this thesis, only two days were considered: March 5, 2019, and September 1, 2019.

For this case study, the EV used is a BMW. The residential building is also equipped with a BESS. The initial State of Charge (SoC) of EVs, at the arrival time, and the minimal allowable SoC, at departure time, are set randomly. The initial SoC of the BESS is zero (0).

Table 4 lists the values of the parameters related to the model, EVs, and BESS.

**Table 4 Values of optimization model parameters.**

| Parameter | Value | Unit |
|---|---|---|
| $\boldsymbol{D}$ | 1 | days |
| $\boldsymbol{\tau}$ | 15 | minutes |
| $\boldsymbol{T}$ | 96 | periods |
| $\boldsymbol{J}$ | 6 | apartments |
| $\boldsymbol{P_{EV}^{c}}$ | 3.7 | kW |
| $\boldsymbol{P_{EV}^{d}}$ | 3.33 | kW |
| $\boldsymbol{\overline{SOC}}$ | 27.2 | kW/h |
| $\boldsymbol{P_{B}^{c}}$ | 6.3 | kW |
| $\boldsymbol{P_{B}^{d}}$ | 5.67 | kW |
| $\boldsymbol{\overline{SOC}_{B}}$ | 50 | kW/h |

## 3.5. CONFIGURATION AND ASSUMPTIONS

The proposed methodology intends to apply energy resource management in a residential building context. This residential building contains six apartments, and it is equipped with a PV generation system, a BESS, EVs, home appliances, and an external electricity grid supply. The load consumption of each apartment and the common services demand are also part of the building. Note that each apartment connects to a PV solar panel which is installed on the buildings’ rooftop and to an EV.

An overview of the building's configuration is visualized in Figure 16, which illustrates the energy flow among the energy resources of the building. The green arrows represent the energy supply and the red the energy demand.

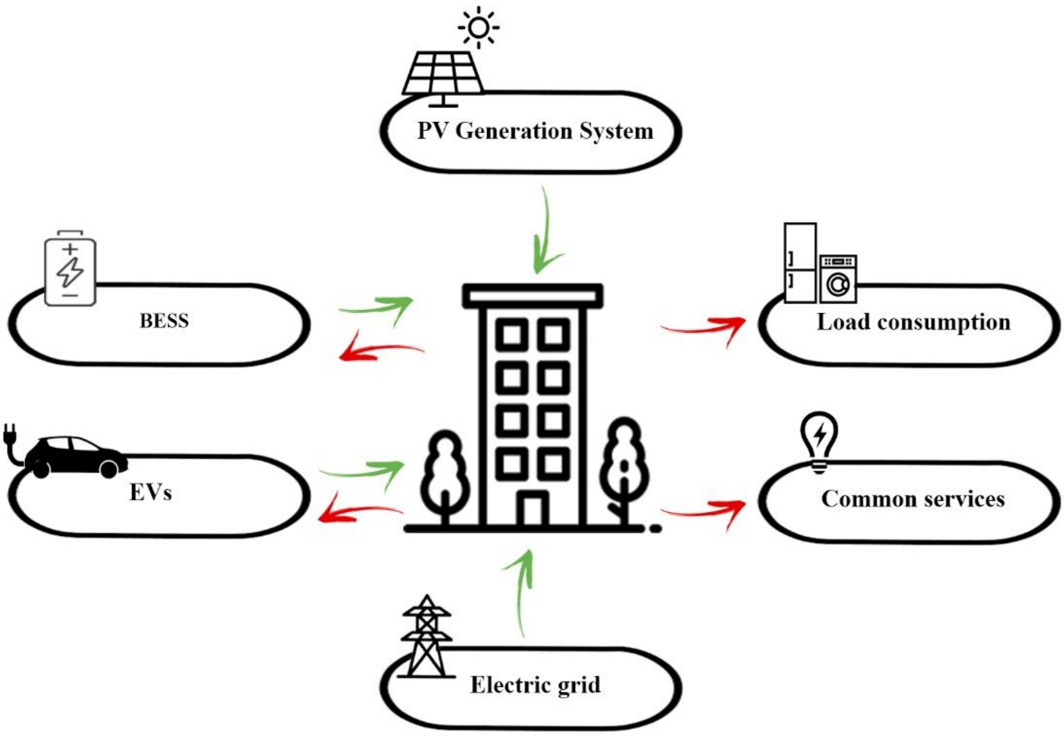



**Figure 16 Building's power flow.**

The building electricity demand is supplied by the on-site generation system – PV generation. The grid power provides energy to the building when the on-site generation is not sufficient to meet the demand. On the other hand, it receives electricity when surplus energy is produced.

To define the model of the building energy resource management, some assumptions are made:

- ✓ The building is connected to an external supplier, the electricity grid;
- ✓ Each EV has a singular daily use, i.e., it only charges once a day. Once parked inside the building, it is plugged into the building's power infrastructure;
- ✓ EV batteries can be charged or discharged through their bidirectional embedded chargers;

- ✓ A BESS is used to optimize the energy resource management of the building;
- ✓ The power generated from PV panels is used to supply load demand from the apartments, charge EV batteries and BESS, and, eventually, inject surplus energy into the external electricity grid.

## 3.6. CONCLUSIONS

In this chapter, the problem description was outlined. First, a theoretical overview, of the optimization models and the uncertainty modeling techniques, was made. Various techniques and models have been developed to deal with uncertainties. Robust Optimization is very recent and has achieved huge popularity among optimization techniques due to its several advantages. Thus, RO was the chosen technique to be further explored and developed in this thesis.

Then, the problem is explained and described. The main purpose of this problem was to minimize the total electricity costs of the building and optimize the scheduling of the energy management system considering the solar generation uncertainty.

The details about the residential building were specified as well as the specifications of each energy resource. The building is composed of six apartments, and they all have the same contracted power, own an EV, and are connected to a PV generation system. Additionally, the building is also equipped with a BESS to guarantee more efficient energy resource management. All of these energy resources are managed by an aggregator, which is responsible for their control and minimizing the costs.

# 4. INTELLIGENT EMS FOR SMART BUILDING CONSIDERING PV UNCERTAINTY

This chapter approaches the optimization model developed to implement the smart management system of the building taking into consideration the uncertainty of solar generation. To deal with the uncertainty, a robust optimization formulation based on a mixed binary linear problem is created. The proposed model is developed for a twenty-four-hour (24 hr.) scheduling horizon considering a time interval of fifteen (15) minutes.

In this chapter, the mathematical formulation, of the deterministic model as well as the notation, is outlined. The method for the PV generation forecast is presented and the obtained values are used in the formulation of the Robust Optimization technique.

## 4.1. DETERMINISTIC MODEL

In this thesis, the optimal operation of the energy resources management of a building is investigated. In this subsection, the deterministic formulation of the optimization problem is developed, along with the parameters notations and also including the description of the objective function and the constraints regarding each energy resource of the building.

### 4.1.1. NOTATION

To develop and implement the proposed deterministic model, the required sets, parameters, and decision variables regarding the energy resources are presented in Table 5 to Table 11.

In this case, the period under consideration contains $D$ days, and each day is divided into step-times with $\tau$ duration. $T$ designates the number of all time-steps and $J$ the number of EVs/apartments.

**Table 5 Sets.**

| Symbol | Set | Index | Description |
|---|---|---|---|
| $\mathbb{T}$ | {1, …, T} | $t$ | Set of time-step numbers |
| $\mathbb{J}$ | {1, …, J} | $j$ | Set of EV numbers |
| $\mathbb{D}$ | {1, …, D} | $d$ | Set of day numbers |

**Table 6 Building's parameters.**

| Parameter | Description | Index |
|---|---|---|
| $\boldsymbol{D}$ | Number of days per time-study | |
| $\boldsymbol{T}$ | Number of time-steps per time-study | |
| $\boldsymbol{\tau}$ | Time-step duration | |
| $\boldsymbol{J}$ | Number of apartments/EVs of the building | |
| $\boldsymbol{P_A(t,j)}$ | Active power demand of apartment $j$ in time-step $t$ | $t \in \mathbb{T}, j \in \mathbb{J}$ |
| $\boldsymbol{P_{CS}(t)}$ | Active power demand of common services in time-step $t$ | $t \in \mathbb{T}$ |
| $\boldsymbol{P_{PV}(t,j)}$ | Active power of PV generations in time-step $t$ | $t \in \mathbb{T}, j \in \mathbb{J}$ |
| $\boldsymbol{\overline{P_G}\ (t)}$ | Maximum power purchased from the grid in time-step $t$ | $t \in \mathbb{T}$ |
| $\boldsymbol{C_G^b\ (t, CP)}$ | Cost of electricity purchased from the grid in time-step t$-th$ | $t \in \mathbb{T}$ |
| $\boldsymbol{C_G^s\ (t)}$ | Cost of electricity sold to the grid in time-step t$-th$ | $t \in \mathbb{T}$ |

**Table 7 Building's decision variables.**

| Variable | Description | Domain | Index |
|---|---|---|---|
| $\boldsymbol{P_{A\to G}\ (t)}$ | Power from aggregator to the grid in time-step $t$ | $\mathbb{R}_0^+$ | $t \in \mathbb{T}$ |
| $\boldsymbol{P_{G\to A}\ (t)}$ | Power from the grid to the aggregator in time-step $t$ | $\mathbb{R}_0^+$ | $t \in \mathbb{T}$ |

**Table 8 EVs parameters.**

| Parameter | Description | Index |
|---|---|---|
| $\boldsymbol{T_{EV}^{in}}\ (\boldsymbol{t},\boldsymbol{j})$ | Time that EV $j$ arrives at parking in day $d$ | $j \in \mathbb{J}, d \in \{0\} \cup \mathbb{D}$ |
| $\boldsymbol{T_{EV}^{out}}\ (\boldsymbol{d},\boldsymbol{j})$ | Time that EV $j$ leaves the parking in day $d$ | $j \in \mathbb{J}, d \in \mathbb{D} \cup \{D+1\}$ |
| $\overline{\boldsymbol{SOC}}\ (\boldsymbol{j})$ | Maximum State of Charge (SoC) of EV $j$ | $j \in \mathbb{J}$ |
| $\boldsymbol{SOC_{in}}(\boldsymbol{d},\boldsymbol{j})$ | Initial SoC of EV $j$ at the beginning of the departure of each day $d$ | $j \in \mathbb{J}, d \in \{0\} \cup \mathbb{D}$ |
| $\underline{\boldsymbol{SOC_{out}}}(\boldsymbol{d},\boldsymbol{j})$ | Minimum allowable SoC of EV $j$ at departure time of each day $d$ | $j \in \mathbb{J}, d \in \mathbb{D}$ |
| $\boldsymbol{P_{EV}^{c}}\ (\boldsymbol{j})$ | Charging power of EV $j$ | $j \in \mathbb{J}$ |
| $\boldsymbol{P_{EV}^{d}}\ (\boldsymbol{j})$ | Discharging power of EV $j$ | $j \in \mathbb{J}$ |
| $\boldsymbol{\eta_c}\ (\boldsymbol{j})$ | Efficiency charge of EV $j$ | $j \in \mathbb{J}$ |
| $\boldsymbol{\eta_d}\ (\boldsymbol{j})$ | Efficiency discharge of EV $j$ | $j \in \mathbb{J}$ |

**Table 9 EVs decision variables.**

| Variable | Description | Domain | Index |
|---|---|---|---|
| $\boldsymbol{\alpha_{EV}}\ (\boldsymbol{t},\boldsymbol{j})$ | Binary variable representing charging state of EV $j$ in time-step $t$ | {0,1} | $t \in \mathbb{T}, j \in \mathbb{J}$ |
| $\boldsymbol{\beta_{EV}}\ (\boldsymbol{t},\boldsymbol{j})$ | Binary variable representing discharging state of EV $j$ in time-step $t$ | {0,1} | $t \in \mathbb{T}, j \in \mathbb{J}$ |
| $\boldsymbol{SOC_{EV}}(\boldsymbol{t},\boldsymbol{j})$ | SoC of EV $j$ in time-step $t$ | $\mathbb{R}_0^+$ | $t \in \mathbb{T}, j \in \mathbb{J}$ |
| $\boldsymbol{P_{A\rightarrow EV}}\ (\boldsymbol{t},\boldsymbol{j})$ | Power from aggregator to EV $j$ in time-step $t$ | $\mathbb{R}_0^+$ | $t \in \mathbb{T}, j \in \mathbb{J}$ |
| $\boldsymbol{P_{EV\rightarrow A}}\ (\boldsymbol{t},\boldsymbol{j})$ | Power from EV $j$ to aggregator in time-step $t$ | $\mathbb{R}_0^+$ | $t \in \mathbb{T}, j \in \mathbb{J}$ |

**Table 10 BESS parameters.**

| Parameter | Description | Index |
|---|---|---|
| $\overline{\boldsymbol{SOC_B}}$ | Maximum State of Charge (SoC) of BESS | |
| $\boldsymbol{SOC_B^{initial}}$ | Initial SoC of BESS at the beginning of period $t$ | |
| $\underline{\boldsymbol{SOC_B}}$ | Minimum SoC of BESS | |
| $\boldsymbol{P_B^c}\ (\boldsymbol{t})$ | Charging power of BESS in period $t$ | $t \in \mathbb{T}$ |
| $\boldsymbol{P_B^d}\ (\boldsymbol{t})$ | Discharging power of BESS in period $t$ | $t \in \mathbb{T}$ |
| $\boldsymbol{\eta_B^c}$ | Efficiency charge of BESS | |
| $\boldsymbol{\eta_B^d}$ | Efficiency discharge of BESS | |

