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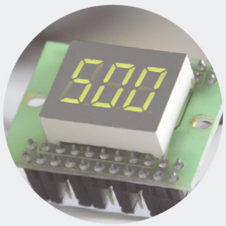

Programação Robusta de Energia para Edifícios Inteligentes considerando a Incerteza em Veículos Eléctricos

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POLITÉCNICO
DO PORTO

ROBUST ENERGY SCHEDULING FOR SMART BUILDINGS CONSIDERING UNCERTAINTY IN ELECTRIC VEHICLES

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“Persistence is the shortest path to success” - Charles Chaplin

Aknowledgement

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Thank you.

Resumo

Nos últimos anos, o consumo de energia tem aumentado juntamente com o crescimento económico e populacional, onde os edifícios representam um dos principais consumidores. Contudo, surgem preocupações a nível ambiental as quais inspiram governos a concentrar-se na concepção de edifícios inteligentes com sistemas de gestão de energia que controlam as fontes de energia renováveis. No entanto, um fator importante a considerar ao lidar com os recursos energéticos é a natureza incerta do seu comportamento. De forma a dar resposta a este desafio, esta tese consiste em propor uma programação ótima dos recursos energéticos baseado na otimização robusta, tendo em conta as incertezas associadas aos veículos elétricos.

A otimização robusta é uma abordagem inovadora e eficaz para resolver problemas de otimização que envolvem incerteza, uma vez que encontra a melhor solução entre os piores cenários possíveis. Inicialmente é formulada uma técnica de Redes Neuronais Artificiais, de modo a lidar com as incertezas. Posteriormente, um problema de Programação Linear Binária é estipulado para reduzir os custos energéticos do edíficio sem considerar incertezas. Numa fase final, o modelo determinístico é transformado num problema robusto, assegurando imunidade contra a incerteza associada aos veículos elétricos.

De modo a simular o modelo de Otimização Robusta foram implementados três cenários diferentes de programação energética com um horizonte de tempo curto. Os resultados apresentaram uma redução de 14.86% no caso do estado da carga inicial, de 6.75% para a hora de chegada e de 14.18% para a hora de partida, revelando que o modelo implementado permite minimizar os custos totais de eletricidade de um edifício, bem como reduzir os problemas associados à incerteza dos veículos elétricos. Além disso, é demonstrado o ajustamento da técnica de otimização robusta de acordo com vários níveis de robustez.

Palavras-Chave

Estado da Carga Inicial, Fontes de Energia Renováveis, Hora de Chegada, Hora de Saída, Incerteza dos Veículos Elétricos, Problema da Otimização Robusta, Sistema de Gestão de Energia de Edifícios.

Abstract

In recent years, electricity consumption has increased along with economic and population growth, with buildings representing one of the main consumers. However, environmental concerns are emerging and inspiring governments to focus on designing intelligent buildings with energy management systems that control renewable energy sources. However, an important factor to consider when dealing with energy resources is the uncertain nature of their behavior. To address this challenge, this thesis proposes optimal scheduling of energy resources based on robust optimization, taking into account the uncertainties associated with electric vehicles.

Robust optimization is an innovative and effective approach for solving optimization problems involving uncertainty since it finds the best solution among the worst-case scenarios. Initially, an Artificial Neural Networks technique is formulated to deal with uncertainties. Afterward, a Binary Linear Programming problem is stipulated to reduce the energy costs of the building without considering uncertainties. In the final step, the deterministic model is transformed into a robust problem, ensuring immunity against the uncertainty related to electric vehicles.

To simulate the Robust Optimization model, three different energy scheduling scenarios with a short time horizon were implemented. The results showed a reduction of 14.86% for the initial State Of Charge (SoC), 6.75% for the arrival time, and 14.18% for the departure time, revealing that the implemented model allows for minimizing the total electricity costs of a building, as well as reducing the problems associated with the uncertainty of electric vehicles. In addition, the adjustment of the robust optimization technique according to various levels of robustness is demonstrated.

Keywords

Arrival Time, Building Energy Management System, Departure Time, Initial State of Charge, Renewable Energy Sources, Robust Optimization Problem, Uncertainty of Electric Vehicles.

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Acronyms and Abbreviations

AEVs	–	All-Electric Vehicles
ANN	–	Artifitial Neural Network
BAPV	–	Building-attached Photovoltaic
BEMS	–	Building Energy Managemnt System
BENEFICE	–	Building Resources Management towards flexible Contracted Power
BESS	–	Battery Energy Storage System
BEV	–	Battery Electric Vehicle
BIPV	–	Building-Integrated Photovoltaic
CAES	–	Compressed Air Energy Storage
CP	–	Contract Power
CS	–	Common Service
ERSE	–	*Entidade Reguladora dos Serviços Energéticos*
ESS	–	Energy Storage System
EVs	–	Electric Vehicles
FES	–	Flywheel Energy Storage
FCEV	–	Fuel Cell Electric Vehicle
Full-HEV	–	Full Hybrid Electric Vehicle

GECAD	–	Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development
GHG	–	GreenHouse Gas
HEVs	–	Hybrid Electric Vehicles
HVAC	–	Heating, Ventilating and Air Conditioning
IGDT	–	Information Gap Decision Theory
IoT	–	Internet of Things
LP	–	Linear Programing
MAE	–	Mean Absolute Error
MILP/MBLP	–	Mixed Integer/Binary Linear Programming
MINP/MBNP	–	Mixed Integer/Binary Non-Linear Programming
nRMSE	–	normalized Root Mean Square Error
NLP	–	Non-Linear Programing
PF	–	Probability Function
PHEV	–	Plug-in Hybrid Electric Vehicle
PHS	–	Pumped Hydroelectric Storage
PV	–	Photovoltaic
RES	–	Renewable Energy Sources
RMPC	–	Robust Model Predictive Control
RO	–	Robust Optimization
SBs	–	Smart Buildings

SMAPE	–	Symmetric Mean Absolute Percentage Error
SMES	–	Electromagnetic Energy Storage
SNG	–	Synthetic Natural Gas
SO	–	Stochastic Optimization
SoC	–	State of Charge
SP	–	Stochastic Programming
V2B	–	Vehicle-to-Building
V2G	–	Vehicle-to-Grid
V2H	–	Vehicle-to-Home
WAPE	–	Weighted Absolute Percentage Error
WT	–	Wind Turbine

Nomenclature

Notation		Description
$\mathbb{I}$	–	Set of time-setp numbers
$\mathbb{J}$	–	Set of EV/apartment numbers
$\mathbb{D}$	–	Set of day numbers
I	–	Number of time-steps per time-study
τ	–	Time-setp duration
J	–	Number of EVs/apartments in the building
D	–	Number of days per time-study
$T_{EV}^{in}(i,j)$	–	Actual value when EV *j* arrives at the parking in period *i*
$T_{EV}^{out}(i,j)$	–	Actual value when EV *j* leaves the parking in in period *i*
$SoC_{EV}^{initial}(i,j)$	–	Actual value of initial SoC of EV *j* at the beginning of the departure of each period *i*
$\widehat{T_{EV}^{in}}(i,j)$	–	Forecasted arrival time output of EV *j* in period *i*
$\widehat{T_{EV}^{out}}(i,j)$	–	Forecasted departure time output of EV *j* in period *i*

$\widehat{SoC_{EV}^{initial}}(i,j)$	–	Forecasted initial SoC output of EV *j* in period *i*
$\Delta T_{EV}^{in}(i,j)$	–	Deviation from the forecasted values of arrival time output of EV *j* in period *i*
$\Delta T_{EV}^{out}(i,j)$	–	Deviation from the forecasted values of departure output of EV *j* in period *i*
$\Delta SoC_{EV}^{initial}(i,j)$	–	Deviation from the forecasted values of initial SoC output of EV *j* in period *i*
$\underline{T_{EV}^{in}}, \overline{T_{EV}^{in}}$	–	Lower bound and upper bound of arrival time forecast
$\underline{T_{EV}^{out}}, \overline{T_{EV}^{out}}$	–	Lower bound and upper bound of departure time
$\underline{SoC_{EV}^{initial}}, \overline{SoC_{EV}^{initial}}$	–	Lower bound and upper bound of initial SoC forecast
$\Gamma_{(j)}$	–	Budget of uncertainty
$\lambda^{\underline{SoC_{EV}^{initial}}}, \lambda^{\overline{SoC_{EV}^{initial}}}$	–	Dual variables of initial SoC uncertainty
$PD_{SB}\ (i,j)$	–	The total power demand of SB at period *i*
$PD_{CS}\ (i)$	–	The total power demand of common services at period *i*
$PG_{PV}\ (i,j)$	–	The total power generated by PVs at period *i*

$P_G^{max}(i)$	–	Maximum power from the external power grid at period *i*
$C_G^{buy}(i, CP)$	–	Cost of electricity purchased from the external power grid in period *i*
$C_G^{sell}(i)$	–	Cost of electricity sold to the external power grid in period *i*
$P_{M \to G}\ (i)$	–	Power from manager to the grid in period *i*
$P_{G \to M}\ (i)$	–	Power from the grid to manager in period *i*
$SoC_{EV}^{max}(j)$	–	Maximum allowable SoC of EV *j*
$SoC_{EV}^{min}(i, j)$	–	The minimum allowable SoC for EV *j* at departure time
$\eta_{EV}^{ch}(j)$	–	Efficiency charge of EV *j*
$\eta_{EV}^{diss}(j)$	–	Efficiency discharge of EV *j*
$AP_{EV}^{ch}(j)$	–	Active power related to the charging process of the EV *j*
$AP_{EV}^{diss}(j)$	–	Active power related to the discharging process of the EV *j*
$\alpha_{EV}\ (i, j)$	–	Binary variable that represents EV*j* charging process in period *i*

$\beta_{EV}\ (i,j)$	–	Binary variable that represents EV*j* discharging process in period *i*
$SoC_{EV}\ (i,j)$	–	SoC of EV *j* in period *i*
$P_{M \to EV}\ (i,j)$	–	Power from manager to EV j in period *i*
$P_{EV \to M}\ (i,j)$	–	Power from EV *j* to manager in period *i*
$SoC_{BE}^{initial}$	–	Initial SoC of BESS at the beginning of period *i*
SoC_{BE}^{max}	–	Maximum SoC of BESS
SoC_{BE}^{min}	–	Minimum SoC of BESS
$AP_{BE}^{ch}(i)$	–	Active power related to the charging process of the BESS in period *i*
$AP_{BE}^{diss}\ (i)$	–	Active power related to the discharging process of BESS in period *i*
η_{BE}^{ch}	–	Efficiency charge of BESS
η_{BE}^{diss}	–	Efficiency discharge of BESS
$\alpha_{BE}\ (i)$	–	Binary variable that represents BESS charging process in period *i*

$\beta_{BE}\ (i)$	–	Binary variable that represents the BESS discharging process in period *i*
$SoC_{BE}\ (i)$	–	SoC of BESS in period *i*
$P_{M \rightarrow BE}\ (i)$	–	Power from manager to BESS in period *i*
$P_{BE \rightarrow M}\ (i)$	–	Power from BESS to manager in period *i*

1. INTRODUCTION

This chapter presents a brief contextualization of the project developed, introducing the motivation that led to the development of the main topic, as well as the main objectives to be taken into consideration. In the end, it is also mentioned the document organization, which will summarize each chapter that will appear afterward.

1.1. MOTIVATION

The work carried out for the development of this document was done in collaboration with the Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development (GECAD), within the Building Resources Management towards flexible Contracted Power (BENEFICE) project. The BENEFICE project[1] aims to solve the problem formulation for optimal energy resource management considering the contracted power flexibility by integrating renewables in residential buildings. Therefore, this thesis emerged from the need to optimize the scheduling of energy resources in Smart Buildings (SBs) while taking into account the uncertainties associated with Electric Vehicles (EVs).

[1] http://www.gecad.isep.ipp.pt/BeNeFiCE/home/

In recent years, energy consumption has increased, with buildings representing one of the main consumers. However, environmental concerns are emerging that inspire governments to focus on designing Buildins Energy Management Systems (BEMS) that control Renewable Energy Sources (RES). The fundamental goal of the various forms of energy resources, such as Photovoltaic (PV), and Energy Storage Systems (ESS), such as EVs and Battery Energy Storage Systems (BESSs), found in buildings is to maximize the flexibility of contracted power, resulting in a large reduction in energy costs [1]. However, the deployment of BEMS has led to a major problem due to the unpredictability of EVs.

Due to the intermittent nature of RES, forecasting techniques are needed to predict electricity production. Nonetheless, these predicted values are not accurate due to the uncertainties associated with electric vehicles. The management of energy resources in residential buildings has been a prominent topic in the literature [1]. Few, on the other hand, fail to mention the uncertainty of integrating EVs into buildings [2]-[3].

The development of optimization techniques and energy resources management will be crucial to increase the efficiency of energy consumption in building. It is predicted to reduce electricity costs significantly and promote effective energy use.

This dissertation proposes the integration of EVs for self-consumption and storage systems in residential buildings. This work will require an energy resource management system, taking into account the uncertainty related to EVs in the residential building to enable efficient scheduling of a building's energy resources and thereby reduce energy costs.

1.2. Objectives

The major goal of this thesis is to find the optimal scheduling of energy resources in the SB by considering the uncertainties in EVs. In this regard, the optimization models concerning energy management for SB and uncertainty in EVs must be developed and implemented to reduce electricity consumption expenses.

The objectives outlined for this thesis are the following:

- Demonstration of the relevance of energy resources for a residential building;
- Demonstration of the importance of a smart building with a management system;

- Consideration of the uncertainty associated with the penetration of EVs in buildings;
- Consideration of various strategies for optimizing energy resources, taking into account uncertainty;
- Implementation of the methodology and mathematical formulation of the models used;
- Development of a case study, through simulations of scenarios, and consequently analysis and discussion of the results.

1.3. DOCUMENT ORGANIZATION

This document's architecture consists of six (6) main chapters:

1. The first chapter concerns the introduction, where a brief contextualization of the project is made, motivations are displayed as well as the work planning and the identification of the objectives to be met;
2. The second chapter contains a theoretical background detailing the various themes that will be held within the proposed work. These topics mainly focus on dealing with the problem of EV uncertainty in SB, defining which optimization method is best to deal with such uncertainty;
3. The third chapter presents the proposed methodology and the mathematical formulation of the optimization problem implemented in this work;
4. The fourth chapter provides the case study, concerning the scenarios created to put the stated methodology into practice. Also, a description of the building and the problem statement are detailed;
5. The fifth chapter displays the analysis and discussion of the results obtained throughout the process;
6. The last chapter concerns the main conclusions drawn from this work. In addition, an improvement for future work is also presented.

2. THEORETICAL BACKGROUND

This chapter presents a review of the state of the art regarding the topic of the proposed work. It introduces the theoretical part of the work within the scope of energy resources in buildings, smart buildings and their management, electric vehicles uncertainty, vehicle-to-grid variants, and optimization models under uncertainty.

2.1. ENERGY RESOURCES IN BUILDINGS

The main purpose of this chapter is to present the different types of energy resources typically found in buildings that are handled by a management entity to optimize energy production and consumption.

2.1.1. PHOTOVOLTAIC POWER GENERATION

Solar energy is a type of renewable energy which is directly produced by the sun in form of heat and light. Since the total amount of incident solar energy is unlimited, it has the advantage of having an inexhaustible supply and a non-polluting character [4].

PV solar energy is one of the best-known technologies and represents the direct conversion of the sun's energy into thermal or electrical energy. Thus, solar energy technologies can harness this energy for a variety of uses, such as generating electricity or heating water for domestic use [4].

In the case of electrical energy, when solar energy is converted into electrical energy, it does through the use of PV panels. PV panels are made of cells consisting of semiconductor materials. When the sunlight hits these cells, electrons are released and flow through the cell generating electricity. This is due to the photovoltaic effect, which is defined as a potential difference at the extremities of a semiconductor material structure as a result of sunlight absorption [5].

PV solar energy has no substantial environmental impact and can help offset the consequences of GreenHouse Gas (GHG) emissions and global warming. Nevertheless, PV has a high initial installation cost and relies on geographical conditions, particularly where solar radiation is scarce [6].

Currently, the usage of RES in buildings, notably PV panels, is rapidly increasing, helping to supply the building's required electric power. From 2012 through 2021, Figure 1, from [7] depicts total national energy production from each renewable source, where PV production appears to be increasing, mainly in 2021 [7].

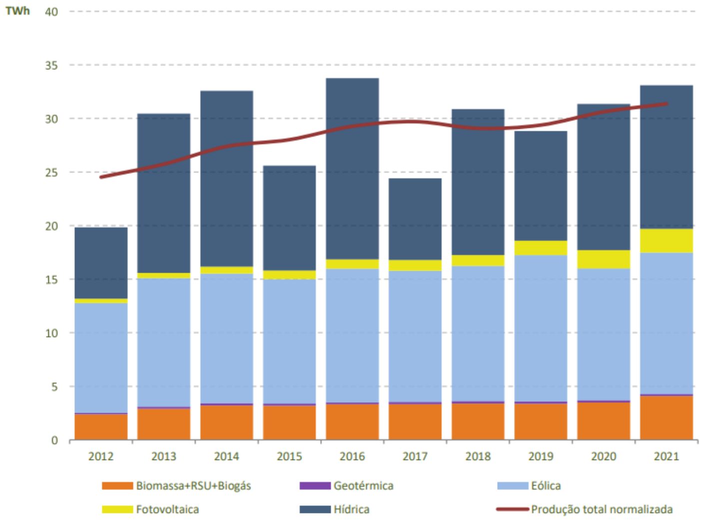

Figure 1 Evolution of renewable electricity generation in Portugal, 2012 to 2021 [7]

The photovoltaic system can be implemented in a building to allow consumers to generate power in their homes by using the electricity produced by the panels for self-consumption instead of using energy provided by the grid [5].

Figure 2, from [8], represents a grid-connected PV system in a building. The basic system consists of photovoltaic panels, an inverter, an electricity meter, and the power grid itself. The electricity produced by the photovoltaic panels is made available in direct current. This current goes to an inverter installed between the panels and the building. Depending on the function of the solar system, this energy is subsequently transmitted in alternating current to the grid after passing through the inverter [8].

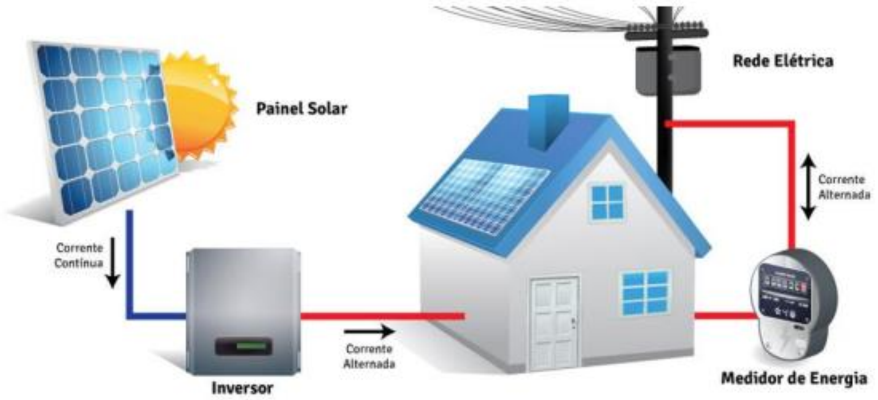

Figure 2 Grid-connected Photovoltaic System [8]

There are two techniques to include PV on buildings: (1) Building-attached PV (BAPV) systems and (2) building-integrated PV (BIPV) systems. BAPV systems are installed on the surface of finished roofs or walls and do not contribute to the structural integrity of the building. BIPV systems, on the other hand, are installed as roofing panels and glass curtain walls, and thus have a direct impact on part of the structure's function by replacing traditional building components like the roof [9]-[10]. Figure 3, from [10] depicts the numerous applications of panels in a building.

Figure 3 Applications of panels in a building [10]

2.1.2. ENERGY STORAGE SYSTEMS

As more renewable energy is created, energy storage, particularly grid-scale electrical energy storage, becomes more relevant and appealing. As a result, finding and implementing cost-effective and sustainable energy storage and conversion systems is essential [11].

ESS devices have become increasingly important in the energy-producing industry. This is because their performance influences the system's efficiency as well as its operating costs. ESS consists of converting one type of energy into another, and, when required, it can return the stored energy in a more efficiently manner. As there is a wide variety of energy production technologies, ESS can also have a wide range of applications [11]-[12].

The most prevalent types of ESSs include mechanical storage systems, chemical storage systems, electrochemical storage systems, and thermal storage systems, which are classified in detail in Figure 4 adapted from [11]-[13]. The type of energy to be stored dictates the sort of storage device that is appropriate for the job.

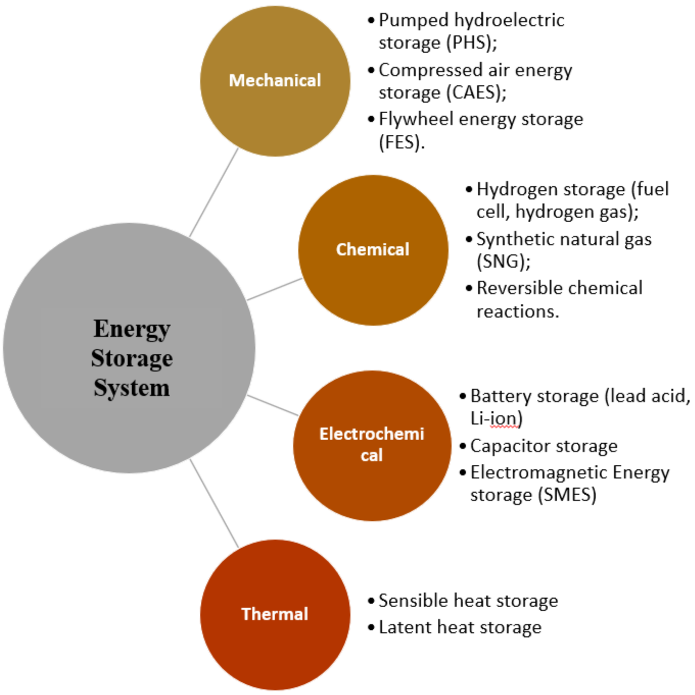

Figure 4 Types of energy storage systems, adapted from [11]-[13]

Among these storage technologies, alternatives like Pumped Hydroelectric Storage (PHS) should also be promoted because they are the most efficient and capable of quickly generating large amounts of energy. Moreover, PHS have a lower environmental impact when compared to other forms of batteries. The installed capacity for ESS is depicted in Figure 5, from [13].

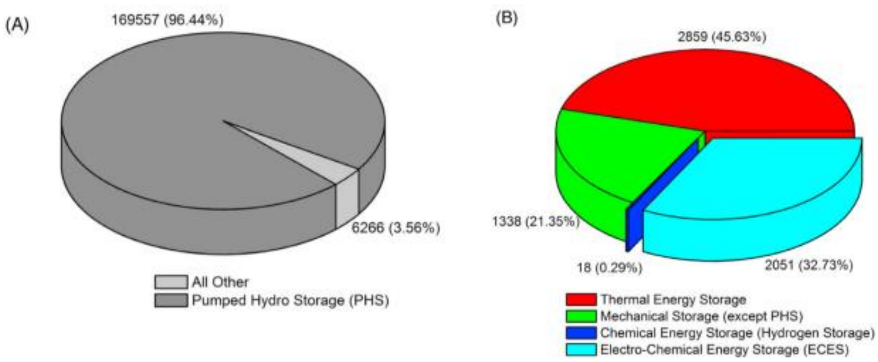

Figure 5 Capacity for energy storage systems [13]

Concerning electrochemical storage systems, batteries of various types and sizes are considered to be one of the most suitable approaches to storing energy. There are several storage technologies represented in Figure 6 from [11]. Batteries come in several forms:

(1) primary batteries; (2) secondary batteries, and (3) battery systems for grid-scale energy provision. The last one has examples such as flow batteries, sodium-sulfur batteries, fuel cells, and electrochemical capacitors are the five categories of batteries. Lithium-ion is the most used form of battery energy storage systems (BESS), accounting for 55% of the global market [11]-[14].

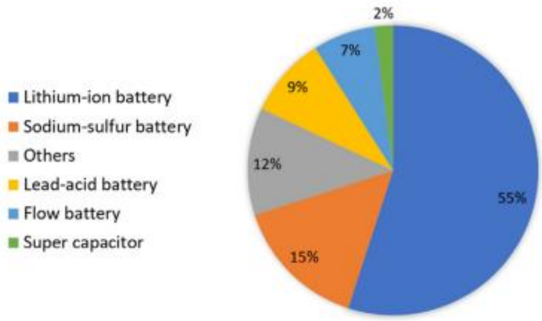

Figure 6 Global battery energy storage system installed capacity [11]

Batteries are efficient, convenient, trustworthy, and simple-to-use energy storage solutions. Additionally, battery shelf life and use life are limited since they are made from many different raw materials, including metals and non-metals. However, the battery industry can produce significant amounts of environmental pollutants, such as greenhouse gas emissions, and toxic gases during various processes (manufacturing, transportation, storage, treatment, and recycling) [11].

One of the main causes of global warming is GHG emissions from electricity production using fossil fuels to meet daily energy demands. RES has been replacing fossil fuels to address this problem and achieve carbon neutrality. However, the high penetration of RES in the grid leads to a significant waste of electrical energy when production exceeds consumption by causing problems of instability in the electrical grid [13]. To avoid energy waste and provide grid flexibility, ESS can support the integration of renewable energy by balancing the power flow in the network, storing energy when demand is low, and releasing it when demand is high [15]-[16].