**Table 11 BESS decision variables.**

| Variable | Description | Domain | Index |
|---|---|---|---|
| $\boldsymbol{\alpha_B}\ (\boldsymbol{t})$ | Binary variable representing charging state of BESS in time-step $t$ | $\{0,1\}$ | $t \in \mathbb{T}$ |
| $\boldsymbol{\beta_B}\ (\boldsymbol{t})$ | Binary variable representing discharging state of BESS in time-step $t$ | $\{0,1\}$ | $t \in \mathbb{T}$ |
| $\boldsymbol{SOC_B}(\boldsymbol{t})$ | SoC of BESS in time-step $t$ | $\mathbb{R}_0^+$ | $t \in \mathbb{T}$ |
| $\boldsymbol{P_{A\rightarrow B}}\ (\boldsymbol{t})$ | Power from aggregator to BESS in time-step $t$ | $\mathbb{R}_0^+$ | $t \in \mathbb{T}$ |
| $\boldsymbol{P_{B\rightarrow A}}\ (\boldsymbol{t})$ | Power from BESS to aggregator in time-step $t$ | $\mathbb{R}_0^+$ | $t \in \mathbb{T}$ |

### 4.1.2. OBJECTIVE FUNCTION

The main objective of this thesis is to minimize the electricity costs of the whole building. The total energy cost is based on the difference between the cost of the energy purchased from the grid and the cost of the energy sold to the grid. The overall cost from the power grid is calculated based on the energy cost that is transferred from the grid to the building (through the aggregator). It is calculated based on the surplus energy that can be injected on the grid (managed by the aggregator), with a certain tariff rate. According to this, the objective function is formulated:

$$\min Z = \sum_{i \in \mathbb{I}} C_G^b\,(t, CP) P_{G\rightarrow A}(t) - \sum_{i \in \mathbb{I}} C_G^s\,(t) P_{A\rightarrow G}(t) \qquad (6)$$

### 4.1.3. CONSTRAINTS

The constraints used in the MBLP model are presented and they ensure that the physical limits of the building's energy resources are not violated.

#### 4.1.3.1. Electric Vehicles

The maximum SoC of the EV battery capacity is described in (7).

$$SOC_{EV}\,(t,j) \leq \overline{SOC}\,(j) \qquad (7)$$

In (8), the initial SoC of the EV $j$ at the arrival time on each day $d$ is presented.

$$SOC_{EV}\,\left(T_{EV}^{in}((d,j)-1),j\right) = SOC_{in}(d,j) \qquad (8)$$

At the departure time, the minimum allowable SoC of the EV $j$ is $\underline{SOC_{out}}\,(j)$ and constraint (9) is considered at the departure time-steps.

$$SOC_{EV}\,(T_{EV}^{out}(d,j)-1,j) \geq \underline{SOC_{out}}\,(j) \qquad (9)$$

The consumed electricity power from the grid to charge the EVs is satisfied in constraint (10), while the obtained power through the discharging process is satisfied in (11). If $\alpha_{EV}\,(i,j) = 1$, the EV $j$ can be charged at the maximum charge power.

$$P_{A\rightarrow EV}\,(t,j) \leq \alpha_{EV}\,(t,j) \cdot P_{EV}^{c}\,(j) \cdot \tau \qquad (10)$$

$$P_{EV\to A}\,(t,j) \leq \; \beta_{EV}\,(t,j) \; \cdot P_{EV}^{d}\,(j) \; \cdot \tau \tag{11}$$

The SoC of the EVs may incur some changes due to the charging/discharging process, which are represented in constraint (12).

$$SOC_{EV}\,(t+1,j) = SOC_{EV}\,(t,j) + \left[P_{A\to EV}\,(t,j) \cdot \eta_c\,(j) \; - \; P_{EV\to A}\,(t,j)/\eta_d\,(j)\right] \tag{12}$$

When the EV is not parked in the building, the charge/discharge process should not occur, as considered in (13).

$$SOC_{EV}\,(t,j) = 0 \tag{13}$$

Lastly, constraint (14) assures that the EVs charging and discharging processes do not happen simultaneously.

$$\alpha_{EV}\,(t,j) \; + \beta_{EV}\,(t,j) \; \leq 1 \tag{14}$$

#### 4.1.3.2. Battery Energy Storage System

The BESS capacity constraint is described in (15).

$$\underline{SOC_B} \leq \; SOC_B(t) \; \leq \overline{SOC_B} \tag{15}$$

The initial value of BESS $(t = 0)$ is presented in (16).

$$SOC_B(0) = SOC_B^{initial} \tag{16}$$

The consumed electricity power from the grid to charge the BESS is satisfied in constraint (17), while the obtained power through the discharging process is satisfied in (18). If $\alpha_B\,(i,j) = 1$, the BESS can be charged at the maximum charge power by the aggregator.

$$P_{A\to B}\,(t) \leq \; \alpha_B\,(t) \; \cdot P_B^{c} \cdot \tau \tag{17}$$

$$P_{B\to A}\,(t) \leq \; \beta_B\,(t) \; \cdot P_{EV}^{d} \cdot \tau \tag{18}$$

The SoC of the BESS may incur some changes due to the charging/discharging process, which are represented in constraint (19).

$$SOC_B\,(t+1) = SOC_B\,(t) + \left[P_{A\to B}\,(t) \cdot \eta_B^{c} \; - \; P_{B\to A}\,(t)/\eta_B^{d}\right] \tag{19}$$

Lastly, constraint (20) assures that the BESS charging and discharging processes do not happen simultaneously.

$$\alpha_B\ (t)\ +\beta_B\ (t)\ \leq 1 \tag{20}$$

4.1.3.3. Power balance

The power balance constraint (21) is used to guarantee all the power supply sourced from the PV power system, the EV batteries, the BESS, and from the grid in each time-step $i$, is equal to the total power demand of the building.

$$\begin{aligned} P_{G\to A}\,(t) + P_{B\to A}\,(t) + \sum_{j\in \mathbb{J}} P_{EV\to A}\,(t,j) + \sum_{j\in \mathbb{J}} P_{PV}\,(t,j) \\ = P_{A\to G}(t) + P_{A\to B}\,(t) + \sum_{j\in \mathbb{J}} P_{A}\,(t,j) + \sum_{j\in \mathbb{J}} P_{A\to EV}\,(t,j) + P_{CS}\,(t), \end{aligned} \tag{21}$$

4.1.3.4. Grid power

The building is connected to the external grid and constraint (22) represents the maximum power that the aggregator can receive from the grid in time-step $t$.

$$P_{G\to A}\,(t) \leq \overline{P_G}\,(t) \tag{22}$$

## 4.2. PV GENERATION FORECAST

To optimize and manage the building energy management system, it is necessary to predict the PV power generation output. In this thesis, a multilayer feed-forward artificial neural network (ANN) is implemented.

In this ANN topology, the information moves in only one direction (forward) from the input nodes, through the hidden nodes, and to the output nodes, lastly. This way, there are no cycles or loops in the network [63]. A hidden layer is added to the neural network to amplify its strength and increase its efficiency. It is located between the input and output layers.

Figure 17 presents the multilayer feed-forward ANN architecture.

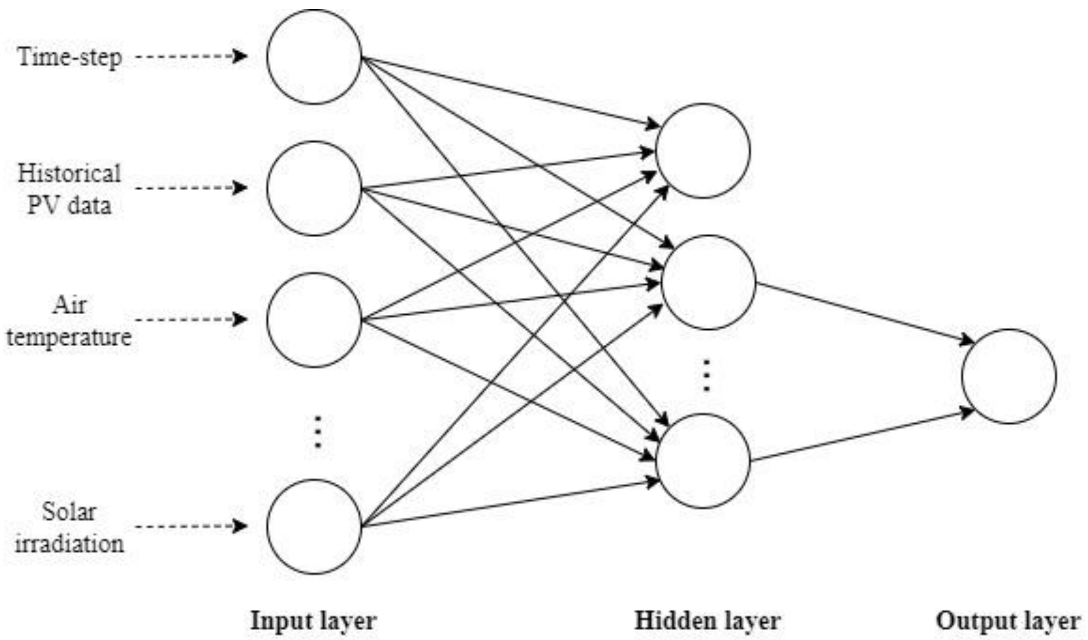



**Figure 17 Multilayer feed-forward Artificial Neural Network architecture.**

The main parameters of the ANN used to forecast the PV power generation for scenarios 1 and 2 are selected as shown in Table 12.

**Table 12 ANN parameters for scenarios 1 and 2.**

| ANN parameters | Scenario 1 | Scenario 2 |
|---|---|---|
| Number of layers | 3 | |
| Number of hidden layer neurons | 2 | 10 |
| Number of output neurons | 1 | |
| Number of input variables | 31 | |
| Training data set | January and February 2019 | June, July, and August of 2019 |
| Testing data set | March 5, 2019 | September 1, 2019 |

A training set is used to ensure that the weights are not over or under adjusted, and a test set is used to evaluate network performance. It used training data sets with similar characteristics (such as air temperature and solar irradiation) of the testing data set for better results. Also, several simulations were made with a different number of hidden layer neurons, 2 for scenario 1 and 10 for scenario 2, to obtain the greatest results.

The input vector is composed of four components: (1) the time-step (t) of the prediction; (2) historical PV power generation data (kW); (3) air temperature (°C); and (4) solar irradiation (W/m$^2$). To predict the PV generation for the next day, the model uses the generation, air temperature, and solar irradiation during the previous day. The time-step duration of the dataset is 15 minutes.

All the simulations of the ANN method were performed using the *R* language in the RStudio program. The used system has 16GB RAM and a Ryzen 5 3500U 2.10 GHz processor running Windows 10.

Figure 18 presents the PV power generation forecast simulation results of each apartment for scenario 1, regarding March 5, 2019.

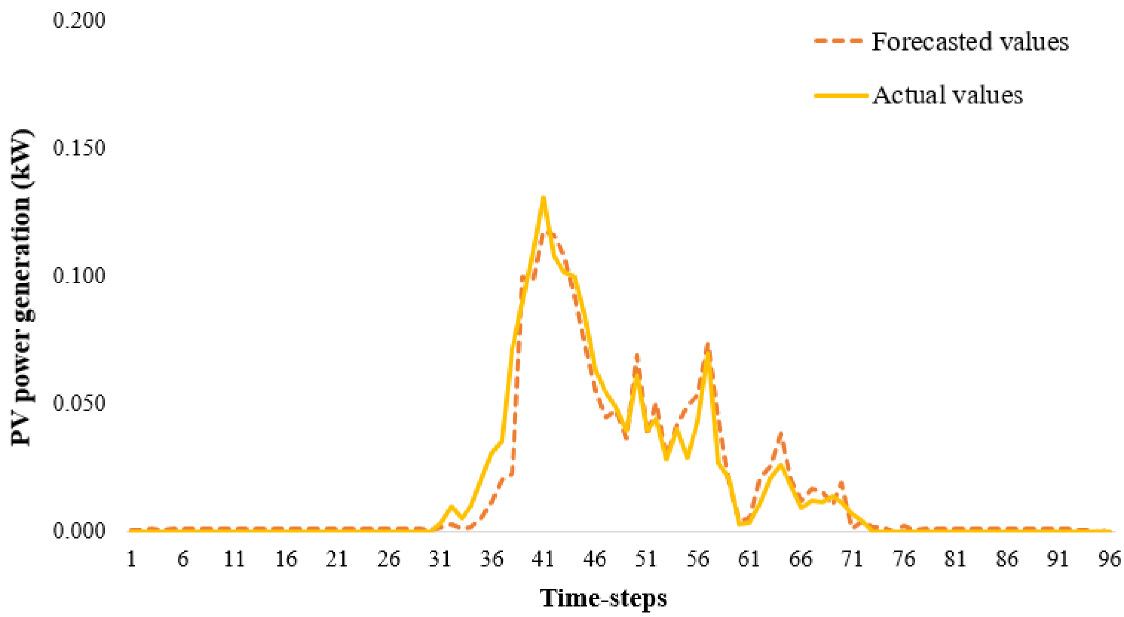



**Figure 18 PV power generation forecast of March 5, 2019.**

Figure 19 shows the PV power generation forecast simulation results of each apartment for scenario 2, regarding September 1, 2019.