ESS are being critical for reducing peak building energy consumption and increasing the usage of renewable energy in buildings and communities. The combination of several types of ESS will be the most effective and appropriate approach to reduce both the amount of electricity produced and the amount of carbon released into the atmosphere during power generation. Since not all generated electricity is used, storing excess energy during off-peak hours can considerably improve system reliability and allow it to meet varied power demands throughout the day [1].

The ESS must be properly controlled, providing a suitable thermal environment for the inhabitants to achieve excellent system performance. However, since ESS faces difficulties in saving costs while providing thermal comfort, establishing the appropriate charging period for a storage system may be problematic. As a result, the decision process should be able to estimate both loads and renewable energy generation [15].

2.1.3. ELECTRIC VEHICLES

The automotive industry is undergoing a transformation affected by climate change and the growing demand for independence from oil, which is until now the primary carrier source in the transportation sector. The dangerous impact of GHGs released by fossil fuels has raised concerns on a variety of levels, including economic, environmental, and industrial [3]. This situation is currently changing, and electricity is increasingly becoming the preferred energy vector for the next generation of road vehicles, and politicians are looking for ways to replace fossil-fuel-based vehicles with EVs [17]-[18].

Significant breakthroughs in battery technology have been made. EVs use batteries, ultra-condensers, and fuel cells as energy sources, rather than fossil fuels, and hence do not create polluting emissions. These sources can be used separately or collectively in an EV, depending on the type of EV [3].

EVs can be divided into two main categories: (1) hybrid electric vehicles (HEVs); and (2) all-electric vehicles (AEVs) [19]. HEVs are equipped with both electrical and internal combustion motors, while AEVs are equipped with only electric motors powered by electrical grids. Figure 7 was adapted from [19] presenting the classification of these different types of EVs.

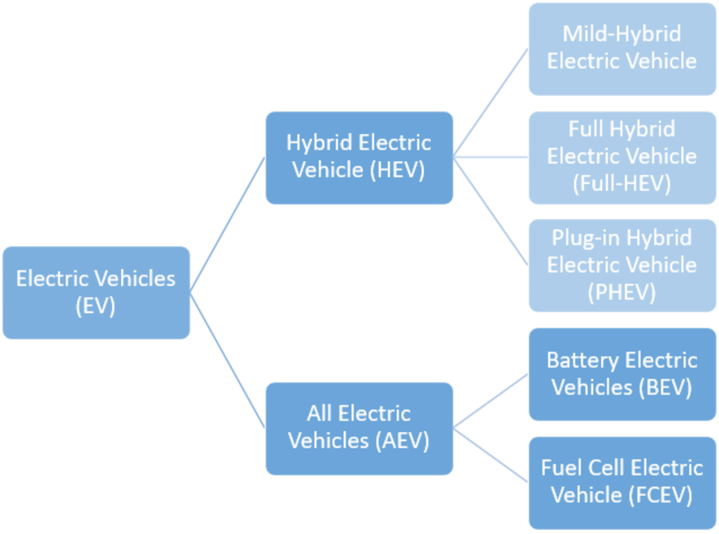

Figure 7 Classification of different types of EVs [19]

When plugged into a charging station or outlet, these EVs store energy in their batteries, which are subsequently utilized by the electric engine. The amount of time it takes for an EV to charge is determined by its storage capacity, the amount of power it can receive, and the amount of energy delivered by the charging station [19].

A growing EV market has resulted in a substantial number of EV charging stations. The charging stations can be divided into two categories: residential and non-residential, and they can support slow or fast charging. In this approach, procedures are targeted at putting recharge stations in residential buildings to reduce pollution and noise, as well as fossil fuel usage [20].

While EVs are parked, they remain connected to the grid and deliver energy from their batteries, which may store and release energy under varying conditions. The usage of EVs in buildings with RES can shift peak-hour demands to off-peak hours cycles. On this matter, either the RES can charge the EV, or the EV battery can act as an ESS, discharging energy. For instance, when energy production exceeds overall demand, the EV charges the batteries. On the other hand, when the building is insufficiently powered, the EV releases stored energy to power the building [21]. However, because of the uncertainties in this paradigm, the integration of RES and EV will have an impact on the planning and operation of power networks. By minimizing the degree of uncertainty, information about EVs' might eventually lead to better grid planning and operation.

2.2. BUILDINGS

Buildings account for 40% of total energy consumption in the European Union, 40% of greenhouse emissions, and 70% of the electricity used in industrialized countries [21]. They utilize more energy than transportation or industry, with heating/cooling, lighting, and electrical appliances accounting for the majority of this. As a result, buildings represent one of the main important energy consumers in cities. Buildings are increasingly required to respond dynamically to changing user needs and/or limited circumstances, both external, such as climate and grid prices, and internal, such as occupant needs [22].

Nowadays, buildings are undergoing a transformation from being immobile to being highly efficient in terms of using, producing, storing, and supplying energy. To cover their energy consumption, boost energy savings, and reduce expenses, buildings must be able to minimize their energy demand and generate renewable energy. Researchers are focusing their efforts on developing SB and building energy management systems (BEMS) that use RES due to concerns about carbon dioxide and greenhouse gas emissions [1], which will be detailed in the following subchapters.

2.2.1. SMART BUILDINGS

The concept of SB was introduced by the Energy Performance Building Directive, as the main enabler for the future of the electric sector. The main goal of SB is to promote renewable energy production, user interaction, and energy flexibility, by allowing the ability of a building to manage its energy consumption and production without compromising the comfort and safety of its occupants [22].

When compared to standard buildings, SB has five basic characteristics: (1) Automation, with the ability to accommodate automatic devices; (2) Multi-functionality, with the ability to allow the performance of more than one function in a building; (3) Adaptability, with the ability to learn and satisfy the needs of users; (4) Interactivity, with the ability to allow the interaction among users, and (5) Efficiency, having the ability to provide energy efficiency and save time and costs [23].

As a first step towards identifying and describing the SB's important qualities, the latter were classified into four primary functions, which serve as macro-categories that specify the features that an SB must have [22]. SB can (1) monitor and control RES, (2) adjust to grid conditions, (3) interact with other buildings, and (4) respond quickly to any change in the building's technical system or the external environment, as well as the energy needs of its occupants. These four primary functions are represented in Figure 8, from [22].

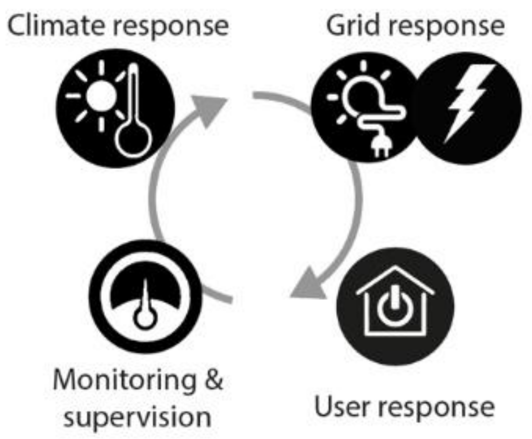

Figure 8 SB primary functions [22]

The most important key technologies related to the functions of SBs are categorized in Figure 9, from [22]. In an SB hundreds of elements should be considered, including control systems, sensors, actuators, smart meters, renewable energy systems, Heating, Ventilating, Air Conditioning (HVAC) systems, ESS, and EVs [22].

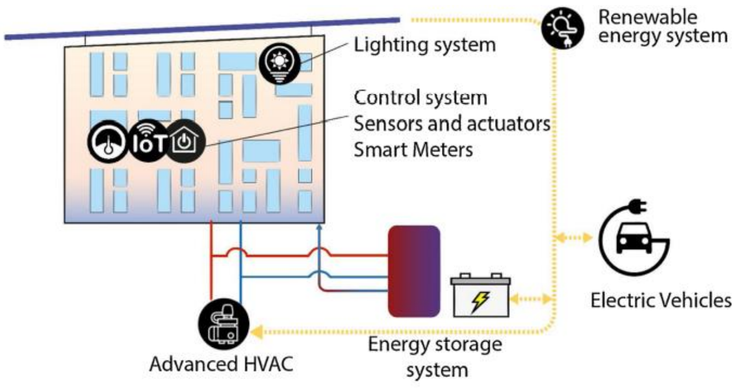

Figure 9 SB key technologies [22]

Advancements in the Internet of Things (IoT) have turned buildings more intelligent and efficient. Sensors, actuators, and microchips are examples of IoT devices that can be used for this improvement. These IoT devices generate a large amount of data that may be filtered, analyzed, and utilized to evaluate consumption habits and, therefore, improve a building's energy efficiency and occupant experience [24].

SB's other key purpose is to remove inefficient energy conversion losses and efficiently integrate distributed RES. This requires a holistic approach that considers the energy production and consumption system as a single unit. As illustrated in Figure 10, adapted from [25], since RES can be implemented in SB, on the system's supply side there is a PV installed to provide energy and meet a portion of the building's power demand. Moreover, BESS gives incredible prospects for SB efficiency, and operation by improving the reliability, security, and resiliency of micro-grid applications [21]. It is considered to be a good way to balance generation and demand by supporting renewable energy deficits when needed and storing primary energy surpluses when possible.

On another hand, from the demand side of the system, EVs and some heating appliances, like HVAC systems are considered some of the largest and most common energy-consuming loads in the residential sector [22]. EVs act as storage devices or as an additional flexibility element to provide energy and capacity to the building and enhance power supply. However, EVs present some uncertainties associated with their scheduling, which will be discussed afterward [21].

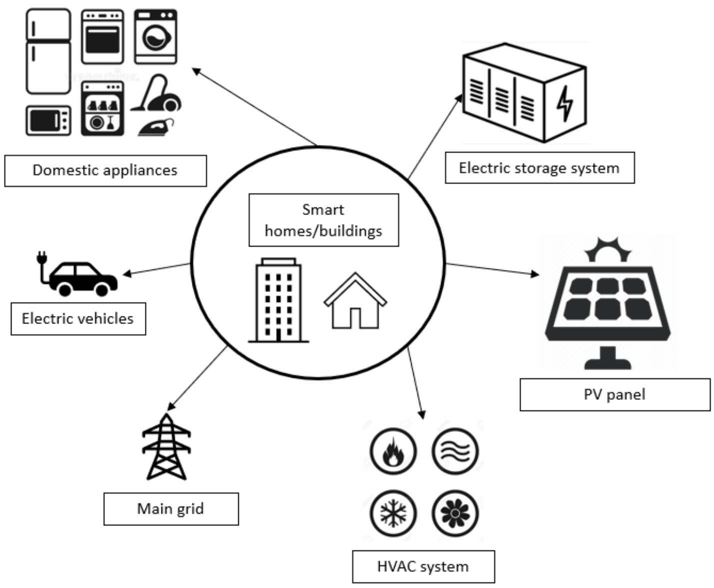

Figure 10 SB system's operation [25]

It is known that the system's operation is influenced by both energy production and consumption units. When the amount of produced energy is insufficient to meet the demand, the requirement for grid-supplied energy increases. On the other hand, when the amount of produced energy is sufficient, the grid does not give any power [25].

2.2.2. BUILDING ENERGY MANAGEMENT SYSTEMS

One of the main elements of SB is BEMS, which must seek energy efficiency as well as smart grid integration, by combining measures to increase a building's energy efficiency and conservation. BEMS must perform important energy management functions such as energy cost optimization, energy supply information monitoring, automatic control, automated demand response, and energy use anomaly detection [21].

BEMS are a great tool for efficiently managing electrical energy. As mentioned before, PV energy, ESS, and EV are all examples of energy resources that can be found in residential buildings [1]. The amount of energy generated by PVs is directly proportional to the amount of sunlight and meteorological conditions. As a result, scheduling the use of BESS and EVs in the context of SB could be beneficial for energy management, particularly when PV is generating electricity [26].

BEMS should consider data gathering for electricity generation and consumption, enabling the management of predicting data for the time. The flexible control of the building energy system must maintain appropriate thermal and visual comfort levels for occupants, as the BEMS' first obligation is to offer a comfortable and productive environment [27]. During the allocated time window, the charging requirements of EVs must also be met. As a result, not only the electric cycle and thermal dynamics are incorporated in the modeling of the BEMS to assess the building's flexibility potential, but also the internal environment comfort and inhabitants' preferences [27].

2.3. ELECTRIC VEHICLES UNDER UNCERTAINTY

When dealing with EVs', one important factor to consider is the unpredictability that unavoidably impacts their behavior, such as arrival time (when the vehicle is connected to the grid), departure time (when the vehicle is disconnected from the grid), the initial battery's State of Charge (SoC at arrival times), and the demanded energy to be charged [28]. In the actual world, the initial SoC of an EV does not always have a linear relationship with the daily driving distance. They make the uncertain model of EV charging behaviors too ideal [2]. Furthermore, while studies have taken into account various uncertainties in terms of arrival times, departure times, and daily driving distance, these are not the only sources of charging behavior uncertainty. Uncertainties are also generated by the final SoC (SoC when an EV is disconnected from the grid) and by the types of charging stations (fast or slow charging), which are not that common to be considered uncertainties [28].

The batteries of EVs can be charged using both regenerative braking and the connection of the electrical grid. However, this last one is by far the most important source of energy for EVs. As a result, EVs are extremely reliant on the electricity grid, posing a risk to the power grid's operation. To mitigate these consequences, both the transmission and the distribution grid systems must be integrated and smart [3]. Since an EV's driving range is limited and its battery should be charged before it runs out, users may need to charge their vehicles away from home. The lack of sufficient publicly accessible charging stations is one of the barriers to EV adoption. As a result, the ideal design of a charging station network that provides consumers with easy and convenient access is critical [17]. On this matter, strategies are targeted in this approach at installing recharge stations in residential buildings.

Uncontrolled EV charging poses a major danger to numerous network factors, including reliability, efficiency, and power quality. As a result, charging and discharging preferences must be adhered to a set of guidelines and rules. The amount of energy that is injected into the system should be determined by the needs of the customers. Periods of charging and discharging must occur at different times, which can allow for conciliatory methods such as charging batteries during low-consumption periods and discharging them during high-consumption periods [20]. Furthermore, EVs' large spatial and temporal variability has made charging management more difficult.

Modeling of uncertainties associated with EV usage is critical for EV coordination. These uncertainties, if not adequately managed, may result in drawbacks, degrading performance, or triggering grid difficulties [2].

2.4. VEHICLE-TO-GRID, VEHICLE-TO-HOME AND VEHICLE-TO-BUILDING

EVs can play a key role in ensuring grid stability, reducing power outages, and increasing global energy efficiency. Existing power systems may not be able to handle the increased electrical consumption required by a large number of EVs. In simple terms, in the presence of high EV penetration, safety and technical limits may be violated [2].

An EV battery is considered insufficient for operation when it reaches 70% to 80% of its original storage capacity, in this case, vehicle-to-grid (V2G) services can be deployed [29]. This technology allows users to take control of their stored EV energy and trade it for a monetary reward, by injecting power into the power grid at appropriate times [30]. Since EVs can be found in a variety of locations, their batteries can be employed as a rolling accumulation system, allowing peak reduction, as well as absorbing or giving energy to the grid, as needed at any given time [17][31].

Combining the use of V2G with its variants, such as vehicle-to-home (V2H), and vehicle-to-building (V2B) will contribute to an increase in the number of EVs in transport and ensure a stronger coupling between energy generation and consumption. In addition, it promotes global energy efficiency as well as improves the energy performance of buildings [30].

V2H technology allows an EV to be used to directly power a household. On the other hand, V2B technology has grown in popularity in recent years as a result of numerous EV acquisitions and its importance in grid regulation, stability, and carbon reduction. This technology is a combination of V2H and V2G and offers significant benefits to EV owners and property owners. The concept revolves around the use of EVs as rolling storage, which allows for the introduction of a large amount of electrical storage into the grid network without any additional investment and with the added benefit of flexibility and mobility [30]. V2H and V2B are two-way systems that allow energy to be injected from an EV into the grid and vice versa. Additionally, they assist residential and commercial energy use, whilst V2G responds to grid circumstances.

Figure 11, from [30] depicts a simplified flow diagram of the procedure for supplying energy to the building for a better understanding of the idea. The V2B method begins with the calculation of the building's energy demand, followed by the usage of a battery charging and discharging model with fixed parameters. The SoC is calculated to achieve the maximum depth of discharge, which ensures that there is enough energy for the journey without harming the battery [30].

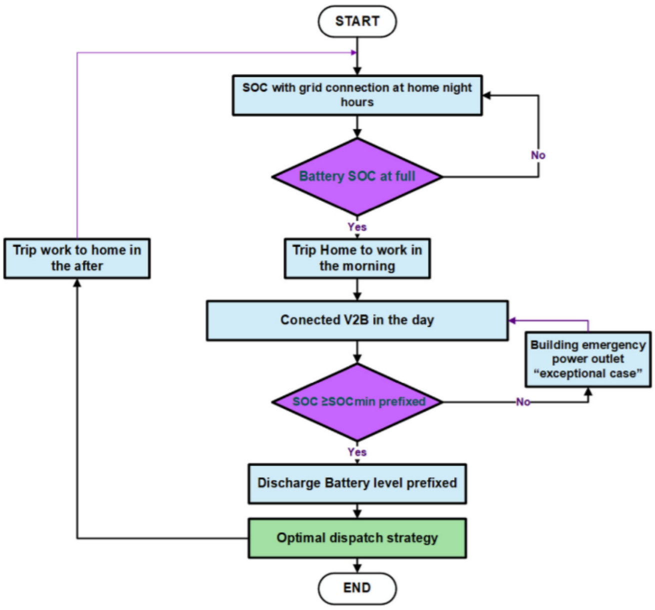

Figure 11 V2B flow diagram for supplying energy to the building [30]

If the building is powered by stored electrical energy during peak hours when the energy is more expensive, the overall cost is lower and additional benefits, such as reduced peak demand, are realized. The results reveal that the building's carbon footprint is dramatically reduced, the maximum demand is up to 50% lower than typical during peak hours of the day, and the plan is lucrative for both employers and employees [30].

This demonstrates that these energy transfer technologies are technically feasible, and the advantages are substantially bigger. The EV must be included as a very important factor in energy dynamics in new energy management models and frameworks. Furthermore, it has been demonstrated that V2B may be used to provide flexibility without impacting the usual functionality of any building [30].

2.5. OPTIMIZATION UNDER UNCERTAINTY

This chapter discusses how to deal with uncertainty in optimization problems using uncertainty modeling techniques. The drawbacks of Stochastic Optimization (SO) and the advantages of using Robust Optimization (RO) to deal with uncertainty are also mentioned, as well as the RO proposed model.

2.5.1. UNCERTAINTY MODELING TECHNIQUES

Since it is nearly impossible to predict the exact value of some parameters in the real world, the results may differ from those expected. Uncertainty, which is linked to data forecasting, is one of the key problems of BEMS since it can influence decision-making. Uncertainty arises from a lack of sufficient and accurate data as a result of prediction, implementation, and measurement errors. Since RES are intermittent, it requires complicated power system planning. As the use of renewable energy grows, so does the level of uncertainty connected with power networks. As a result, uncertainty modeling is critical [32].

Hence, various methods for modeling uncertainty have been developed for power systems. The traditional and deterministic approaches in power systems, such as Mixed Integer Linear Programming (MILP) model, do not consider uncertainty in the data. On the other hand, uncertainty can be classified into three categories: (1) Randomness, when a probability distribution of previous data can be found; (2) Epistemic, when the available data is insufficient, or the probability distribution drawn from past data is unreliable for the future; and (3) Deep uncertainty, associated with a lack of information, making it impossible to extract a probability distribution [32].

Figure 12 shows a review of different types of uncertainty and associated modeling methodologies based on [33]. The current methods for modeling uncertainty include a broad variety, such as (1) probabilistic methods, like Stochastic Optimization (SO); (2) possibilistic methods (e.g., fuzzy approach or metaheuristics); (3) hybrid methods; (4) Information Gap Decision Theory (IGDT), such like risk averse; (5) Robust Optimization (RO); and (6) interval analysis [33].

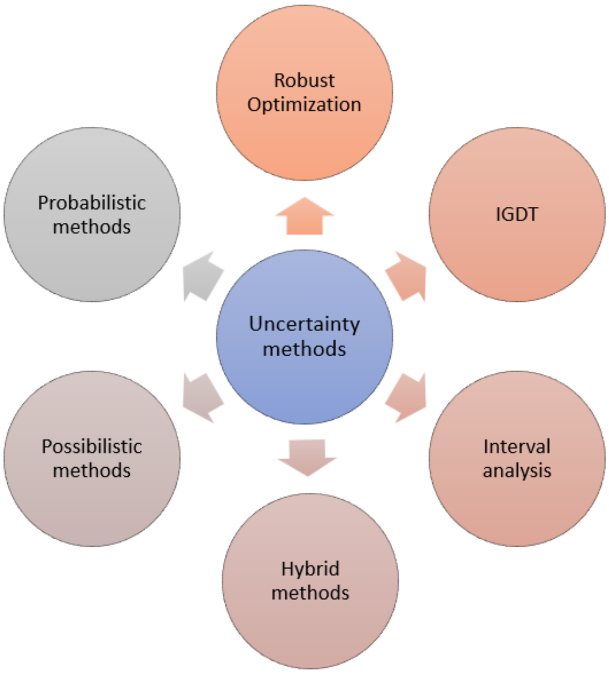

Figure 12 Different types of uncertainty methodologies [33]

It has been possible to compare these methods, highlighting their advantages and disadvantages summarized in Table 1 adapted from [33]-[34].

Table 1 Optimization methodologies when dealing with uncertainty [33]-[34]

Methodologies	Functionality	Disadvantages
MILP	Can limit the search space by employing the given set of rules and constraints and simultaneously optimizing the solution.	Lacks the ability to think socially, randomness in search is very high, and takes a log time to converge, and the solution time is much shorter.
Metaheuristics	Simple and effective solutions.	Convergence takes longer, a larger area must be searched for a probable solution, and the best choice is not always available.
Probabilistic methods (linear based)	Fast.	It is not possible to obtain high-order moments with precision.

Possibilistic methods (fuzzy)	Can acquire the output variable's membership function.	Can not model correlation and takes time.
Hybrid possibilistic-probabilistic method	Can simulate the condition of the real world.	Takes time.
IGDT	Useful for making decisions in situations of high uncertainty.	Complexity.
Interval analysis	Helpful when there is an interval.	Difficult to apply to nonlinear issues.

This comparison aids the decision-maker in selecting the optimal approach for the given uncertain problem to protect his choice from dangers brought on by uncertain circumstances. Meta-heuristics in conjunction with uncertainty models like RO models that take into account a variety of uncertainties could provide a good solution [34]. The RO and SO models are the most widely used models when it comes to dealing with the uncertainty of EVs, and will be detailed in the next subchapter.

2.5.2. COMPARISON BETWEEN STOCHASTIC AND ROBUST OPTIMIZATION

In the BEMS domain, MILP is often used, since it describes quite well and solves the optimization problem at an appropriate time [35]. However, EV uncertainties are not that commonly considered when dealing with the MILP model. SO and RO are the most well-known approaches when dealing with EV uncertainties in the literature [25].

One of the fundamental modeling elements of SO is the representation of uncertainty, which is done by using Stochastic Programming (SP) to model future events. SO is appropriate when the probability function (PF) parameters of the unknown parameter can be easily obtained from historical data. The probability distribution of uncertain data has to be known or estimated. However, it also entails the generation of multiple scenarios, which may increase the computational running period. The solution in stochastic optimization is immune to stochastic uncertainty in some probabilistic sense, and hence the solution may be infeasible for some implementations [25].

RO is a novel approach to solving optimization problems involving uncertainty, especially where there is a lack of information about the nature of uncertainty. Since the additional difficulty of including uncertainty can be limited in many situations, RO is practical for implementing in BEMS. RO does not simulate the probability distribution, but only requires moderate information about the uncertainty, such as the mean and upper and lower limits [25]. Furthermore, the optimal solution derived from a RO model comprises all realizations of the uncertainty across a certain set of parameters. However, similarly to SO, RO recognizes the presence of intrinsic ambiguity and uncertainty in a real-world system [25]. Based on [36]-[37], the comparison between SO and RO can be summarized in Table 2.

Table 2 Comparison between Stochastic Optimization and Robust Optimization

Comparison	Stochastic Optimization	Robust Optimization
Historical data and PF	Appropriate when historical data is available and a prior understanding of the PF.	Appropriate when avoiding PF selection skepticism.
Advantages	A probabilistic guarantee of the solution's viability.	Immunity against all potential realizations of the uncertain data within a deterministic uncertainty set; Better for risk-based applications since it considers multiple scenarios, such as the worst-case scenario, while staying within the parameters' bounds.
Limitations	The method used to generate scenarios has an impact on the solution's accuracy; A significant number of scenarios are needed, which increases the size of the problem and the amount of computing needed.	This method has not been widely adopted since it is conservative under worst-case conditions.
Parameters	Parameters have a known distribution.	Parameters are inside specified constraints.

Targets decisions	Decisions that have multiple stages of decision-making.	Decisions that have to be made here and now.
Formulation	Needs PF of uncertainties, which are difficult to estimate in practice.	Using sets to describe uncertainties (upper and lower bounds).

The need to develop the use of RES in today's power system, as well as their inherent uncertainty, has made using robust techniques more feasible. As a result, there have been few studies that have used the RO approach, where its components, dimensions, and characteristics have been thoroughly addressed. Table 3 presents a summary of the literature review on RO models.