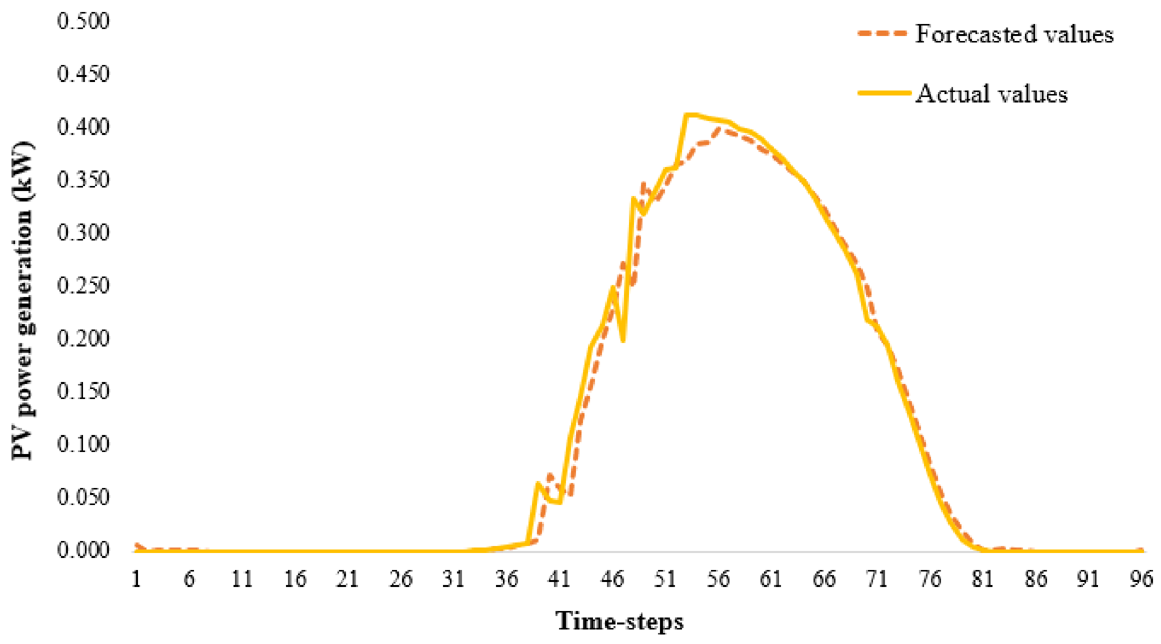



**Figure 19 PV power generation forecast of September 1, 2019.**

Analyzing both Figures 18 and 19, it is possible to observe that the actual values curve is very similar to the forecasted values curve, resulting in a good accuracy of the forecasting technique.

To assess this forecasting method's accuracy, the most common error indexes have been calculated: Absolute Error (AE) and Mean Absolute Error (MAE), defined in Equation (23) and (24).

$$AE = \left|P_{PV} - \hat{P}_{PV}\right| \tag{23}$$

$$MAE = \frac{1}{N}\sum_{t=1}^{N}\left|P_{PV} - \hat{P}_{PV}\right| \tag{24}$$

Table 13 presents the maximum and minimum values of AE and MAE values for the two scenarios.

**Table 13 AE and MAE values for the two scenarios.**

| | Scenario 1 | Scenario 2 |
|---|---|---|
| **Maximum AE** | 0.04830 | 0.08402 |
| **Minimum AE** | 0.00002 | 0.00005 |
| **MAE** | 0.0041 | 0.0080 |

Comparing both scenarios, scenario 1 has a lower absolute error and MAE than scenario 2. However, both scenarios present results with low absolute errors which means that this technique is very accurate.

## 4.3. Robust Optimization

The robust optimization approach applied in this thesis is based on [57] and [64] and it is formulated to deal with the uncertainty of PV power generation outputs.

Initially, the MBLP model, described in Section 4.1., is formulated to optimize the energy resources management of the building. Then, it is transformed into a robust counterpart whose main objective is to minimize the total costs of electricity of the residential building under the given uncertainty bounds.

Figure 20 describes the essential stages in a Robust Optimization formulation.

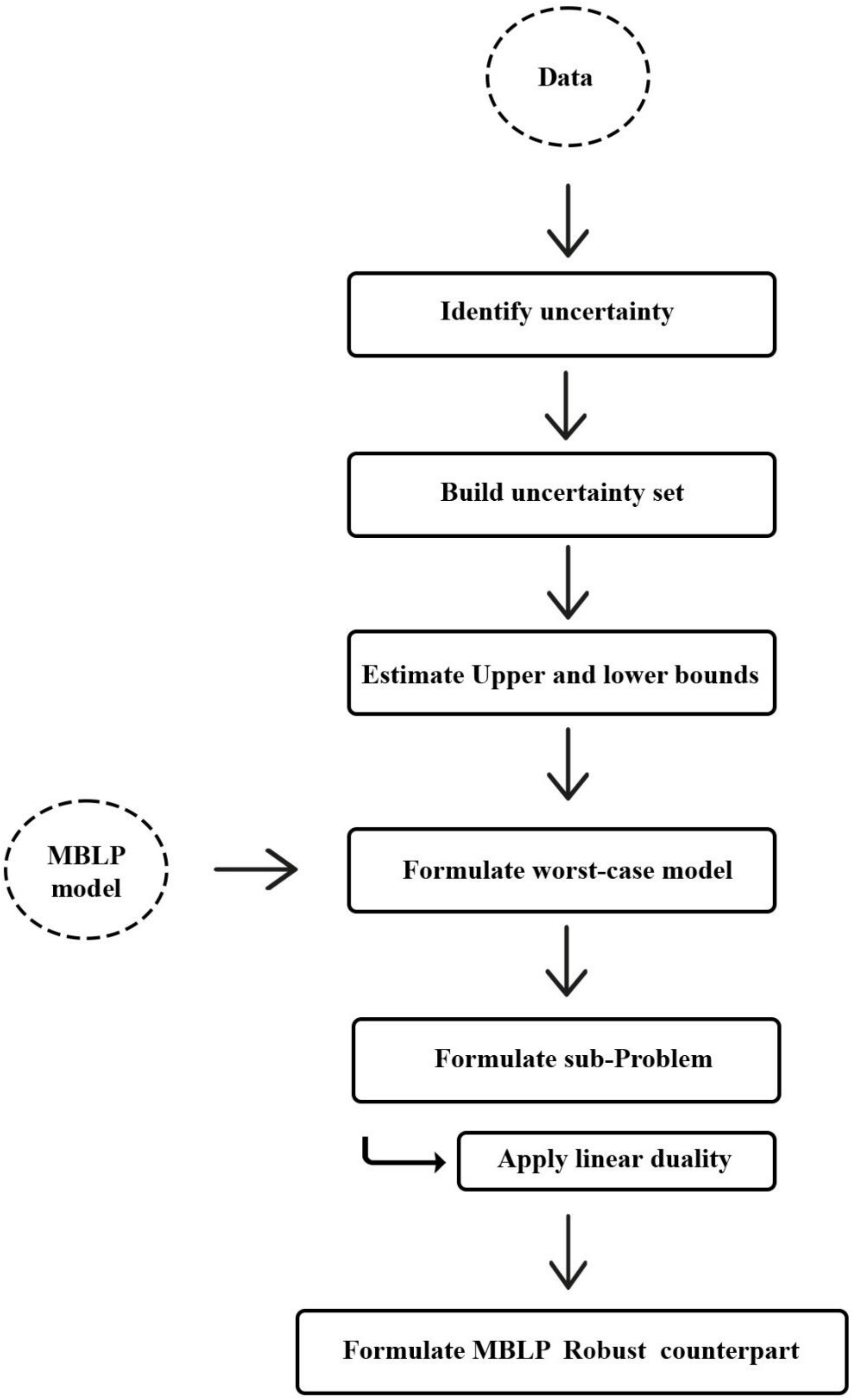



**Figure 20 Steps of Robust Optimization formulation.**

First, it is necessary to identify which is the uncertainty parameter to be considered and, in this case, it is the PV power generation. Then, the uncertainty set is built and with the values of the PV production forecast, the upper and lower bounds are estimated. The deterministic model was already formulated, so the next step is to transform it into the worst-case model. The worst-case model contains a sub-problem that can be solved applying the linear duality theory. Then, a trackable Robust counterpart is formulated to overcome the obstacles of uncertainties, and lastly, it is included in the MBLP model.

### 4.3.1. NOTATION

Table 14 presents the parameters used to model the PV power output uncertainty.

**Table 14 Uncertainty parameters.**

| Parameter | Description |
|---|---|
| $\boldsymbol{\widehat{P}_{PV}\ (t, j)}$ | Forecasted PV output of apartment $j$ in time-step $t$ |
| $\boldsymbol{\Delta_{PV}\ (t, j)}$ | Deviation from the forecasted values of PV output of apartment $j$ in time-step $t$ |
| $\boldsymbol{\Gamma_{PV}\ (t)}$ | Budget of uncertainty for the PV in time-step $t$ |
| $\boldsymbol{\overline{P_{PV}}}$ | Upper bound of PV power forecast |
| $\boldsymbol{\underline{P_{PV}}}$ | Lower bound of PV power forecast |
| $\boldsymbol{\lambda^{\overline{P}}, \lambda^{\underline{P}}}$ | Dual variables |

The budget of uncertainty $\Gamma_{PV}\ (t)$ is a parameter used to adjust the robustness of the method against the level of conservatism of the solution and it does not have to take an integer value. The maximum value of $\Gamma_{PV}$ depends on the number of uncertain random variables. In this case, $\Gamma_{PV} = 1$ because there is only one uncertainty source considered (PV power generation). When the budget of uncertainty reaches its maximum value, it is considered the worst-case realization and each PV has a chance to reach its upper or lower bounds. This scenario might be over-conservative and lead to unnecessary costs. On the contrary, if $\Gamma_{PV} = 0$, no uncertainty is considered in the PV output prediction [64], [65].

### 4.3.2. ROBUST FORMULATION

In this subsection it has formulated the robust optimization model to deal with the PV power generation forecast uncertainty, considering the deterministic model previously formulated.

#### 4.3.2.1. Estimation of upper and lower bounds of PV uncertainty

Once the predicted solar power output is obtained (Section 4.2.), it is necessary to estimate the uncertainty deviations ($\Delta_{PV}$). Based on several literature, it was considered that $\Delta_{PV} = 20\%$.

To obtain the upper and lower bounds, it is necessary to multiply the prediction values by their respective uncertainty deviation as shown in Equations (25)-(26), respectively.

$$\overline{P_{PV}} = \hat{P}_{PV} + \Delta_{PV} \cdot \hat{P}_{PV} \tag{25}$$

$$\underline{P_{PV}} = \hat{P}_{PV} - \Delta_{PV} \cdot \hat{P}_{PV} \tag{26}$$

Therefore, the upper and lower bounds will deviate about 20% from the forecasted values, as shown in Figures 21 and 22 that correspond to scenarios 1 and 2, respectively.