Table 3 RO literature review summary

Reference	Method	Uncertainties	Results
[38]	RO with a coordination of several sources (electric grid, battery, combined heat and power).	Randomness of electric, and thermal loads, and PV production.	Ability of the CHP unit and battery to reduce the impact of uncertainty.
[39]	RO for load scheduling of smart homes.	PV power output.	Verify the effectiveness and benefit of the suggested strategy.
[40]	Monte Carlo simulation and RO considers electrical and thermal demand responde programs.	Electricity prices.	By implementing the DR programs, the overall cost to customers can be decreased.
[41]	Adaptive robust optimization-based operation method.	Arrival and departure time of EVs.	Decreases the difficulty of computing big mixed-integer issues for microgrids in unpredictable situations.

[36]	RO-based scheduling.	RES and forecasted electric loads.	Prove the robustness of proposed strategy.
[42]	RO and Monte Carlo simulatiom.	Transition of EVs.	The real case of of Ontario, Canada served to demonstrate the methodology's usefulness.

Through this table, it's possible to observe that the RO model is widely used to deal with uncertainties, such as thermal and electrical loads, PV production, electricity prices, arrival and departure time of EVs, RES, and transition of EVs. It can be noted that this model is mostly referenced in smart houses/buildings to deal with the uncertainty associated with PV production. However, it is not yet widely used in BEMS, and even less to deal with EV uncertainties. As a result, in this thesis, RO is chosen as the optimization method that will be used to schedule SB energy considering EV uncertainties, such as arrival time, departure time, and initial SoC.

2.5.3. ROBUST OPTIMIZATION MODEL

The MILP model will initially be designed to optimize the building's energy resource management. Then it will be transformed into a robust equivalent with the main goal of minimizing the total electricity costs of a building within the stated uncertainty limitations.

In RO formulation, several stages must be completed, which are described in Figure 13, adapted from [36]. Firstly, it is vital to choose which uncertainty parameter should be taken into account, which in this case concerns EVs. The uncertainty set is then created, and the upper and lower bounds are estimated using EV forecast. Afterwards, a deterministic model is created and the worst-case model is developed. The worst-case model has a sub-problem, which is solved using linear duality theory. Finally, a tractable robust counterpart can be formulated to tackle the challenges of uncertainty. Within the provided uncertainty constraints, the budget of uncertainty is used to define a trade-off between conservatism and the probability of unworkable solutions [36].

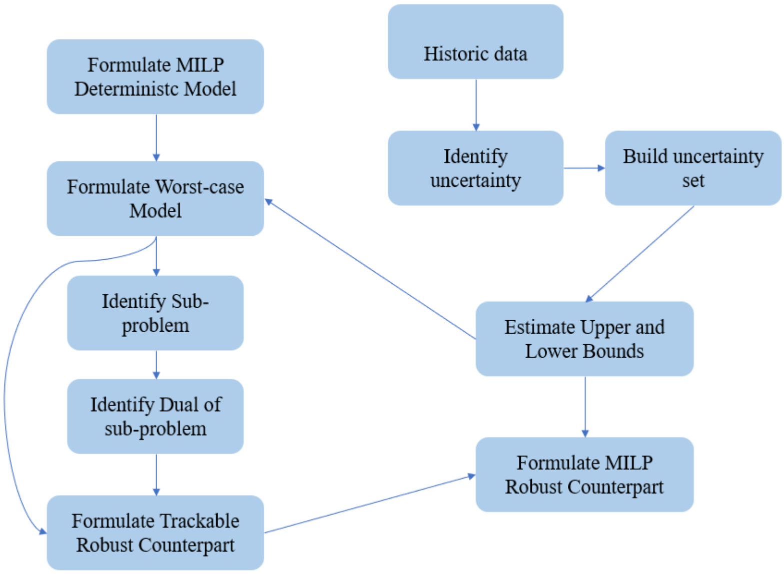

Figure 13 Steps of robust optimization formulation [36]

2.6. Conclusions

This chapter provides a review of the literature on the thesis's topic. Several topics were presented to demonstrate the relevance of consolidating the principle of energy resources optimization, especially in the case of EVs in an SB concept.

Initially, three types of energy resources that exist in buildings are mentioned with the main emphasis on EVs since they will be the main topic throughout this thesis. Subsequently, a study is made on buildings, as SB and BEMS provide for a state of transition from existing structures to highly efficient and effective structures that can create, store, consume, and supply energy.

Uncontrolled EV penetration might pose a substantial threat to the electric system, posing serious operational issues like grid congestion and overloading. Therefore, it has been demonstrated that V2B may be used to provide flexibility without impacting the usual functionality of any building. However, this predicament is primarily caused by the uncertain charging patterns of these vehicles' users. To tackle this issue, multiple strategies and techniques for optimizing these resources are presented, concluding from the research carried out that RO is the method with more advantages in terms of uncertainties. Therefore, RO will be the method used for the optimal scheduling of energy resources in the SB while accounting for EV uncertainty.

3. METHODOLOGY

This chapter provides the methodology for the mathematical formulation, uncertainty generation, and algorithm optimization of the models used. First, a machine learning approach is considered to deal with EV uncertainties, and then an optimization model is formulated. The optimization model is created using a mixed binary linear problem which is then transformed into a robust optimization model by taking into account the ANN model values.

3.1. MACHINE LEARNING APPROACH

According to Figure 13, the first step when building a robust optimization technique is to identify the uncertainty, build the uncertainty set and estimate upper and lower bounds. To identify the uncertainties of EVs, three uncertainties of EVs were considered for this thesis: arrival time, departure time, and initial SoC. Therefore, the next step was to build the uncertainty set and estimate the upper and lower bounds, which was done by forecasting the EV uncertainties to optimize BEMS.

Many studies have developed forecasting techniques and models to improve the accuracy of forecasting. Machine learning and data-driven artificial intelligence methods have proven to be effective in forecasting a variety of EV uncertainties by using previous data, such as sampling probability distributions [43], and deep-learning-based algorithms [44]. In the most relevant literature, the study in [45] used the Monte Carlo simulation method to obtain EV forecast information from the probability distribution. In contrast, the authors in [46] used a truncated Gaussian distribution to predict EV arrival and departure time, as well as the State Of Charge (SoC) at arrival in parking lots. Throughout most of the literature, Artificial Neural Networks (ANNs) are the most widely utilized statistical methods when it comes to forecasting EVs.

3.1.1. ARTIFICIAL NEURAL NETWORK TECHNIQUE

ANNs are computing systems inspired by the neurons in our brain and by the way they work and pass information. A neural network consists of numerous layers of neurons in their most basic form, each of which is fully connected to the next. These neurons are split among three layers: an input layer, where the data set is, a hidden layer, between the input and output layers, used to amplify the power of the neural network and increase its efficiency, and an output layer. Each neuron receives and processes information from other neurons as well as from the outside world [47].

There are two different ways to use ANN: (1) feed-forward propagation; (2) back-propagation method with error propagation, as demonstrated by Figure 14 from [50]. The network is named feed-forward since each layer's neurons only feed the output to the next layer [47]. To create the desired output and reduce the error between the network output value and the target value, the network seeks to adjust the weights of connections between neurons [48], [49]. The training procedure adjusts the weights connecting each of the layers and their neurons. By altering the weights of the connections, the error in the output is propagated back from one layer to the preceding layer during this process. This is known as the error back-propagation method.

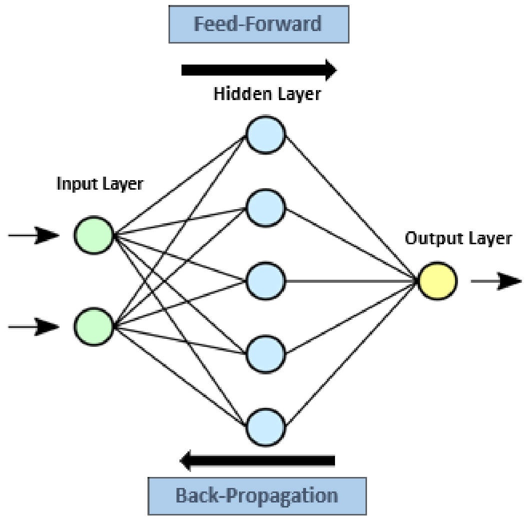

Figure 14 ANN structure with feed-forward propagation and back-propagation [50]

In this thesis, a rough multilayer ANN with error back-propagation learning method is implemented to employ EV uncertainties forecast through rough neurons (upper and lower bounds), which outperforms traditional methods in terms of robustness [28]. Figure 15 from [28], demonstrates the rough multilayer ANN with error back-propagation structure.

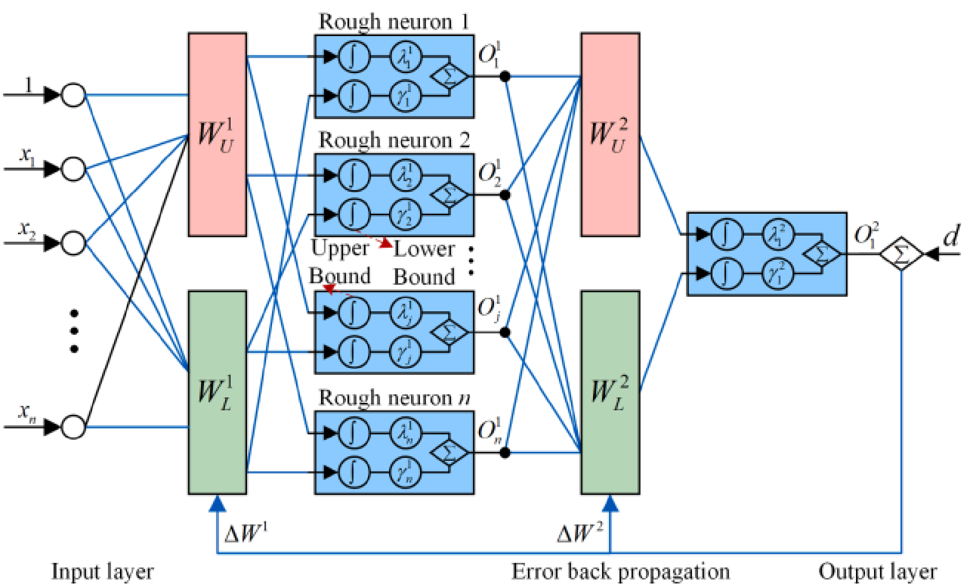

Figure 15 ANN architecture with rough hidden layer and back-propagation [28]

The uncertainty set for this model, including the EVs uncertainty forecast and the estimation of the upper and lower bounds are described afterward.

Below the uncertainty set, denoted by the letter U, is used to describe the uncertainty of arrival time, departure time and initial SoC outputs:

$$U_{T_{EV}^{in}} = \left\{ \begin{matrix} \widehat{T_{EV}^{in}}(i,j) - \Delta T_{EV}^{in}(i,j) \leq T_{EV}^{in}(i,j) \leq \widehat{T_{EV}^{in}}(i,j) + \Delta T_{EV}^{in}(i,j), \ \forall_{i,j} . \\ \sum_{i} \frac{\left| T_{EV}^{in}(i,j) - \widehat{T_{EV}^{in}}(i,j) \right|}{\Delta T_{EV}^{in}(i,j)} \leq \Gamma_{(j)}, \forall_{j} . \end{matrix} \right\} \tag{1a}$$

$$U_{T_{EV}^{out}} = \left\{ \begin{matrix} \widehat{T_{EV}^{out}}(i,j) - \Delta T_{EV}^{out}(i,j) \leq T_{EV}^{out}(i,j) \leq \widehat{T_{EV}^{out}}(i,j) + \Delta T_{EV}^{out}(i,j), \ \forall_{i,j} . \\ \sum_{i} \frac{\left| T_{EV}^{out}(i,j) - \widehat{T_{EV}^{out}}(i,j) \right|}{\Delta T_{EV}^{out}(i,j)} \leq \Gamma_{(j)}, \forall_{j} . \end{matrix} \right\} \tag{1b}$$

$$U_{SoC_{EV}^{initial}} = \left\{ \begin{matrix} \widehat{SoC_{EV}^{initial}}(i,j) - \Delta SoC_{EV}^{initial}(i,j) \leq SoC_{EV}^{initial}(i,j) \leq \widehat{SoC_{EV}^{initial}}(i,j) + \Delta SoC_{EV}^{initial}(i,j), \ \forall_{i,j} . \\ \sum_{i} \frac{\left| SoC_{EV}^{initial}(i,j) - \widehat{SoC_{EV}^{initial}}(i,j) \right|}{\Delta SoC_{EV}^{initial}(i,j)} \leq \Gamma_{(j)}, \forall_{j} . \end{matrix} \right\} \tag{1c}$$

These equations depict in the first part that the real value of each uncertainty lies between two limits: upper and lower, which depend on the predicted values and the considered deviation. In the second part, it is verified that the difference between the actual value and the predicted value, according to the deviation, will depend on the value of the budget of uncertainty, which is used to change the solution's level of robustness or conservatism.

The input and output of a neuron are governed by certain mathematical equations. Arrival time, departure time, and initial SoC uncertainty sets can be described according to the study in [41], as:

$$U_{T_{EV}^{in}} = T_{EV}^{in} + \Delta T_{EV}^{in} . \ ; \ \underline{T_{EV}^{in}} \leq \ \Delta T_{EV}^{in} \leq \overline{T_{EV}^{in}} . \tag{2a}$$

$$U_{T_{EV}^{out}} = T_{EV}^{out} + \Delta T_{EV}^{out} . \ ; \ \underline{T_{EV}^{out}} \leq \ \Delta T_{EV}^{out} \leq \overline{T_{EV}^{out}} . \tag{2b}$$

$$U_{SoC_{EV}^{initial}} = SoC_{EV}^{initial} + \Delta SoC_{EV}^{initial} \ . \ ; \ \underline{SoC_{EV}^{initial}} \leq \ \Delta SoC_{EV}^{initial} \leq \overline{SoC_{EV}^{initial}} \ . \tag{2c}$$

Once the forecast values are obtained through the ANN model, it is necessary to estimate the uncertainty deviations. The upper and lower bounds are calculated in numerous publications by multiplying the forecast values by their uncertainty deviation as shown in Equations (3a) – (3c) for arrival time, departure time, and initial SoC, respectively [51]:

$$\overline{T_{EV}^{in}} = \widehat{T_{EV}^{in}} + \widehat{T_{EV}^{in}} * \Delta T_{EV}^{in} \ . ; \underline{T_{EV}^{in}} = \widehat{T_{EV}^{in}} - \widehat{T_{EV}^{in}} * \Delta T_{EV}^{in} \ . \tag{3a}$$

$$\overline{T_{EV}^{out}} = \widehat{T_{EV}^{out}} + \widehat{T_{EV}^{out}} * \Delta T_{EV}^{out} \ . ; \ \underline{T_{EV}^{out}} = \widehat{T_{EV}^{out}} - \widehat{T_{EV}^{out}} * \Delta T_{EV}^{out} \ . \tag{3b}$$

$$\begin{gathered} \underline{SoC_{EV}^{initial}} = \widehat{SoC_{EV}^{initial}} - \widehat{SoC_{EV}^{initial}} * \Delta SoC_{EV}^{initial} \ . \\ \overline{SoC_{EV}^{initial}} = \widehat{SoC_{EV}^{initial}} + \widehat{SoC_{EV}^{initial}} * \Delta SoC_{EV}^{initial} \ . \end{gathered} \tag{3c}$$

Where the deviation value can be defined as 20%, based on [51]. The deviation value implies that the actual values will fall within the forecast intervals with varying probabilities.

3.2. Optimization model

This subchapter discusses the optimization model developed to implement the building's smart management system. Mathematical optimization corresponds to the selection of the best solution from a set of available alternatives in a particular context. The best decision is often decided according to an objective function and some constraint functions. An objective function $f : X \mapsto \mathbb{R}$ is a function that determines the objective value $f(x)$ of a choice $x \in X$, where x is possible if $x \in X$. The concept of best decision is defined as a viable solution that has either the maximum or minimum attainable objective value. An optimization problem can be demonstrated as [52]:

$$\text{minimize or maximize } f(x)\,. \tag{4a}$$

$$\text{subject to } x \in X\,. \tag{4b}$$

Optimization problems are divided into two types based on the properties of the feasible set X and the objective function f [52]:

- Linear Programming (LP): The set X can be specified by a finite number of inequalities and the objective function f is linear.

- Non-Linear Programming (NLP): The objective function f or some of the constraint functions are non-linear.

The simplest form of mathematical optimization is linear programming, in which the objective and constraints are affine functions. The goal of LP is always maximization or minimization of some linear function of the decision variables. Decision variables are numbers that have been determined by the best possible method. The following is a formulation of the LP problem [53]:

Objective function:

$$\text{min or max } z = \sum_{j=1}^{n} c_j x_j\,. \tag{5a}$$

Constraints:

$$\sum_{j=1}^{n} a_{ij} x_j = b_i (i = 1, \ldots, m)\,. \tag{5b}$$

$$x_j \geq 0\ (j = 1, \ldots, n)\,. \tag{5c}$$

where m is the number of constraints and n is the number of decision variables. Equation (5c) determines that all the decision variables should be positive, while Equation (5b) can be defined as equality (=), or inequality ($\geq, \leq$) aligned to a linear combination of decision variables. The solution is thought optimal if it reaches the required maximum or minimum value [54].

Although LP can be solved in polynomial time, they may not be accurate enough to reflect the building energy system [54]. In this manner, LP and NLP optimization problems can be divided into two different categories according to the problem:

- Mixed Integer/Binary Linear Programming (MILP/MBLP): comprise integer variables. Despite being non-linear, offers more freedom in modeling, such as binary variables, but also requires algorithms like branch-and-bound to address.

- Mixed Integer/Binary Non-Linear Programming (MINP/MBNP): can be extremely difficult to solve, and even if a solution exists, it does not ensure that it will be found.

Mathematical optimization is frequently used to solve difficulties involving the management of building energy resources [54]. MILP is frequently utilized in the field of BEMS. MILP models accurately represent building energy systems and address optimization challenges at an appropriate time [36]. Nonetheless, MBLP will be the one adopted in this thesis, and can be expressed as:

Objective function:

$$\min z = c^T x \, . \tag{6a}$$

Constraints:

$$\mathrm{A}x \geq b \, . \tag{6b}$$

$$x_i \in \{0,1\}, i \in I \, . \tag{6c}$$

Set I denotes the set of indices of variables that are specified to be binary in the optimization problem, and commonly represent decisions. The designation of MBLP comes from the fact that relaxing the binary requirements (6c) results in an LP, which is an optimization problem with affine constraints and a linear objective function [52]. The

MBLP used for this thesis will be discussed in more detail in the following subchapter. Afterward, the RO model will be detailed at the end of this chapter.

3.2.1. DETERMINISTIC MODEL

Subsequently, a deterministic model (MBLP), is created to formulate the worst-case model. The deterministic formulation of the optimization problem is established in this subsection, along with the decision variables, and descriptions. This section also includes a description of the objective function and the constraints related to each energy resource of the building.

This model is based on article [1]. On this article, all of the building's energy resources, including PV, EV, and BESS, are thought to be managed by a management entity, taking into account the consumption from apartments and Common Services (CS), to reduce the electricity bill. The SB is designed with flexible Contract Power (CP) for each electrical consumer and a single CP for the entire collective residential building. The authors formulated a mixed binary optimization problem to develop where the best schedule for charging and discharging EVs and BESS is determined while accounting for PV generation and load consumption profiles. The developed framework is put into practice for three different scenarios: in the first case a "traditional multi-unit residential building" without entity management is taken into account; in the second case, a management entity is considered and MBLP is formulated such that its solution offers a guide on how to manage the distribution of power among building resources for the management entity; the third case is similar to the second one, but a BESS is thought to ensure and take advantage of improved management of the energy resources in the housing building. The findings demonstrate that it performs well and significantly reduces electricity costs, by about 47% in the third case. However, here the authors did not mention the problem of uncertainty, which will be included in this thesis through Robust Optimization.

3.2.1.1. OBJETCIVE FUNCTION AND CONSTRAINTS

The main goal of this thesis is to reduce the total electricity consumption cost of the building. The total electricity cost is defined by the energy cost transferred from the power grid to the building and the excess electricity that can be sold to the external power grid. Both of them are managed through a building manager entity and a certain tariff rate. Additionally, a cost that is determined by the residential building contract power's value is added. The mathematical model within the objective function and constraints are formulated as follows:

$$min\ \mathcal{J} = SCP(CP) + \sum_{i \in \mathbb{I}} C_G^{buy}(i, CP)\, P_{G\rightarrow M}(i) - \sum_{i \in \mathbb{I}} C_G^{sell}(i)\, P_{M\rightarrow G}(i)\,. \tag{7}$$

Where *SCP(CP)* is a cost that depends on the value of the residential building CP. Regarding the constraints used in the MBLP model they are demonstrated as follows:

- **Electric Vehicles Constraints**

The capacity constraints of *j*th EV's battery is formulated as:

$$SoC_{EV}(i,j) \leq SoC_{EV}^{max}(j)\ ,\ \boldsymbol{i} \in \mathbb{I}, \mathbf{j} \in \mathbb{J}\,. \tag{8}$$

The value of the initial charge of *j*th EV at the arrival time in each day can be written as:

$$SoC_{EV}\left(T_{EV}^{in}((d,j) - 1), j\right) = SoC_{EV}^{initial}(d,j), \mathbf{j} \in \mathbb{J}, \boldsymbol{d} \in \{\mathbf{0}\} \cup \mathbb{D}\,. \tag{9}$$

The consumed electricity from the external power grid to charge EVs is defined as follows:

$$P_{M\rightarrow EV}(i,j) \leq \alpha_{EV}(i,j) \cdot AP_{EV}^{ch}(j) \cdot \tau,\ \ \boldsymbol{i} \in \mathbb{I}, \mathbf{j} \in \mathbb{J}\,. \tag{10}$$

It's worth noting that if the binary variable that represents EV*j* charging process in period *i* equals zero, then the manager does not charge EV *j* in time-step *i*. On another hand, if it equals one then the EV *j* can be charged by the manager.

The obtained power by discharging EVs can be modeled as:

$$P_{EV\to M}(i,j) \le \beta_{EV}(i,j)\cdot AP_{EV}^{diss}(j)\cdot\tau, \boldsymbol{i} \in \mathbb{I}, \mathbf{j} \in \mathbb{J}\ . \tag{11}$$

Since the SoC can be changed due to the charging/discharging process, SoC needs to be updated as follows:

$$SoC_{EV}(i+1,j) = SoC_{EV}(i,j) + \left[P_{M\to EV}(i,j)\cdot\eta_{EV}^{ch} - \frac{P_{EV\to M}(i,j)}{\eta_{EV}^{diss}}\right], \tag{12}$$

$$\boldsymbol{j} \in \mathbb{J}, \boldsymbol{d} \in \{0\} \cup \mathbb{D}, \boldsymbol{i} = T_{EV}^{in}(d,j) - 1, \ldots, T_{EV}^{out}(d+1,j) - 2\ .$$

To be considered at departure time:

$$SoC_{EV}(T_{EV}^{out}(d,j)-1,j) \ge\ SoC_{EV}^{min}(j), \mathbf{j} \in \mathbb{J}, \boldsymbol{d} \in \mathbb{D}\ . \tag{13}$$

Is worth mentioning that when the EV is not in the parking, the charging and discharging procedures should not take place, therefore Equation 14 is presented:

$$SoC_{EV}(i,j) = 0, \mathbf{j} \in \mathbb{J}, \boldsymbol{d} \in \mathbb{D}, \boldsymbol{i} = T_{EV}^{out}(d,j), \ldots, T_{EV}^{in}((d+1,j)-2)\ . \tag{14}$$

To ensure that the charging and discharging of EVs do not take place at the same time, the limits for each EV are represented by the following:

$$\alpha_{EV}(i,j) + \beta_{EV}(i,j) \le 1, \boldsymbol{i} \in \mathbb{I}, \mathbf{j} \in \mathbb{J}\ . \tag{15}$$

It's worth noting that if any tenant (j) lacks an EV, Equation 16 can be used to include them in the model:

$$\mathrm{SoC}_{\mathrm{EV}}^{\mathrm{max}}(\mathrm{j}) = 0\ . \tag{16}$$

- **Power Generation Constraints**

The following mathematical formulation should be examined to achieve power balance in each period:

$$P_{G\to M}(i) + \sum_{j\epsilon J} P_{EV\to M}\,(i,j) + \sum_{j\epsilon J} PG_{PV}\,(i,j) + P_{BE\to M}$$

$$= P_{M\to G}(i) + \sum_{j\epsilon J} PD_{SB}\,(i,j) + \sum_{j\epsilon J} P_{M\to EV}\,(i,j) + P_{M\to BE} + P_C(i),\, i\ \in \mathbb{I}\,. \tag{17}$$

This equation is composed by the EVs and BESS discharging process as well as the power generated by PV. It also takes into account the energy required by the managing entity to meet the load demand of each apartment, the common services and charging the EV and BESS. When the building consumes electricity from the external power grid or injects electricity from the building into the external power network, the following constraints apply:

$$P_{G\to M}(i) \leq CP, i \in \mathbb{I}\,. \tag{18}$$

$$P_{M\to G}(i) \leq \frac{1}{2}CP, i \in \mathbb{I}\,. \tag{19}$$

- **Grid Constraints**

The building is connected to the external grid, therefore constraint (20) indicates how much electricity the aggregator can take in from the grid in one time step.

$$\mathrm{P}_{\mathrm{G}\to\mathrm{M}}(\mathrm{i})\ \leq\ P_G^{max}(i), \mathrm{i}\ \in\ \mathbb{I}\,. \tag{20}$$

- **BESS Constraints**

BESS capacity is formulated as:

$$SoC_{BE}^{min} \leq SoC_{BE}\,(i) \leq SoC_{BE}^{max}, \boldsymbol{i} \in \mathbb{I}\,. \tag{21}$$

The initial value of BESS in i = 0 can be written as:

$$SoC_{BE}\,(0) = SoC_{BE}^{initial}\,. \tag{22}$$

The transferred power from management to charge BESS is defined as follows:

$$P_{M\to BE}\,(i) \leq \alpha_{BE}\,(i) \cdot AP_{BE}^{ch} \cdot \tau,\ \boldsymbol{i} \in \mathbb{I}\,. \tag{23}$$

The obtained power by discharging BESS can be modeled as:

$$P_{BE\to M}\,(i) \leq \beta_{BE}\,(i) \cdot AP_{BE}^{diss} \cdot \tau, \boldsymbol{i} \in \mathbb{I}\,. \tag{24}$$

Such like EV, if the binary variable that represents the BESS charging process in period i equals zero, then the manager does not charge BESS in time-step i. On another hand, if it equals to one then the BESS can be charged by the manager.