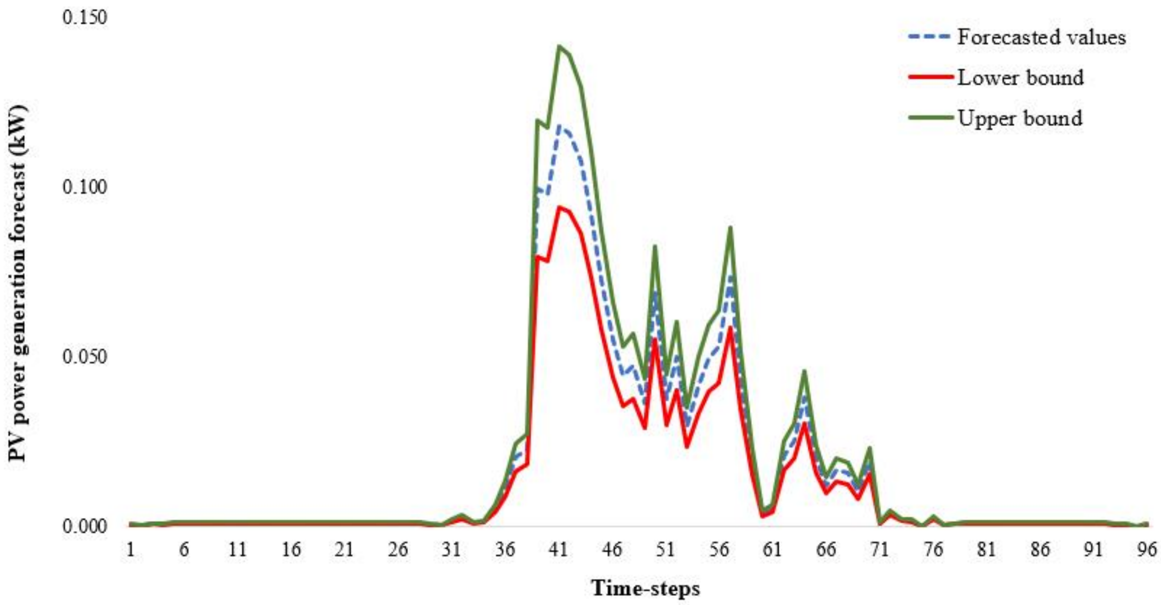



**Figure 21 Upper and lower bounds of PV forecasted values – Scenario 1.**

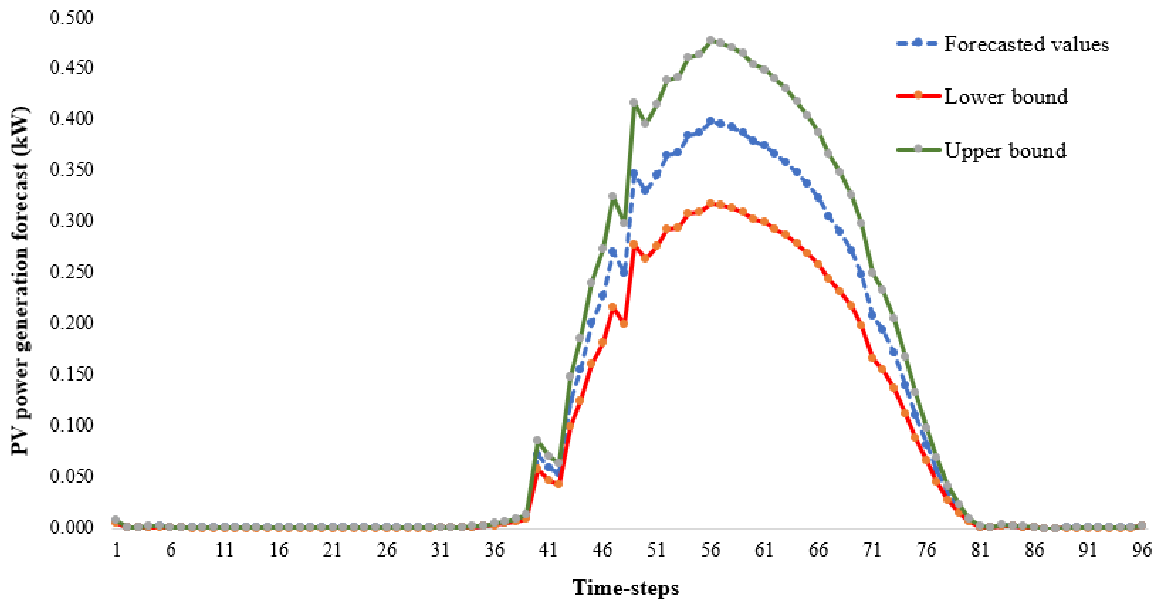



**Figure 22 Upper and lower bounds of PV forecasted values – Scenario 2.**

In the robust optimization model, instead of relying on a single PV power output, which is often different from the real values, the decision-maker can rely on the upper and lower bounds of the PV power forecasts [66].

#### 4.3.2.2. Uncertainty set

First, it is necessary to build an uncertainty set (denoted as $\boldsymbol{U}$), which is used to describe the uncertainties of PV power generation outputs, as shown in Equation (27).

$$U = \left\{ \begin{matrix} \hat{P}_{PV}\,(t,j) - \Delta_{PV}\,(t,j) \;\leq\; P_{Pv}\,(t,j) \;\leq \hat{P}_{PV}\,(t,j) + \Delta_{PV}\,(t,j), \quad \forall t,j \\ \sum_{i} \frac{\left|P_{Pv}\,(t,j) - \hat{P}_{PV}\,(t,j)\right|}{\Delta_{PV}\,(t,j)} \leq \Gamma_{PV}\,(j), \qquad \forall j \end{matrix} \right\} \tag{27}$$

#### 4.3.2.3. Load balance

According to the deterministic model presented in Section 4.1., the objective function is not subject to uncertainty, so the objective function of the robust model is the same as Equation (6).

The load balance constraint is the only one subject to uncertainty due to the $P_{PV}\,(t,j)$ parameter. Hence, this constraint of the deterministic model should be met when the worst-case of uncertainties occur. In this case, the worst-case scenario occurs at the maximum decrease in the PV power generation.

According to this, the worst-case load balance is given by Equation (28), corresponding to the function $f(x)$.

$$
\begin{aligned}
f(x) \;=\; & P_{G\to A}(t) + P_{B\to A}(t) + \sum_{j\in \mathbb{J}} P_{EV\to A}(t,j) + \sum_{j\in \mathbb{J}} P_{PV}(t,j) \;-\; P_{A\to G}(t) \\
& - P_{A\to B}(t) - \sum_{j\in \mathbb{J}} P_{A}(t,j) - \sum_{j\in \mathbb{J}} P_{A\to EV}(t,j) - \; P_{CS}(t)
\end{aligned}
\tag{28}
$$

#### 4.3.2.4. Sub-problem and Dual

After transforming the deterministic model into the worst-case model, the next step in the robust optimization formulation is to formulate the sub-problem and find the dual of the sub-problem.

The sub-problem creates the worst scenario, which is the maximum decrease of PV generation and then minimizes its impact, converting the sub-problem into a dual problem. Consequently, it consists in maximizing for the worse and then minimizing to find the optimal solution among the worse. Briefly, the sub-problem is solved to find the worst-case PV scenario.

The first objective is the maximization of the uncertainty factor ($P_{PV}$) contained in the load balance equation. To formulate the sub-problem, it is required to transform Equation (26) to the objective function and define the uncertainty bounds as constraints as $P_{PV} \in [\underline{P_{PV}}\,, \overline{P_{PV}}]$.

The formulation of the sub-problem is characterized in Equations (29a) - (29c).

$$
max\;\; f(x) \tag{29a}
$$

s.t.

$$
\overline{P_{PV}} \; - P_{PV} \;\geq\; 0 \tag{29b}
$$

$$
P_{PV} \;-\; \underline{P_{PV}} \;\leq\; 0 \tag{29c}
$$

The sub-problem needs to be converted into a dual problem to make the robust counterpart tractable [1]. When the sub-problem is linear, it is possible to apply the linear duality theory on the sub-problem and dual variables are required.

The formulation of the dual of the sub-problem is characterized in Equation (30a) which is the dual objective function of the sub-problem and in Equation (30b) which is the dual constraint subjected to the dual objective function.

$$min\ \lambda^{\underline{P}} \cdot (P_{PV} - \underline{P_{PV}}) + \lambda^{\overline{P}} \cdot (\overline{P_{PV}} - P_{PV}) \tag{30a}$$

s. t.

$$\lambda^{\underline{P}},\ \lambda^{\overline{P}} \geq 0 \tag{30b}$$

#### 4.3.2.5. MBLP Tractable Robust Counterpart

The formulation of the robust counterpart of the deterministic model is given in Equations (31a) - (31r), using the dual problem developed previously. The objective function is the same as the deterministic model, as well as the constraints. The main difference is that the MBLP robust counterpart problem includes two new constraints, associated with the sub-problem.

$$min\, Z = \sum_{i \in \mathbb{I}} C_G^b\,(t, CP) P_{G\to A}(t) - \sum_{i \in \mathbb{I}} C_G^s\,(t) P_{A\to G}(t) \tag{31a}$$

s.t.

$$SOC_{EV}\,(t, j) \leq \overline{SOC}\,(j) \tag{31b}$$

$$SOC_{EV}\,\left(T_{EV}^{in}((d, j) - 1), j\right) = SOC_{in}(d, j) \tag{31c}$$

$$SOC_{EV}\,(T_{EV}^{out}(d, j) - 1, j) \geq \underline{SOC_{out}}\,(j) \tag{31d}$$

[1] Tractable: Word used to refer to problems that can be reformulated into equivalent problems for which there are known solution algorithms; Ease of obtaining a mathematical solution [68].

$$P_{A\to EV}(t,j) \le \alpha_{EV}(t,j) \cdot P_{EV}^{c}(j) \cdot \tau \tag{31e}$$

$$P_{EV\to A}(t,j) \le \beta_{EV}(t,j) \cdot P_{EV}^{d}(j) \cdot \tau \tag{31f}$$

$$SOC_{EV}(t+1,j) = SOC_{EV}(t,j) + \left[P_{A\to EV}(t,j) \cdot \eta_c(j) - P_{EV\to A}(t,j)/\eta_d(j)\right] \tag{31g}$$

$$SOC_{EV}(t,j) = 0 \tag{31h}$$

$$\alpha_{EV}(t,j) + \beta_{EV}(t,j) \le 1 \tag{31i}$$

$$\underline{SOC_B} \le SOC_B(t) \le \overline{SOC}_B \tag{31j}$$

$$SOC_B(0) = SOC_B^{initial} \tag{31k}$$

$$P_{A\to B}(t) \le \alpha_B(t) \cdot P_B^{c} \cdot \tau \tag{31l}$$

$$P_{B\to A}(t) \le \beta_B(t) \cdot P_{EV}^{d} \cdot \tau \tag{31m}$$

$$SOC_B(t+1) = SOC_B(t) + \left[P_{A\to B}(t) \cdot \eta_B^{c} - P_{B\to A}(t)/\eta_B^{d}\right] \tag{31n}$$

$$\alpha_B(t) + \beta_B(t) \le 1 \tag{31o}$$

$$P_{G\to A}(t) \le \overline{P_G}(t) \tag{31p}$$

$$\begin{gathered} \mathit{Min\ max}_{(P_{pv})} \left( P_{G\to A}(t) + P_{B\to A}(t) + \textstyle\sum_{j\in \mathbb{J}} P_{EV\to A}(t,j) + \sum_{j\in \mathbb{J}} P_{PV}(t,j) - \right. \\ \left. P_{A\to G}(t) - P_{A\to B}(t) - \textstyle\sum_{j\in \mathbb{J}} P_A(t,j) - \sum_{j\in \mathbb{J}} P_{A\to EV}(t,j) - P_{CS}(t) \right) \end{gathered} \tag{31q}$$

$$P_{PV} \in [\underline{P_{PV}}(i,j), \overline{P_{PV}}(i,j)] \tag{31r}$$

## 4.4. CONCLUSIONS

The mathematical formulation of the robust optimization based on an MBLP model has been presented in this chapter. The first sub-section concerned the mathematical formulation of the mixed binary linear problem and included the description of all the parameters along with the objective function and constraints regarding all energy resources of the building.

To control the building energy management system, it was necessary to forecast the PV generation output using an Artificial Neural Network technique. After obtaining the forecasted values, the upper and lower bounds of the forecast PV generation were calculated to build the uncertainty set of the robust formulation.

The cost minimization MBLP was transformed into a robust counterpart with the main purpose of providing immunity against PV uncertainty within the determined bounds. First, the deterministic model is converted into a sub-problem that consists in the maximization of the uncertainty factor (creates the worst scenario) and then minimizes it to find the best solution. Then, a traceable robust counterpart was formulated, which consisted in adding the constraints associated with the sub-problem to the deterministic model.

# 5. Case Study and Results

In this chapter, the methodology proposed in Chapter 4 is implemented and evaluated. A brief review of the case study is made. Then, the two scenarios of this thesis case study are described, and the results of the simulations are presented and briefly discussed.

## 5.1. Case Study: Energy Smart Management Considering PV Uncertainty

A case study for the energy resources management of a residential building is used to assess the proposed mathematical formulation, with the objective of minimizing the energy costs of the building considering the uncertainty of solar generation.

Besides the EVs, the energy smart management of the building also involves the use of a BESS to satisfy the demand during energy consumption peaks.

The main objective of this case study is to compare the electricity costs considering PV uncertainty on a cloudy day with a sunny day. Also, it investigated the effect of the usage of energy storage systems such as EVs and a BESS in the scheduling of the energy management system.

The historic data used in this case study include the energy demand of common services, the energy consumption, and the photovoltaic power generation of each apartment. This data can be found at "Arxiv".

## 5.2. SCENARIOS DESCRIPTION

To visualize the impact of PV uncertainty, two scenarios with three case studies each have been simulated in this study. It is considered a short-term scheduling horizon (twenty-four (24) hours) with a 15-minute time interval.

Cloudy days are distinguished by a mean solar irradiation value in the range [5-150 $W/m^2$] and sunny days by a mean value of the solar irradiance higher than 150 $W/m^2$ [67]. For scenario 1: March 5, 2019, was chosen due to its very low medium solar irradiation, which was 97.5 $W/m^2$. Regarding scenario 2: September 1, 2019, was chosen because it was a summer day with high medium solar irradiation values (437.7 $W/m^2$).

Table 15 summarizes the main characteristics of each scenario, in which "✓" indicates that resource is integrated into the building.

**Table 15 Scenario's characterization.**

| | **Scenario 1** | | | **Scenario 2** | | |
|---|---|---|---|---|---|---|
| | 1.a | 1.b | 1.c | 2.a | 2.b | 2.c |
| **Day** | March 5, 2019 | | | September 1, 2019 | | |
| **Aggregator** | | ✓ | ✓ | | ✓ | ✓ |
| **PV generation system** | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| **EVs** | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| **BESS** | | | ✓ | | | ✓ |

In both scenarios, it was assumed that the PV generation values, and the common services demand were the same for all the consumers.