The SoC of BESS can be changed as well by the charging or discharging process, therefore SoC needs to be updated as follows:

$$SoC_{BE}\,(i+1) = SoC_{BE}\,(i) + \left[P_{M\to BE}\,(i) \cdot \eta_{BE}^{ch} - \frac{P_{BE\to M}(i)}{\eta_{BE}^{diss}}\right], i = 0, \dots, I\,. \tag{25}$$

Similarly to EV, the charging and discharging of BESS should not take place at the same time being represented by:

$$\alpha_{BE}\,(i) + \beta_{BE}\,(i) \leq 1, \boldsymbol{i} \in \mathbb{I}\,. \tag{26}$$

3.2.2. ROBUST OPTIMIZATION FORMULATION

The robust optimization method applied in this thesis is based on [36]-[39]-[55] and is designed to deal with EV's uncertainties.

According with Figure 13, initially the ANN approach, is implemented in order to forecast the EV uncertainties and estimate the upper and lower bounds. Afterwards, MBLP model, described in subsection 3.2.1, is formulated to optimize the energy resource management of the buiding. In the end, the MBLP model is transformed into a robust counterpart whose main goal is to reduce the residential building's overall electricity costs within the specified uncertainty limitations. Therefore, this subsection formulates RO model when dealing with EV uncertanties, through ANN approach, and considering the MBLP model mentioned previously. The developed model provides immunity against the worst-case realization within the provided uncertainty bounds.

RO is formulated according with an uncertainty set as in (27a)-(27b). The objective function is fixed and has no associated uncertainty. The constraint functions can be considered separately, and they must be satisfied for all *u* [56].

$$Minimize\ f(x)\ . \tag{27a}$$

Constraint:

$$max\ f_i(x,u) \leq 0\ . \tag{27b}$$

The uncertainty set consists on a set of values employed to describe the uncertainty of input paramenters that are considered in the RO problem [57]. For the worst-case realization of the uncertain parameter within a given set, the resultant decisions remain optimal [33]. Therefore, RO concentrates on reducing the impact of the worst-case scenario [53], similarly to the deterministic model.

3.2.2.1. EVs constraints

The objective function presented in Equation 7 does not depend on any of the uncertainties, so it will also be used for the robust model. Since this thesis mentions the uncertainties of EVs, it is only in the constraints that depend on these uncertainties that there will be a change, since they are the only ones subject to uncertainty due to arrival time, departure time, and initial SoC parameters. These constraints of the deterministic model should therefore be satisfied when the worst-case scenario of uncertainty occurs.

In this way, the constraints that depend on the EV uncertainties are respectively Equation 9, for the case of initial SoC and arrival time, and Equation 13 in the case of departure time. According with these Equations, the worst-case of each Equation are given on Equations 28 and 29.

$$f(x) = SoC_{EV}\left(T_{EV}^{in}((d,j) - 1), j\right) - SoC_{EV}^{initial}(d,j), \mathbf{j} \in \mathbb{J}, \boldsymbol{d} \in \{\mathbf{0}\} \cup \mathbb{D}\,. \tag{28}$$

$$g(x) = SoC_{EV}(T_{EV}^{out}(d,j) - 1, j) - SoC_{EV}^{min}(j), \mathbf{j} \in \mathbb{J}, \boldsymbol{d} \in \mathbb{D}\,. \tag{29}$$

However, Equations 12 and 14 also change. These Equations are relative to the SoC which depends indirectly on the arrival time and departure time. Therefore, the charge/discharge of the EV will change due to these uncertainties.

3.2.2.2. Sub-problem and dual for intial SoC

After converting the deterministic model into the worst-case model, the next stage in the RO formulation is to formulate the sub-problem and identify its dual. The sub-problem develops the worst-case and then reduces its effects, turning it into a dual problem. The sub-problem is used to find the uncertainty worst-case scenario, which means that it consists in maximizing the worst-case scenario and then minimizing to identify the best possible outcome among the worst.

The maximization of the uncertainty factor (T_{EV}^{in}, T_{EV}^{out} and $SoC_{EV}^{initial}$) found in the earlier

Equations is the primary objective. The sub-problem is formulated by transforming Equations 28 and 29 to the objective function and establish the uncertainty bounds as constraints. Equations (30a) – (30c) describe how the sub-problem is formulated for initial SoC:

Objective function:

$$\underset{soc^{initial}}{\text{Maximize}} f(x) = SoC_{EV}(T_{EV}^{in}((d,j) - 1),j) - SoC_{EV}^{initial}(d,j), \mathbf{j} \in \mathbb{J}, \boldsymbol{d} \in \{\mathbf{0}\} \cup \mathbb{D}. \quad (30a)$$

Constraints:

$$\overline{SoC_{EV}^{initial}} - SoC_{EV}^{initial} \geq 0. \quad (30b)$$

$$SoC_{EV}^{initial} - \underline{SoC_{EV}^{initial}} \geq 0. \quad (30c)$$

To make the robust counterpart tractable, the subproblem must be converteed into a dual problem. When the sub-problem is linear, it is possible to use the linear duality theory on the sub-problem and dual variables are needed. The following equations (31a) - (31b) and describe how the dual of the subproblem is formulated.

Objective function:

$$min\ \lambda^{\underline{SoC_{EV}^{initial}}} \cdot \left(SoC_{EV}^{initial} - \underline{SoC_{EV}^{initial}}\right) + \lambda^{\overline{SoC_{EV}^{initial}}} \cdot \left(\overline{SoC_{EV}^{initial}} - SoC_{EV}^{initial}\right). \quad (31a)$$

Constraint:

$$\lambda^{\underline{SoC_{EV}^{initial}}}, \lambda^{\overline{SoC_{EV}^{initial}}} \geq 0. \quad (31b)$$

The Lagrangian of the problem is obtained as:

$$L\left(\lambda^{\underline{SoC_{EV}^{initial}}}, \lambda^{\overline{SoC_{EV}^{initial}}}, P_1, P_2\right) = \lambda^{\underline{SoC_{EV}^{initial}}}\left(SoC_{EV}^{initial} - \underline{SoC_{EV}^{initial}}\right) +$$

$$\lambda^{\overline{SoC_{EV}^{initial}}}\left(\overline{SoC_{EV}^{initial}} - SoC_{EV}^{\ initial}\right) - P_1\lambda^{\underline{SoC_{EV}^{initial}}} - P_2\lambda^{\overline{SoC_{EV}^{initial}}} \quad (32)$$

Next, the Karush-Kuhn-Tucker (KKT) conditions are applied to transform the above formula:

$$\frac{dL\left(\lambda^{\underline{SoC_{EV}^{initial}}},\lambda^{\overline{SoC_{EV}^{initial}}},P_1,P_2\right)}{d\lambda^{\underline{SoC_{EV}^{initial}}}}=0\,. \tag{33a}$$

$$\frac{dL\left(\lambda^{\underline{SoC_{EV}^{initial}}},\lambda^{\overline{SoC_{EV}^{initial}}},P_1,P_2\right)}{d\lambda^{\overline{SoC_{EV}^{initial}}}}=0\,. \tag{33b}$$

$$\frac{dL\left(\lambda^{\underline{SoC_{EV}^{initial}}},\lambda^{\overline{SoC_{EV}^{initial}}},P_1,P_2\right)}{dP_1}=0\,. \tag{33c}$$

$$\frac{dL\left(\lambda^{\underline{SoC_{EV}^{initial}}},\lambda^{\overline{SoC_{EV}^{initial}}},P_1,P_2\right)}{dP_2}=0\,. \tag{33d}$$

$$P_1\lambda^{\underline{SoC_{EV}^{initial}}}=0,\qquad P_2\lambda^{\overline{SoC_{EV}^{initial}}}=0\,. \tag{33e}$$

$$\lambda^{\underline{SoC_{EV}^{initial}}},\ \lambda^{\overline{SoC_{EV}^{initial}}}\geq 0\,. \tag{33f}$$

3.2.2.3. MBLP tractable robust counterpart

The robust counterpart's aim is to eliminate the negative effects generated by uncertainty [36]. The formulation of the RO model has the same objective function and contraints as MBLP. However it differs on having new constraints attached to the sub-problem. Equations (34a) – (34v) provide the formulation of the robust counterpart of the deterministic model:

Objective function:

$$min\ \mathcal{J} = SCP(CP) + \sum_{i \in \mathbb{I}} C_G^{buy}(i, CP)\, P_{G\rightarrow M}\,(i) - \sum_{i \in \mathbb{I}} C_G^{sell}(i)\, P_{M\rightarrow G}\,(i)\,. \tag{34a}$$

Constraints:

$$0 \leq\ SoC_{EV}\,(i,j) \leq\ SoC_{EV}^{max}(j)\ \ ,\ \boldsymbol{i}\ \in\ \mathbb{I}, \mathbf{j} \in \mathbb{J}\,. \tag{34b}$$

$$P_{M\rightarrow EV}\,(i,j) \leq \alpha_{EV}\,(i,j) \cdot AP_{EV}^{ch}(j) \cdot \tau,\ \ \boldsymbol{i}\ \in\ \mathbb{I}, \mathbf{j}\ \in\ \mathbb{J}\,. \tag{34c}$$

$$P_{EV\rightarrow M}\,(i,j) \leq \beta_{EV}\,(i,j) \cdot AP_{EV}^{diss}(j) \cdot \tau, \boldsymbol{i}\ \in\ \mathbb{I}, \mathbf{j}\ \in\ \mathbb{J}\ . \tag{34d}$$

$$SoC_{EV}(i+1,j) = SoC_{EV}(i,j) + \left[P_{M\rightarrow EV}(i,j) \cdot E_{EV}^{ch} - \frac{P_{EV\rightarrow M}(i,j)}{E_{EV}^{diss}}\right], \tag{34e}$$

$$\boldsymbol{j} \in \mathbb{J}, \boldsymbol{d} \in \{0\} \cup \mathbb{D}, \boldsymbol{i} = T_{EV}^{in}(d,j) - 1, \dots, T_{EV}^{out}(d+1,j) - 2\,.$$

$$SoC_{EV}(i,j)\ = 0, \mathbf{j} \in \mathbb{J}, \boldsymbol{d}\ \in \mathbb{D}, \boldsymbol{i} = T_{EV}^{out}(d,j), \dots, T_{EV}^{in}((d+1,j) - 2)\,. \tag{34f}$$

$$\alpha_{EV}\,(i,j) + \beta_{EV}\,(i,j) \leq 1, \boldsymbol{i}\ \in\ \mathbb{I}, \mathbf{j}\ \in\ \mathbb{J}\,. \tag{34g}$$

$$\begin{aligned} &P_{G\rightarrow M}(i) + \textstyle\sum_{j\epsilon J} P_{EV\rightarrow M}\,(i,j) + \sum_{j\epsilon J} PG_{PV}\,(i,j) + P_{BE\rightarrow M} \\ &= P_{M\rightarrow G}(i) + \sum_{j\epsilon J} PD_{SB}\,(i,j) + \sum_{j\epsilon J} P_{M\rightarrow EV}\,(i,j) + P_{M\rightarrow BE} + P_C(i), i\ \in \mathbb{I}\,. \end{aligned} \tag{34h}$$

$$P_{G\rightarrow M}(i) \leq CP, i \in \mathbb{I}\,. \tag{34i}$$

$$P_{M\rightarrow G}(i) \leq \frac{1}{2} CP, i \in \mathbb{I} \,. \tag{34j}$$

$$\mathrm{P}_{\mathrm{G}\rightarrow\mathrm{M}}(\mathrm{i}) \; \leq \; P_G^{max}(i), \mathrm{i} \; \in \; \mathbb{I} \,. \tag{34k}$$

$$SoC_{BE}^{min} \leq \; SoC_{BE} \; (i) \leq \; SoC_{BE}^{max}, \boldsymbol{i} \; \in \; \mathbb{I} \,. \tag{34l}$$