The scenarios are divided into three sub-scenarios each, as follows.

*Scenario a: Reference scenario*

In this reference scenario, smart management is not considered. Each apartment is provided with an individual PV generation system and uses an EV but there is no energy smart management system applied in these resources. The EV starts charging when it enters the building and stops when it is fully charged. In this case, there is no charging schedule.

To calculate the electricity costs of the building, it was assumed that all consumers have an energy contract with a bi-hourly tariff and a contracted power of 6.9 kVA. The energy prices of this tariff for each period are annually fixed by Entidade Reguladora dos Serviços Energéticos (ERSE) and Table 16 presents the prices of 2019 considered in this scenario.

**Table 16 Energy tariffs for sale to low voltage consumers by ERSE in 2019.**

| **Power** | | **Prices** |
|---|---|---|
| Contracted power | 6.9 kVA | 0.2935 €/day |
| Bi-hourly tariff (≤6.9 kVA) | Off-peak hours | 0.1014 (€/kWh) |
| | Peak hours | 0.2008 (€/kWh) |

The bi-hourly tariff can follow a weekly or daily cycle. In this case, a weekly cycle was chosen. The off-peak and peak periods also vary depending on the time of the year, i.e., if it is summer or winter.

Table 17 exhibits the duration of off-peak and peak periods for each day of the week.

**Table 17 The weekly cycle of bi-hourly tariff.**

| Weekdays | Winter | | Summer | |
|---|---|---|---|---|
| | Off-peak hours | Peak hours | Off-peak hours | Peak hours |
| Monday to Friday | 0h00-7h00 | 7h00-24h00 | 00h00-7h00 | 7h00-24h00 |
| Saturday | 00h00-9h30<br>13h00-18h30<br>22h00-24h00 | 9h30-13h00<br>18h30-22h00 | 00h00-9h00<br>14h00-20h00<br>22h00-24h00 | 9h00-14h00<br>20h00-22h00 |
| Sunday | 00h00-24h00 | | 00h00-24h00 | |

*Scenario b: Smart management considering EVs*

In scenario b, the developed robust scheduling in Section 4.4. is tested on the building energy system proposed in Figure 16.

The following assumptions are made:

- An aggregator is responsible for controlling all building energy resources and for the energy trade-off between the building and the grid;
- Each apartment has its own PV generation system;
- Each apartment uses one EV and its charging and discharging processes are managed and controlled.

*Scenario c: Smart management considering EVs and BESS*

This scenario is very similar to the previous one and the following assumptions are made:

- An aggregator is responsible for controlling all building energy resources and for the energy trade-off between the building and the grid;
- Each apartment has its own PV generation system;

- Each apartment uses one EV and its charging and discharging processes are managed and controlled.
- A BESS is used as an energy resource of the building.

## 5.3. DISCUSSION OF RESULTS

In this section, the robust scheduling results of each scenario are presented, and observations are made.

### 5.3.1. SCENARIO 1

#### 5.3.1.1. Scenario a

The reference case of scenario 1 consists in calculating the energy costs of each consumer for a specific day, without optimizing the energy scheduling of the resources. According to the RO, the worst-case scenario is contemplated, which consists of considering the lower bounds of the forecasted PV generation.

First, the total energy consumption of each apartment is calculated. This scenario corresponds to a winter Tuesday, so the duration of off-peak and peak periods for this day provided by Table 17 are used. Table 18 exhibits the total energy consumption for each consumer.

**Table 18    Energy consumption of each consumer.**

| Consumer | Off-peak hours consumption (kWh) | Peak hours consumption (kWh) | Total consumption (kWh) |
|---|---|---|---|
| **1** | 3.699 | 23.212 | +26.911 |
| **2** | 1.303 | 18.340 | +19.644 |
| **3** | 2.405 | 13.550 | +15.956 |
| **4** | 2.856 | 49.592 | +52.449 |
| **5** | 2.775 | 21.407 | +24.183 |
| **6** | 4.938 | 27.306 | +32.245 |
| **Total** | 17.979 | 153.410 | +171.389 |

Table 19 presents the total electricity costs for the reference case of scenario 1.

**Table 19   Total electricity cost of each consumer regarding scenario 1.a.**

| Consumer | Common services consumption (kWh) | EV demand (kWh) | PV generation (kWh) | Total consumption (kWh) | Total price (€) |
|---|---|---|---|---|---|
| **1** | +5.371 | + 26.414 | -1.337 | 57.360 | 6.897 |
| **2** | +5.371 | +25.258 | -1.337 | 48.936 | 5.727 |
| **3** | +5.371 | +17.327 | -1.337 | 37.318 | 4.365 |
| **4** | +5.371 | +21.905 | -1.337 | 78.389 | 10.361 |
| **5** | +5.371 | +26.537 | -1.337 | 54.755 | 6.583 |
| **6** | +5.371 | +22.259 | -1.337 | 58.539 | 7.128 |
| **Total** | +32.231 | +139.702 | -8.024 | 335.299 | 41.064 |

Equation 32 demonstrates how the total electricity cost of each consumer is calculated. It consists of adding the energy demanded from apartments, common services, and EVs and subtracting the PV generation that is listed in Tables 18 and 19. Then, it is multiplied by the energy price presented in Table 16, according to the period when the energy is consumed (off-peak or peak periods).

$$\begin{aligned}&[Apartment\ consumption\ +\ Common\ services\ consumption\\&\quad +\ EV\ consumption\ -\ PV\ generation]\ (kWh)\\&\quad \times\ Energy\ price\ (€/kWh)\end{aligned} \tag{32}$$

5.3.1.2. Scenario b

The optimal robust optimization scheduling results were obtained for the worst-case scenario. In this scenario, the worst-case occurs when there is a maximum decrease of the PV power production, based on the condition that $\Gamma_{PV}\ (t) = 1$.

Figure 23 present the robust scheduling simulation results of all the building's energy resources, regarding scenario 1.b. Through the worst possible solution, RO found the best solution for the worst-case scenario of PV generation, which is presented in this figure.

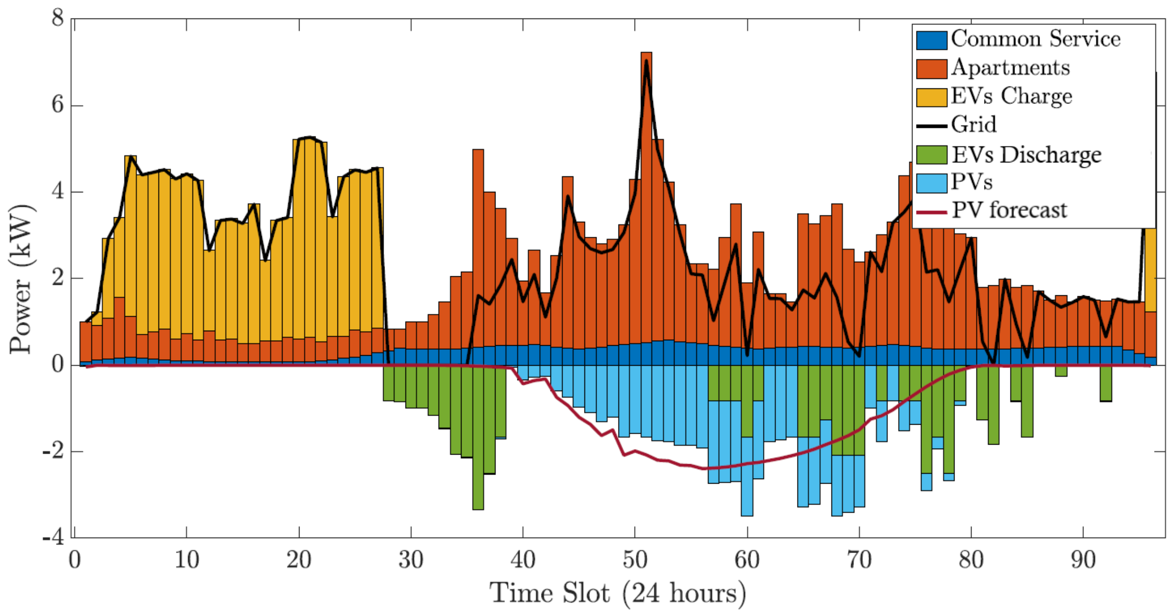



**Figure 23 Robust Optimization optimal scheduling results for scenario 1.b.**

This optimization technique operates within the uncertainty set bounds. This means that the obtained results for the PV generation values (symbolized in blue) represent the robust values obtained between the considered upper and lower bounds of the forecasted generation. In comparison with the real solar generation values, these values suffer a huge decrease when the RO model is implemented.

The EVs are scheduled to charge during the night (0h00 – 06h30) when the energy consumption from apartments and common services is low. Also, since these are considered off-peak periods in the bi-hourly tariff, the EVs charge when the energy price is cheaper. Therefore, the energy purchasing price from the grid is low.

Since the charging power of the EVs is 3.7 kW and their charged power was higher than this value during periods 0-27, they are scheduled to discharge some of that power in the following periods.

In the early morning (7h15-9h15), the energy demand slowly begins to rise and the EVs are scheduled to discharge while they are still in the building. During some of these periods, it was not necessary to buy energy from the grid because the power from the EVs discharge was able to fulfill the demand.

Despite near null power values, PV panels start generating around period 36 and gradually increase throughout the morning. The peak of energy consumption from the apartments is reached at 12h30 (period 51), as also the peak of energy received from the grid because the energy from PV generation is not enough to meet the high demand.

In the majority of the afternoon periods, the PV generation is not sufficient to satisfy the required consumption from the apartments and common services. Also, during the rest of the day, the energy price is the highest, which leads to an increase in the electricity bill. The EVs start the discharging process, again, during some of the afternoon and night periods.

The PV forecast line represents the best solution for PV generation obtained by the RO technique between the upper and lower bounds of the forecasted values.

#### 5.3.1.3. Scenario c

Similarly, to scenario 1.b, the robust scheduling results were obtained for the worst-case and more conservative scenario, which consists of the maximum decrease of PV generation. The main difference concerning the last scenario is the inclusion of a new energy resource, a BESS.

Figure 24 shows the robust optimization scheduling results regarding scenario 1.c.

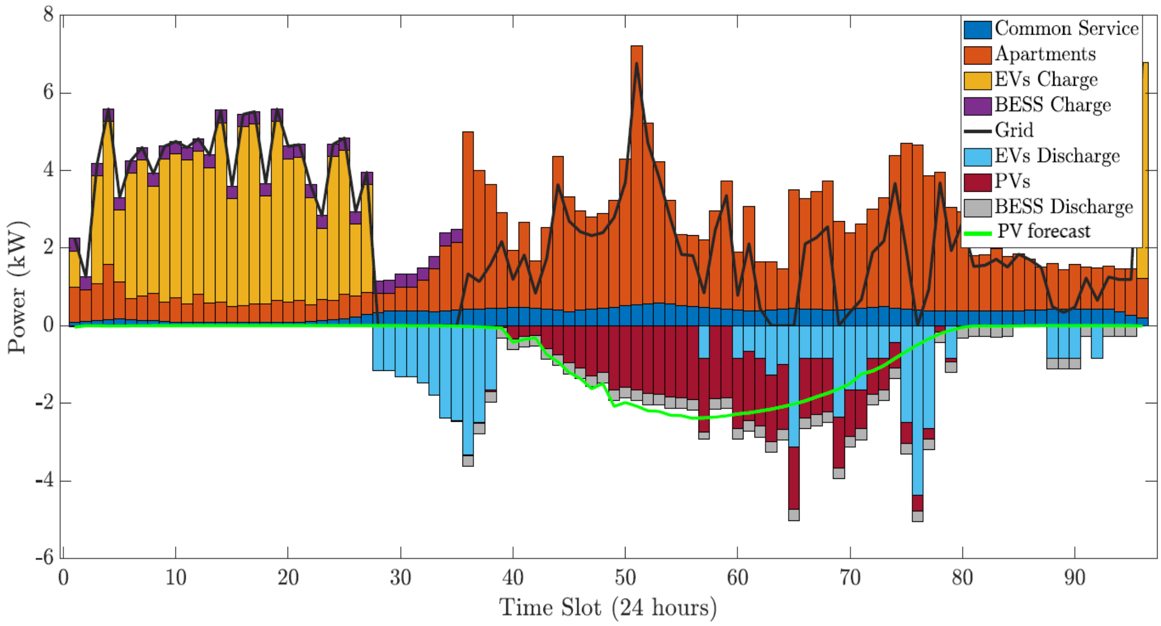



**Figure 24 Robust Optimization optimal scheduling results for scenario 1.c.**

The energy consumption of the apartments and common services, as also the robust and forecast PV generation values, remain the same as in scenario 1.b. The scheduling charge and discharge of EVs and BESS and the power from the grid are the resources that are adjusted.

The charging process of the EVs and BESS starts during periods 0 to 27, like scenario 1.c. Consequently, the power from the grid is higher because there is no generation source to fulfill the charging consumption. In these periods, the energy consumption from the apartments and common services is low, as is the energy price. The grid line follows the demand pattern there is no other source of supply.

During periods 28 to 35, the BESS continues to charge to reach the targeted SOC values and the EVs start discharging to supply their load demand. After these periods, the energy consumption of the apartments begins to increase as well as the PV generation, but it is not enough to satisfy it. Therefore, the BESS discharge feature is used in these periods where the external prices are higher and there are peak loads.

Between periods 63 and 77, there are a few periods where the aggregator does not have to request more energy from the grid due to PV generation and BESS and EVs discharge. From period 81 forward, the demand is assured through the EVs and BESS discharging process and the power from the grid.

Comparing both scenarios, in scenario 1.c it is possible to note a slight decrease in the energy purchased from the grid in the periods where the BESS starts to discharge.

### 5.3.2. SCENARIO 2

#### 5.3.2.1. Scenario a

The main purpose of the reference case of scenario 2 is the same as scenario 1. In this case, this scenario corresponds to a summer Sunday and, according to Table 17, every period of this day corresponds to off-peak hours. Therefore, there is no need to segregate the off-peak and peak periods to calculate the total energy consumption of each consumer on this day.

Table 20 presents the total electricity costs for the reference case of scenario 2.

**Table 20 Total electricity cost of each consumer regarding scenario 2.a.**

| Consumer | Apartment consumption (kWh) | Common services consumption (kWh) | EV demand (kWh) | PV generation (kWh) | Total consumption (kWh) | Total price (€) |
|---|---|---|---|---|---|---|
| **1** | +7.451 | +4.242 | + 22.247 | -8.169 | 25.771 | 3.971 |
| **2** | +8.130 | +4.242 | +27.235 | -8.169 | 31.437 | 4.848 |
| **3** | +17.472 | +4.242 | +22.489 | -8.169 | 36.034 | 5.553 |
| **4** | +40.426 | +4.242 | +7.787 | -8.169 | 44.286 | 6.827 |
| **5** | +18.950 | +4.242 | +28.262 | -8.169 | 43.285 | 6.671 |
| **6** | +36.914 | +4.242 | +3.496 | -8.169 | 36.482 | 5.612 |
| **Total** | +129.345 | +25.453 | +111.516 | -49.017 | 217.297 | 33.485 |

Equation 33 demonstrates how the total electricity cost of each consumer is calculated. It consists of adding the energy demanded from apartments, common services and EVs and subtracting the PV generation that is listed in Table 20. Then, it is multiplied by the energy price of the off-peak periods presented on Table 16 because, as already stated, the off-peak consumption corresponds to the total energy consumption on Sundays.

$$\begin{aligned}&[Apartment\ consumption\ +\ Common\ services\ consumption\\&\quad +\ EV\ consumption\ -\ PV\ generation]\ (kWh)\\&\quad \times\ Energy\ price\ (€/kWh)\end{aligned} \tag{33}$$

5.3.2.2. Scenario b

The robust optimization scheduling results were obtained for the worst-case scenario. In this situation, the worst-case occurs when there is a maximum decrease of the PV power production, based on the condition that $\Gamma_{PV}\ (t) = 1$.

The simulation results of the building energy management system for scenario 2.b are shown in Figure 25.

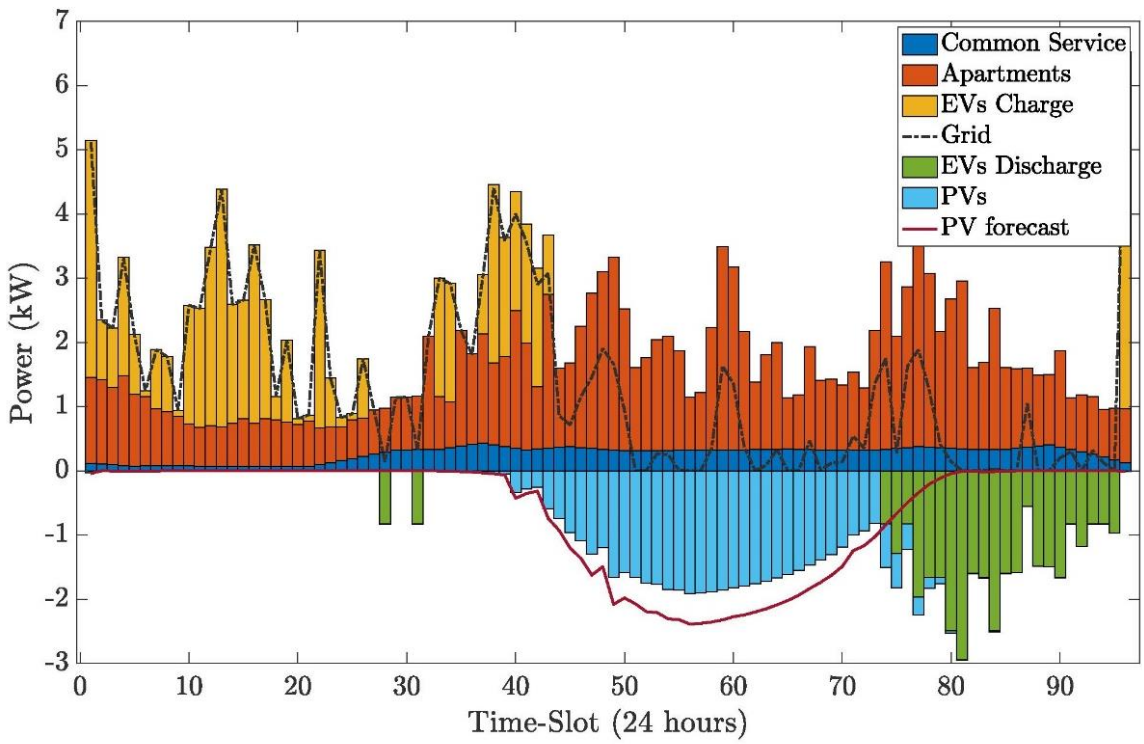



**Figure 25 Robust Optimization scheduling results for scenario 2.b.**

As in scenario 1.b, the robust technique finds the optimal PV generation values within the upper and lower bounds of forecasted values, and it represents the best value among the worst. These represent the lowest values of the solar production because it corresponds to the worst scenario.

During the night period (periods 0-30), the EVs are charging with power from the grid. Also, in these periods, the energy consumption of the apartments and common services is low in comparison with the rest of the day. So, the EVs charge during periods with low energy price and low energy demand. As known, there are no PV power outputs during these periods. It is possible to note in the figure that when there is no source of renewable generation (during the night and early morning), the aggregator needs to purchase all the energy from the grid, increasing the electricity bill.

In periods 40-75 it is possible to visualize some periods with energy demand peaks and that the PV generation cannot meet its load demand. Consequently, in these peak periods, the energy from the grid is higher to meet the demand. But the opposite also happens. There are periods that the aggregator does not have to buy energy from the grid because the PV generation can meet the load demand from the apartments and common services.

In periods 75-95, the energy demand is consistently higher compared to the other periods. It is supposed that the EV owners return home at the end of the afternoon and the EVs start to discharge when they are plugged in. Since the PV generation considerably decreases, the power discharged from the EVs is used to satisfy the energy demand and, as a result, the energy requested from the grid diminishes.

The charge and discharge of the EVs at low and high demand times, respectively, allows optimal scheduling of the building energy resources and also a decrease in the electricity costs.

#### 5.3.2.3. Scenario c

Like the previous scenario, the RO scheduling results were obtained for the worst-case situation, considering that $\Gamma_{PV}\ (t) = 1$.

The simulation results of the building energy management system for scenario 2.c are shown in Figure 26.

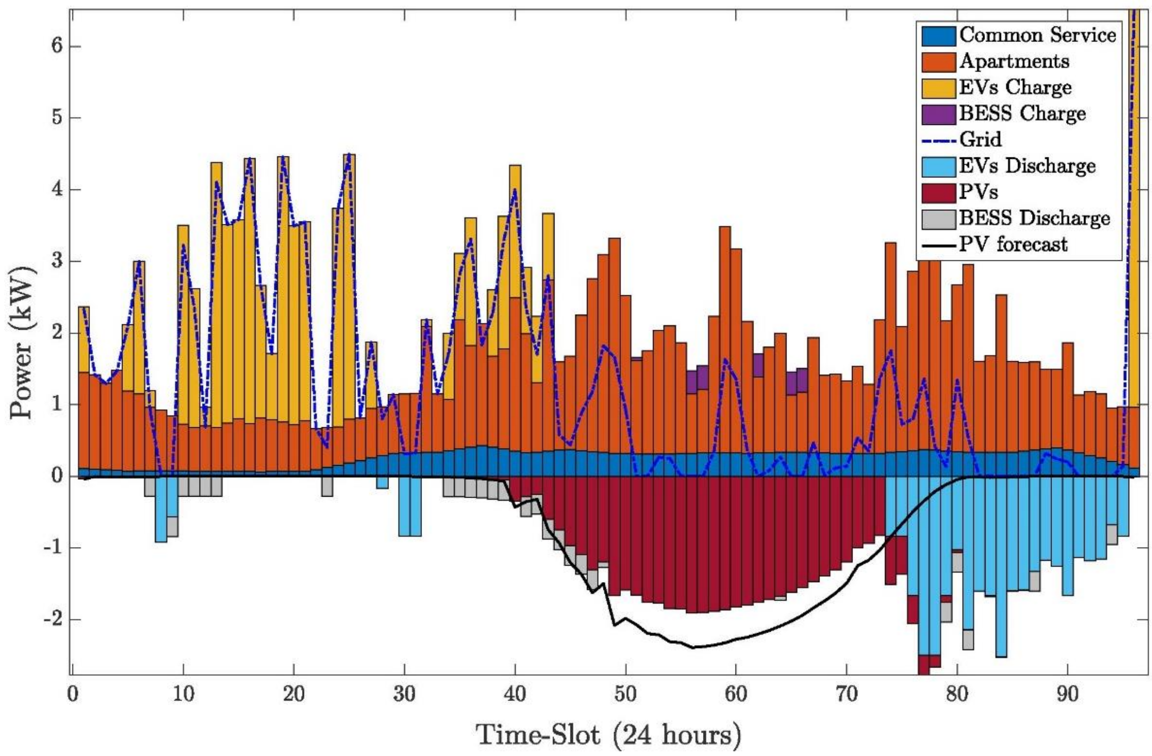



**Figure 26 Robust Optimization scheduling results for scenario 2.c.**

In the night periods (0-30), there is no generation from the PV panels, and the energy demand from the apartments and common services is very low. Thus, in some periods, the BESS and EVs are scheduled to discharge for demand-supply. In the majority of the time intervals of night-time, the aggregator purchases power from the grid to charge the EV batteries, to achieve the respective SOC values when they leave the building in the morning.

In the morning periods (33-40), it can be observed that the BESS discharges to satisfy the energy needs from the EVs charging, apartments, and common services since there is no PV generation yet.

During the day, in some periods between 51-66, it is possible to observe that the energy demand is low, and the PV power generation is high which means that the energy from PV panels is not being totally consumed by the apartments. As a result, the BESS stores the surplus energy mostly at periods with low energy demand.

During periods 74-95 (night-time), there is a high energy demand from the apartments and common services and very low PV generation to satisfy the needs. To smooth the energy consumption from the grid, the EVs and BESS start their discharging process to fulfill the energy demands.

### 5.3.3. Comparison of Scenarios

Scenario 1 presented higher consumption values than scenario 2, which is expected because energy consumption in winter tends to be higher than in summer. On the other hand, the PV generation reaches higher values in scenario 2. The load profiles of the six consumers regarding scenarios 1 and 2 are described in Figures 27 and 28, respectively.

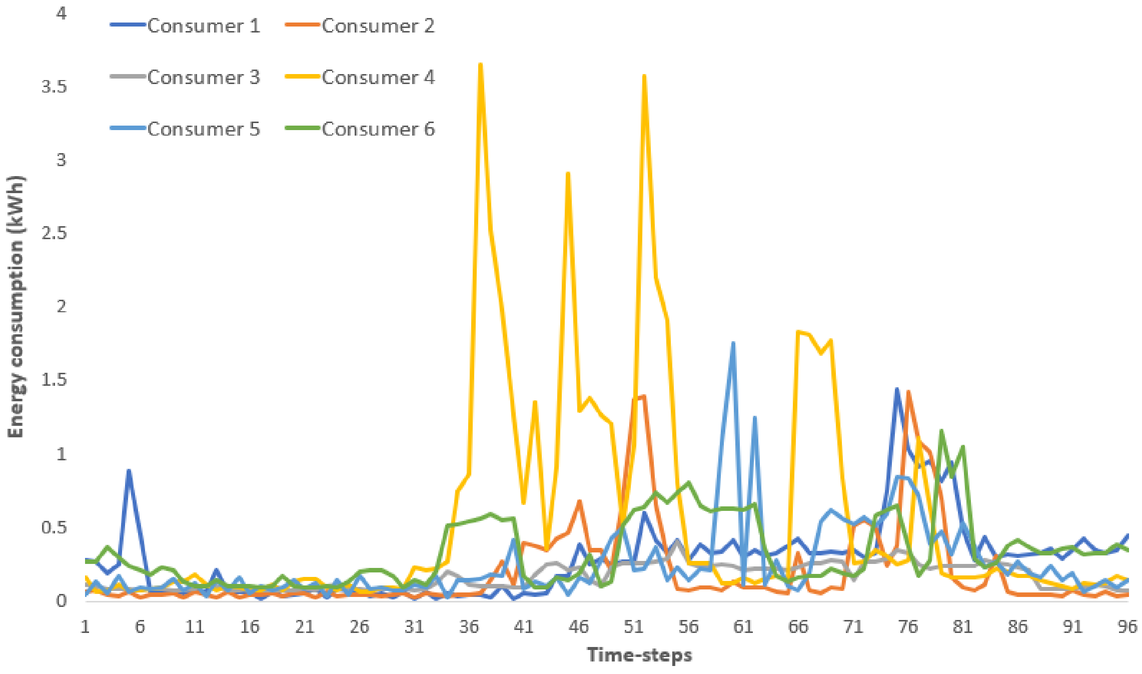



**Figure 27 Load profile of each consumer regarding scenario 1.**

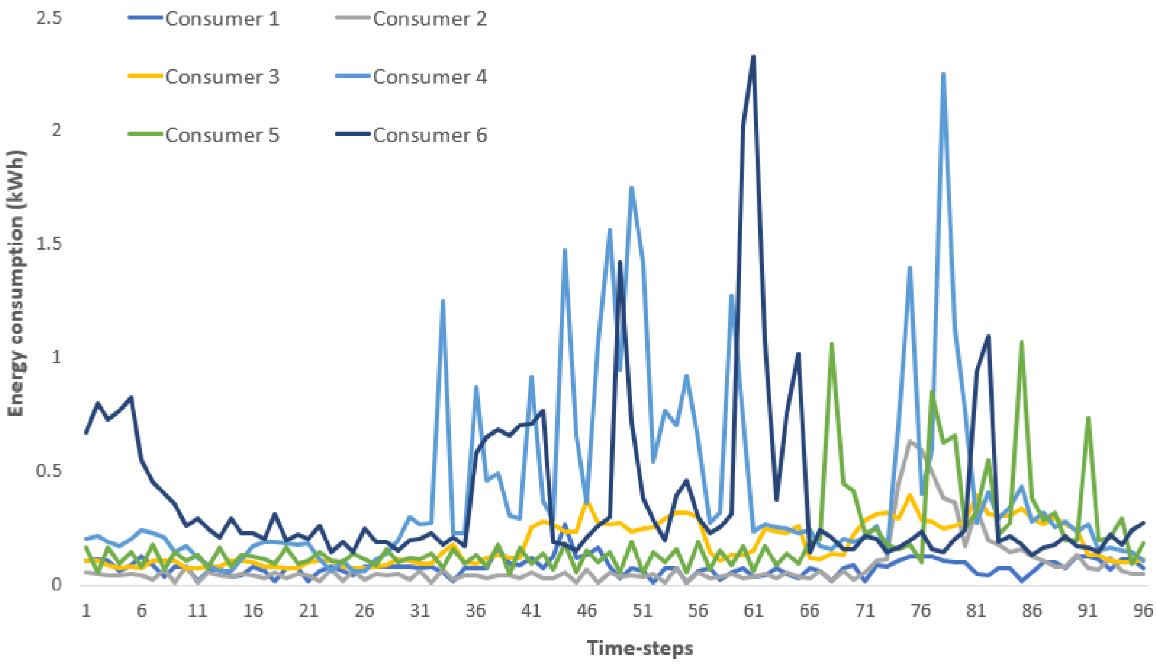



**Figure 28 Load profile of each consumer regarding scenario 2.**

Weather conditions have a significant impact on the power generated by the PV system. Figure 29 presents the real and forecasted values of PV power generation of each apartment, regarding both scenarios to analyze the impact of the weather, more specifically the solar irradiation.

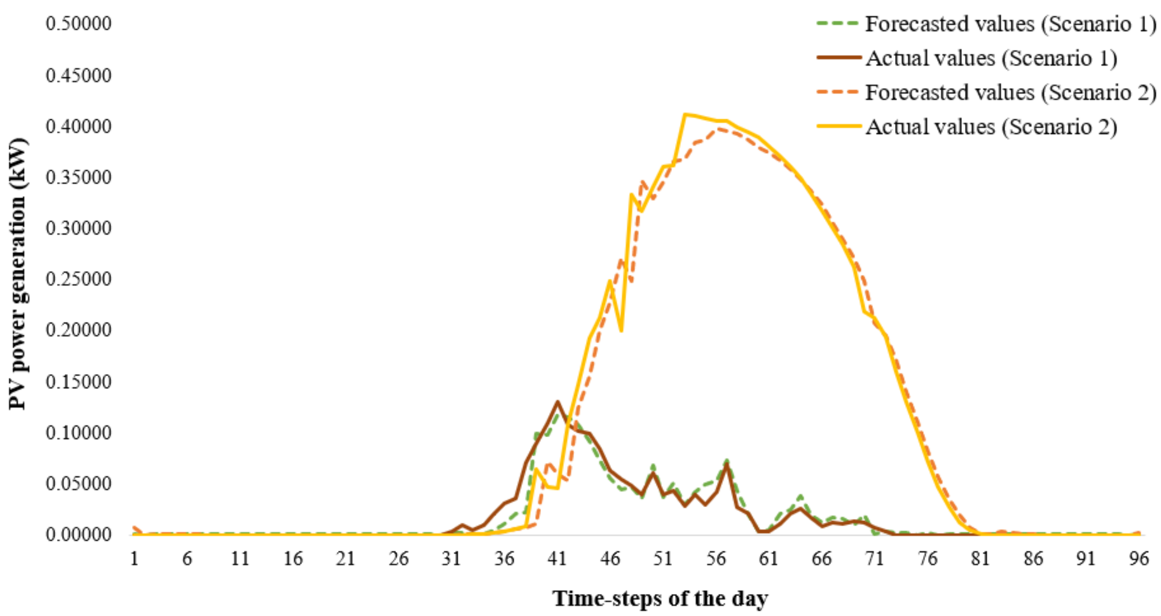



**Figure 29 Real and forecasted values of PV power generation of each apartment for both scenarios.**

For a cloudy day (scenario 1), the power profile shows highly unpredictable fluctuations, which increases the inherent uncertainty related to the PV generation. On a clear sunny day, the PV power output is the highest and follows a bell-shaped curve as shown in the figure above.

Figure 30 indicates the total electricity costs (€) for all six case studies of the two scenarios.

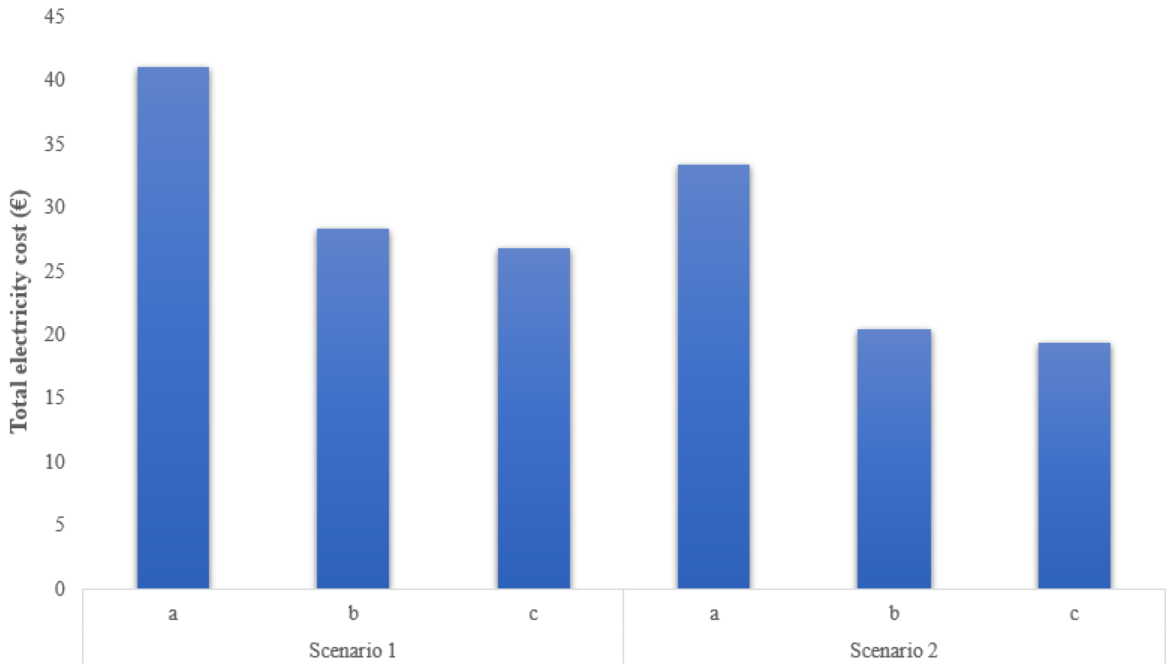



**Figure 30 Total electricity costs for scenarios 1 and 2.**

As expected, the chosen cloudy day has higher total electricity costs than the sunny day. On a cloudy day, the PV generation reaches low values, and the energy consumption is very high, in contrast with the sunny day. As a consequence, more energy is required from the grid because the PV power generation is very low, which leads to a scheduling cost increase. When the uncertainty is bigger, the system adopts more conservative scheduling, resulting in higher costs.

Comparing the three case studies of each scenario, it can be observed that the electricity cost suffers a decrease from one to another case study. As expected, the scenarios with no smart management represent higher costs. The use of both EVs and BESS exemplifies that smart management and scheduling of these energy resources can lead to an electricity bill reduction.

### 5.3.4. ANALYSIS OF BUDGET OF UNCERTAINTY

For this analysis, it only considered scenario 2 because it presented better scheduling costs than in scenario 1. Also, the reference case study of scenario 2 is not contemplated because it does not implement smart management.

It is considered five different values for the budget of uncertainty ($\Gamma_{PV}$), in a range from 0 to 1. Table 21 presents the energy management system scheduling costs under five different budgets of uncertainty, regarding scenarios b and c.

**Table 21 EMS scheduling costs under different $\Gamma_{PV}$ $(t)$.**

| $\Gamma_{PV}$ $(t)$ | Total cost for scenario 2.b (€) | Total cost for scenario 2.c (€) |
|---|---|---|
| **0** | 19.12 | 17.80 |
| **0.25** | 19.41 | 18.17 |
| **0.50** | 19.73 | 18.57 |
| **0.75** | 20.09 | 18.98 |
| **1** | 20.47 | 19.40 |

For both scenarios, as the value of the budget of uncertainty increases, the total energy costs also increase. With the increase of $\Gamma_{PV}$ $(t)$, the uncertainty level of the PV power forecast increases as well. Consequently, there is a big probability of a decrease in the PV power output.

When $\Gamma_{PV}$ $(t) = 0$, no uncertainty is considered and as a result, the real values of PV power outputs are equal to the forecasted PV values. This way, no immunity is taken against uncertainties in solar power generation and the influence of PV uncertainty in the constraint is ignored. This budget of uncertainty value corresponds to the lower robustness level. Moreover, when the budget of uncertainty is null, the model can be considered deterministic, and the uncertain PV output is not considered in the scheduling problem.

Besides, when $\Gamma_{PV}$ $(t) = 1$, the energy costs are higher due to the consideration of the worst-case scenario because, when there is a maximum decrease of PV generation, the aggregator needs to buy energy from the grid to satisfy the load demand. As a result, the EMS is scheduled to purchase more electricity from the grid, increasing the total cost. Besides the fact that a higher value of $\Gamma_{PV}\ (t)$ leads to higher conservatism solutions and, consequently, higher economic costs, it provides a better risk performance. Also, it is guaranteed full protection against PV uncertainties.

When analysing the results of both scenarios, it is noted that scenario 2.c has lower energy costs than scenario 2.b for each value of the budget of uncertainty. This way, it is possible to conclude that the use of a BESS leads to a decrease in the total costs for every $\Gamma_{PV}$, in comparison with scenario 2.b, in which only EVs are used.

Figure 31 shows the scheduling results of the energy management system for scenario 2.c, considering different values for the budget of uncertainty.

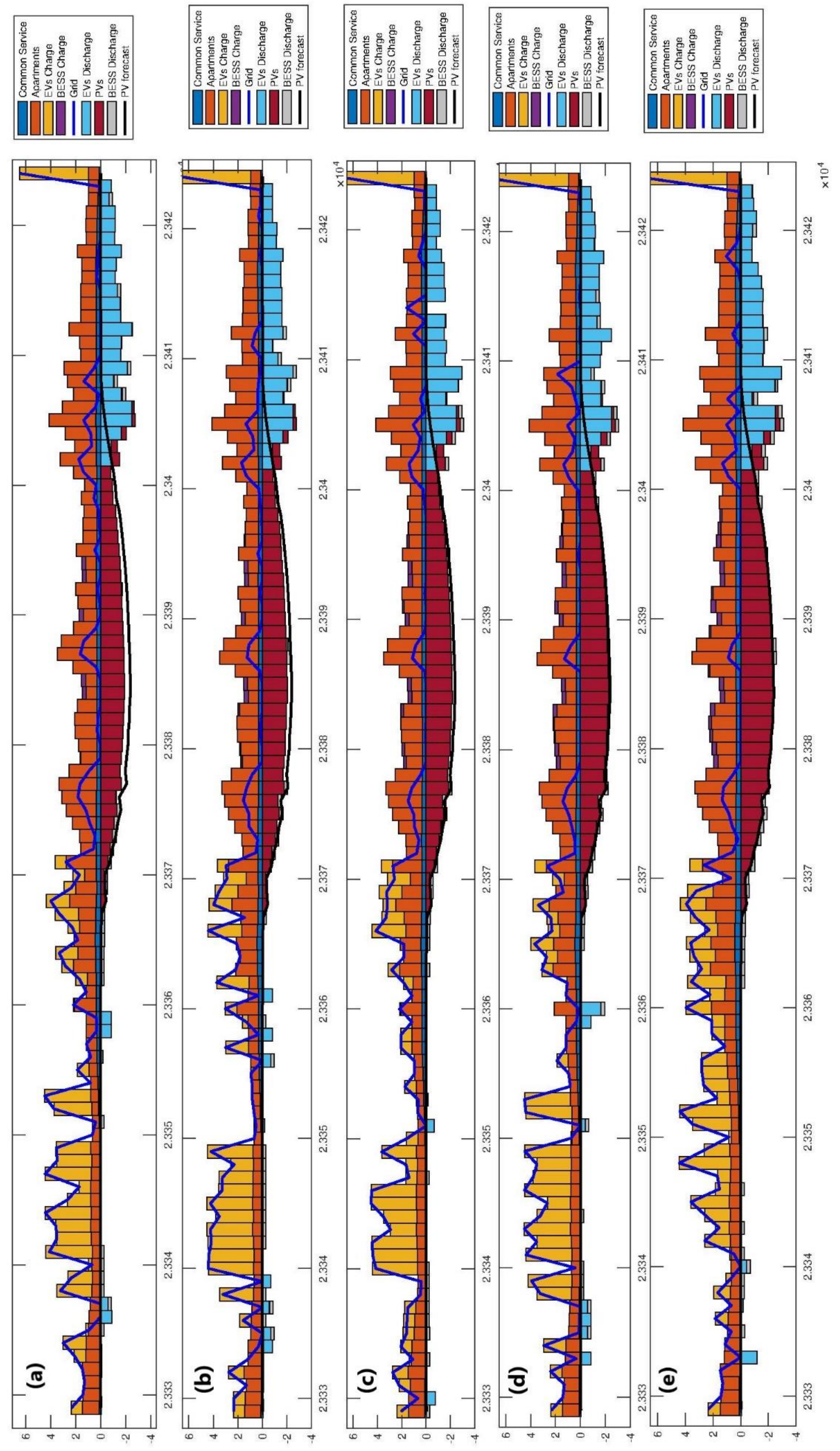



**Figure 31 Robust scheduling results of scenario 2.c for (a) $\Gamma_{PV} = 1$, (b) $\Gamma_{PV} = 0.75$, (c) $\Gamma_{PV} = 0.5$, (d) $\Gamma_{PV}\ (t) = 0.25$, (e) $\Gamma_{PV} = 0$.**

The PV generation uncertainty can be modeled by the budget of uncertainty. Consequently, the robust parameter selection will have an impact on the scheduling results. For every simulation of the selected $\Gamma_{PV}$ value, the upper and lower bounds are used in a proposed RO-based energy scheduling technique.

When analyzing this figure, it is possible to observe that there is no uncertainty gap when $\Gamma_{PV}\ (t)\ = 0$, because the real values are the same as the forecasted values. Also, the uncertainty gap gets wider as the value of $\Gamma_{PV}$ increases. A higher value of $\Gamma_{PV}$ turns the EMS scheduling more conservative.

Observing Figure 31 (a)-(e), as the value of $\Gamma_{PV}$ increases, the uncertainty level of PV generation also increases, which can reflect a decrease in PV power output because the worst-case scenario occurs when the budget of uncertainty is the highest and it represents a maximum decrease of PV generation. The PV generation forecast reaches lower values than the actual values when the budget of uncertainty is the maximum because it corresponds to the worst situation. A decrease in the PV generation results in more power purchased from the grid, increasing the costs.

Comparing the five graphs, the schedule charging and discharging processes of the EVs and BESS differ for each $\Gamma_{PV}$ value. In all situations, the EVs charge during night and early morning periods (0h00-9h00) and discharge during the first peak intervals (20h00-0h00) after they are plugged in. Generally, the batteries charge during the periods with cheaper energy prices and discharge when it is more expensive. Nevertheless, it is possible to observe that the EVs and BESS discharge during few periods between the periods that the EVs are charging to supply the demand.

The aggregator does not need to require energy from the grid when the PV generation is equal to or higher than the energy demand from the building. When it is higher, it is possible to see in the graph that the BESS starts its charging process. On the contrary, when the PV generation is not able to meet the demand or when there is no PV generation (night-time), the BESS starts its discharging process to reduce the energy consumed from the grid.

Comparing the five scenarios (a)-(e), the optimization technique adjusts the energy resources scheduling to the selected conservatism/robustness level. The load demand from the apartments and common services remains the same for the five situations. The charge/discharge process of EVs and BESS suffer some alterations due to the variation of the PV generation values according to the level of conservatism defined by the budget of uncertainty.

The aggregator can choose a suitable value of the budget of uncertainty to control the conservatism level of the solution and, consequently, to adjust the robust energy scheduling. It is known that a higher $\Gamma_{PV}\ (t)$ leads to over-conservative solutions and unnecessary costs. With a null value of $\Gamma_{PV}\ (t)$, no PV uncertainty is considered. Accordingly, the aggregator must choose a suitable value between the considered range of the budget of uncertainty, which in this case is $\Gamma_{PV}\ (t) = 0.5$. This way, a compromise between the optimality and the robustness of the solution is achieved.

## 5.4. CONCLUSIONS

This chapter presented the description of a case study and scenarios. Two scenarios have been simulated to compare the PV uncertainty in a cloudy and a sunny day through the implementation of the RO approach. Three different scheduling scenarios are discussed: uncoordinated EV charging scenario (no smart management), coordinated EV charging/discharging scenario, and coordinated EV and BESS charging/discharging scenario. The simulations made for the three scenarios were based on the worst-case scenario, that is the maximum decrease of the PV generation.

According to the results, scenario 1 obtained higher total electricity costs than scenario 2. On the chosen cloudy day, the PV generation profile shows unpredictable fluctuations and, consequently, the uncertainty is bigger than on a sunny day. Also, the aggregator needs to purchase more energy from the grid on a cloudy day, increasing the electricity cost.

The simulation results of scenario 1 illustrate that the coordinate charging/discharging of EVs can reduce the total cost by about 30% compared to the uncoordinated charging mode. Also, the total electricity costs can be further reduced by about 5,5% by using BESS and EVs. The results of scenario 2 present a significant reduction of about 40% from the reference scenario to the scenario of the coordinated charge of EVs. The scenario with the smart management of EVs and BESS present a cost decrease of about 5,2% in comparison to the scenario with only the EVs scheduling. Accordingly, the use of EVs and BESS results in the lowest values of electricity costs, comparing all the scenarios.

Also, the impact of the parameters of a budget of uncertainty on the energy management system scheduling of scenario 2 is analysed. As the value of the budget of uncertainty increases, the total energy costs also increase. When the budget of uncertainty is null, the PV uncertainty is not considered and the model can be considered deterministic, so the scheduling costs are the lowest. When the budget of uncertainty is one, it represents the worst-case scenario (lowest PV generation), which corresponds to the most conservative solution and, consequently, the most expensive. The RO technique adjusts the energy scheduling according to the selected robustness level.

# 6. CONCLUSIONS

This chapter presents a final summary of this thesis and states the main conclusions about the implemented methodology. The main contributions accomplished with this work are summarized. Also, some limitations found along the developed work and a few suggestions for future research work, aligned with the results obtained in this thesis are identified.

## 6.1. FINAL CONCLUSIONS

The penetration of renewable energy sources in energy grids has significantly increased, leading to a transformation in the energy system paradigm. Therefore, it is necessary to develop new coordination mechanisms to assure affordable energy, such as building energy management systems. Smart buildings manage and control their energy system intending to reduce energy costs and improve efficiency, through energy scheduling.

Even though the integration of renewable generation can result in significant cost savings and environmental benefits, it introduces uncertainty to the scheduling problem because photovoltaic generation follows an unpredictable pattern. For this reason, in recent years, uncertainty management has become a research issue in energy scheduling problems and uncertainty modelling techniques have been developed.

This thesis focused on Robust Optimization, a very recent and effective approach to deal with uncertainty. The main purpose of this method is to find the worst-case scenario that the building energy management system might face, focusing on minimizing its impact by obtaining the best solutions among the worst. It guarantees immunity against all possible realizations of the uncertain parameter within the uncertainty bounds. In this case, the worst-case scenario consists of the maximum decrease of the photovoltaic power generation.

The main approach of this work was the development of a day-ahead robust scheduling strategy for the optimal control of building energy management system with solar generation system, electric vehicles, battery energy storage system, and load demand. The robust optimization has been used for energy resources scheduling considering uncertainty in solar power generation.

To deal with the energy scheduling problem, a mathematical model based on a deterministic model (Mixed Binary Linear Programming) was formulated. Then, it was transformed to a robust counterpart, to minimize the daily energy cost but also conferring immunity against the worst-case scenario under the given uncertainty set (upper and lower bounds). The conservatism of the solution can be adjusted by selecting an appropriate value of the budget of uncertainty.

To evaluate the effectiveness and the performance of the proposed method, the robust model was implemented on a practical residential building energy system and two scenarios with three case studies each have been simulated. The scenarios corresponded to the energy scheduling on a cloudy day and on a sunny day, considering the non-smart management of the electric vehicles charging process and the smart management of the electric vehicles and battery energy storage system scheduling charging and discharging.

Simulation results prove that the use of energy storage systems (electric vehicles and a battery) can achieve the lowest electricity costs for both scenarios. In comparison with sunny days, cloudy days present highly unpredictable fluctuations, which increases the inherent uncertainty regarding the photovoltaic generation and, consequently, the energy costs.

The results have demonstrated that the robust model can guarantee immunity against the worst-case scenario, which is the maximum uncertainty of solar power generation. The highest protection against uncertainty is also the most conservative, which leads to higher energy costs but a better risk performance.

The developed robust model in this thesis can be used to address the issue of day-ahead energy resource management, enabling the aggregator to solve the problem with a more conservative perspective about the photovoltaic uncertainty. The results indicate that this technique minimizes the increase of the energy costs caused by uncertainty and also allows a trade-off between the conservatism and robustness of the optimal solution.

## 6.2. CONTRIBUTIONS

In this thesis, it is proposed a robust day-ahead energy scheduling of a residential building energy management system considering the uncertainty of photovoltaic power generation.

The work developed and presented in this dissertation has led to the publication of the following scientific publications:

- Inês Tavares, Ricardo Manfredini, José Almeida, João Soares, Sérgio Ramos, Zahra Foroozandeh, Zita Vale (2021). Comparison of PV Power Generation Forecasting in a Residential Building using ANN and DNN. 11th IFAC Symposium on Control of Power and Energy Systems (CPES 2022) Conference (under review);

- Inês Tavares, Zahra Foroozandeh, João Soares, Sérgio Ramos, Zita Vale (2021). Robust energy scheduling for smart buildings considering uncertainty in PV generation. IEEE PES Innovative Smart Grid Technologies Asia (ISGT-Asia 2021) Conference (under review);

- Inês Tavares, José Almeida, João Soares, Sérgio Ramos, Zita Vale, Zahra Foroozandeh, (2021). Optimizing Energy Consumption of Household Appliances using PSO and GWO. Progress in Artificial Intelligence. EPIA 2021. Lecture Notes in Computer Science, vol 12981. Springer, Cham. https://doi.org/10.1007/978-3-030-86230-5_11

- Sérgio Ramos, João Soares, Zahra Foroozandeh, Inês Tavares, António Gomes (2021). Intelligent resource management in the context of a microgrid of smart buildings. Renewable Energy and Power Quality Journal, 19, 465-470. DOI: 10.24084/repqj19.320

- Sérgio Ramos, João Soares, Samuel Cembranel, Inês Tavares, Zahra Foroozandeh, Zita Vale, Rubipiara Fernandes (2021). Data mining techniques for electricity customer characterization. Procedia Computer Science, 186, 475-488. https://doi.org/10.1016/j.procs.2021.04.168

- Sérgio Ramos, Zahra Foroozandeh, João Soares, Inês Tavares, Pedro Faria, Zita Vale (2021). Shared PV production in energy communities and buildings context. Renewable Energy and Power Quality Journal, 19, 459-464. DOI: 10.24084/repqj19.318

## 6.3. Limitations and Future Work

During the development of this work, some limitations were found. Since Robust Optimization is a very recent technique, there is not much research literature about this topic, especially about its application on buildings' energy management system.

Also, there are some issues that can be further studied and improved in future work:

- Consider the several uncertain factors related to the building energy management system that can influence the energy scheduling and shall be considered, such as the uncertainty in energy consumption and market prices;
- Modification of some building's parameters, for example, consider a bigger number of apartments and electric vehicles and a different battery capacity value;
- Explore other uncertainty modelling techniques and compare to the Robust Optimization;
- Implement the Robust Optimization model using another mathematics programming instead of Mixed Binary Linear Programming, such as Goal Programming or Multi-Objective Optimization.

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