$$P_{M\rightarrow BE} \; (i) \leq \alpha_{BE} \; (i) \cdot \; AP_{BE}^{ch} \; \cdot \tau, \;\; \boldsymbol{i} \; \in \; \mathbb{I} \,. \tag{34m}$$

$$P_{BE\rightarrow M} \; (i) \leq \beta_{BE} \; (i) \cdot AP_{BE}^{diss} \cdot \tau, \boldsymbol{i} \; \in \; \mathbb{I} \,. \tag{34n}$$

$$SoC_{BE} \; (i+1) = SoC_{BE} \; (i) + \; \left[P_{M\rightarrow BE} \; (i) \cdot E_{BE}^{ch} - P_{BE\rightarrow M} \; (i)/E_{BE}^{diss}\right], i = 0, \ldots, I \,. \tag{34o}$$

$$\alpha_{BE} \; (i) + \beta_{BE} \; (i) \leq 1, \boldsymbol{i} \; \in \; \mathbb{I} \,. \tag{34p}$$

$$\frac{dL\left(\lambda^{\underline{SoC_{EV}^{initial}}}, \lambda^{\overline{SoC_{EV}^{initial}}}, P_1, P_2\right)}{d\lambda^{\underline{SoC_{EV}^{initial}}}} = 0 \,. \tag{34q}$$

$$\frac{dL\left(\lambda^{\underline{SoC_{EV}^{initial}}}, \lambda^{\overline{SoC_{EV}^{initial}}}, P_1, P_2\right)}{d\lambda^{\overline{SoC_{EV}^{initial}}}} = 0 \,. \tag{34r}$$

$$\frac{dL\left(\lambda^{\underline{SoC_{EV}^{initial}}}, \lambda^{\overline{SoC_{EV}^{initial}}}, P_1, P_2\right)}{dP_1} = 0 \,. \tag{34s}$$

$$\frac{dL\left(\lambda^{\underline{SoC_{EV}^{initial}}},\lambda^{\overline{SoC_{EV}^{initial}}},P_1,P_2\right)}{dP_2}=0\,. \tag{34t}$$

$$P_1\lambda^{\underline{SoC_{EV}^{initial}}}=0, \qquad P_2\lambda^{\overline{SoC_{EV}^{initial}}}=0\,. \tag{34u}$$

$$\lambda^{\underline{SoC_{EV}^{initial}}},\ \lambda^{\overline{SoC_{EV}^{initial}}}\geq 0\,. \tag{34v}$$

Now by considering the uncertainty of initial time, we consider the following Sub-problem:

Objective function:

$$\max f(x)\,. \tag{35a}$$

Constraint:

$$\overline{T_{EV}^{in}}-T_{EV}^{in}\geq 0\,.\,;\ T_{EV}^{in}-\underline{T_{EV}^{in}}\geq 0\,. \tag{35b}$$

And for uncertainty case of departure time, we have the following Sub-problem:

Objective function:

$$\max g(x)\,. \tag{36a}$$

Constraints:

$$\overline{T_{EV}^{out}}-T_{EV}^{out}\geq 0\,.\,;\ T_{EV}^{out}-\underline{T_{EV}^{out}}\geq 0\,. \tag{36b}$$

Regarding the uncertainty of arrival time, since the initial time T_{EV}^{in} is bounded to $[\underline{T_{EV}^{in}}, \overline{T_{EV}^{in}}]$, so for $T_{EV}^{in} = \overline{T_{EV}^{in}}$ the total cost is maximized. In other words, $T_{EV}^{in} = \overline{T_{EV}^{in}}$ is the worst-case for the main problem. In the similar manner, the uncertainty in departure time T_{EV}^{out} is bounded to $[\underline{T_{EV}^{out}}, \overline{T_{EV}^{out}}]$, so for $T_{EV}^{out} = \underline{T_{EV}^{out}}$ the total cost is maximized. In other words, in the case of uncertainty of T_{EV}^{out}, the worst case for the main problem is $T_{EV}^{out} = \underline{T_{EV}^{out}}$.

3.3. CONCLUSIONS

This chapter presents the mathematical formulation of the ANN approach and robust optimization based on an MBLP model. In the first subchapter, the EVs forecasting through the ANN technique is done. After obtaining these values the uncertainty set is created and the upper and lower bounds of each uncertainty forecast are estimated.

Afterward, to optimize the energy resource management of the building, the mixed binary linear problem is determined. Likewise, this model also details the mathematical formulation and the description of all the parameters as well as the objective function and the constraints used for all the energy resources previously discussed.

Finally, the robust optimization is formulated transforming the deterministic model into a robust counterpart, providing immunity against the uncertainty associated with the EVs within the obtained bounds. The MBLP model is firstly converted into a sub-problem that consists of maximizing the uncertainty factor, creating the worst-case scenario, and then minimizing it to find the best solution. Afterward, a robust traceable counterpart was developed, that consists of the addition of constraints of the subproblem to the MBLP model.

4. CASE STUDY

In this chapter, the case study is presented taking into account the methodology proposed previously in Chapter 3. First, the description of the building and the problem formulation are presented. Then, a brief review of the case study is given and the ANN description for this thesis is provided. Finally, the optimization scenarios are detailed at the end of this chapter.

4.1. BUILDING DESCRIPTION

In this study, a smart building containing 15 apartments and a common service is taken into consideration. Each apartment has its EV and is connected to a PV solar panel, installed on the building’s rooftop. Each apartment was considered to have a maximum installed PV power of 0.5 kW. A BESS is also included in the residential building.

The building also includes the load consumption of each apartment, an external grid supply of electricity, as well as common services consumption. Figure 16 depicts the energy flow between the building's energy resources.

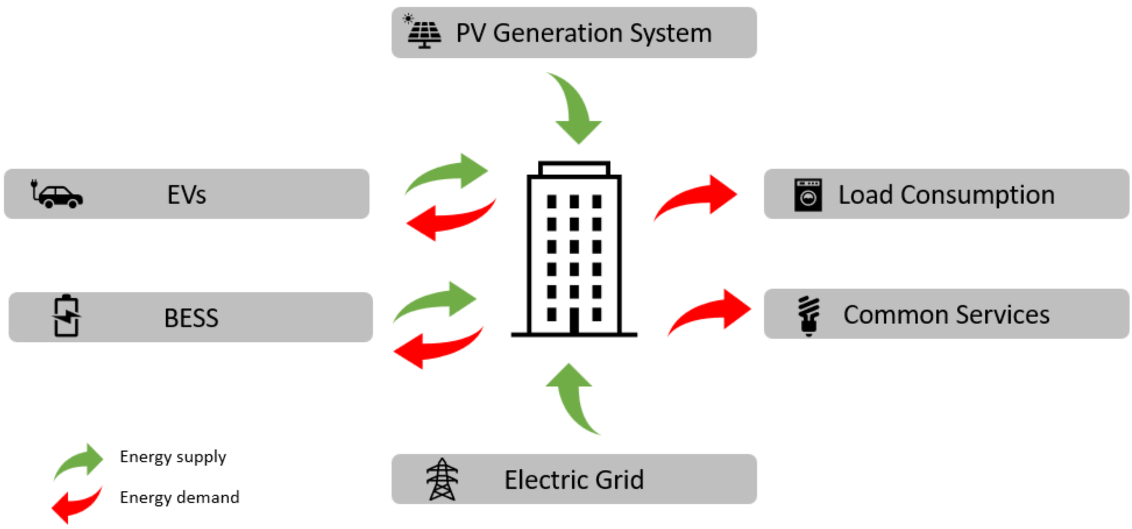

Figure 16 Building's power flow

The consumer’s total power cost is defined by the apartment and CS consumption, the charge/discharge process of EVs and BESS, and the power injected from the PV-producing system. Both EVs and BESS have bidirectional chargers, meaning that they have converters that can either charge through the power provided by the building or discharge to the building to help minimize the cost of electricity. The grid power supplies energy to the building when energy resources (PV generation, EV discharge, and BESS discharge) are not sufficient to meet demand.

Some assumptions are made to define the building's energy resource management model:

- The building is connected to the power grid, to provide energy when EV, BESS, and PV are not sufficient to meet the demand;
- The management entity is responsible for managing all building energy resources as well as energy transfers between the building and the grid;
- Each EV has a single daily use and is immediately plugged into the building’s electrical system upon arrival;
- EVs have bidirectional chargers, so they can charge/discharge their storage according to the building’s needs;

- BESS is utilized to improve the building's energy management, and can also charge/discharge its storage;

- The energy produced by the PV panels is used to meet the load demands of the apartments, CS, and help charge EV and BESS batteries.

Electricity has different prices depending on when it is consumed. The hourly period is how electricity consumption is distributed over the 24 hours of each day and the 7 days of the week. In addition, the energy tariff can integrate two different cycles: the daily cycle, where the hourly periods are the same on every day of the year, and the weekly cycle, where the hourly periods differ between weekdays and weekends. For each cycle, there is a summer and winter schedule, which reflects the change in legal time. There are three different types of electricity tariffs available to each consumer: (1) simple; (2) bi-hourly; and (3) tri-hourly tariffs [58]. This information is important for choosing the best tariff option for consumption in the apartment.

The Portuguese bi-hourly tariff, with 2 periods during the day is where the highest price occurs during periods of highest consumption (peak periods), and the lowest during off-peak hours (night and weekends) [58], and the weekly cycle were applied to this study.

The dataset of PV-generated power, the energy consumption of each apartment, and common services utilized in this thesis are known and correspond to the complete year of 2019 being recorded every 15-minute intervals for all 24 hours of the day. As a result, each day is divided into 24 * 4 = 96 time-steps, and consequently, the time-period contains I = 96 * 365 = 35,040 time-steps. On the other hand, the dataset of arrival time, departure time, and initial SoC are set randomly and correspond to the same year, being recorded daily. Nevertheless, for this thesis, only one month was considered, October 2019, therefore, for the same number of time-steps per day, the time-period will contain I = 96 * 31 = 2,976 time-steps.

4.2. PROBLEM DESCRIPTION

The problem consists of optimizing the energy schedule and minimizing energy costs in a residential building with energy resources. This optimization is done by employing an energy resource management system while considering the uncertainty of EVs.

Typically, each apartment has an independent CP source, and EVs are plugged in and charged as soon as they enter the building. These situations result in higher electricity costs for consumers, as there is no schedule for charging EVs. The consumer can choose the CP value from several options. However, customers may unintentionally choose an inaccurate or improper CP value, which may result in an unwarranted extra charge being added to the electricity account. Therefore, selecting the best CP option, and scheduling EV charging may result in a decrease in energy costs. The approach taken by this thesis takes the following factors into account to reduce the cost of electricity:

- Considering a single CP for the entire building;
- Centralize the charging/discharging schedule of EVs;
- Centralize the EV's battery discharging process during peak hours;
- Utilizing a BESS.

Given these factors, an energy resource management entity is essential. This entity is an aggregator responsible for managing all the building's energy resources to reduce the building's total electricity costs. This strategy also takes into consideration that all residents must consent to be a part of the new player's management. Consequently, the building is seen as a single unit, instead of being considered as having several independent electrical units.

4.3. CASE STUDY: ENERGY RESOURCE MANAGEMENT CONSIDERING EV UNCERTAINTY

The case study concerns the energy resource management of a residential building to reduce the building's energy costs while considering the uncertainties of an EV. The smart energy management of the building includes PV generation, EV, and BESS charging/discharging scheduling processes to meet the demand during energy consumption peaks.

This case study's primary goal is to compare the electricity costs between the three EV uncertainties, arrival time, departure time, and initial SoC. It still makes a small comparison between weekdays and weekends, since on weekends there is a greater possibility of charging EVs. Additionally, it examines the effect of using ESS (EVs and a BESS) in the scheduling of the energy management system and even adjusts the robust optimization technique according to various levels of robustness. Thus, and taking into consideration the study done by article [1], the following parameters were established for this thesis (Table 4), regarding the fact that each apartment is supposed to include an EV:

Table 4 Parameters values

Parameter	Value	Unit
D	31	Days
I	2976	Periods
J	15	EVs/Apartments
$SoC_{EV}^{max}(j)$	27.2	kWh
$AP_{EV}^{ch}(j)$	3.7	kW
$AP_{EV}^{diss}(j)$	3.33	kW
SoC_{BE}^{max}	50	kWh
$AP_{BE}^{ch}(i)$	6.3	kW
$AP_{BE}^{diss}(i)$	5.67	kW
$SoC_{BE}^{initial}$	0	kWh

In this thesis, the period being considered consists of *D* days, with each day being divided into step-times with τ duration. *I* stand for the total number of time-steps, and *J* for the total number of EVs/apartments.

Thus, initially it is necessary to describe the ANN approach that was used in this thesis, to calculate the uncertainty prediction and estimate its limits. Subsequently, the scenarios that will be used to describe how the building energy cost was calculated according to the optimization models are presented. The main objective of these scenarios is to present a building resource scheduling solution, such that the load demand of the residential building is satisfied and the cost of electricity is minimized.

4.3.1. ARTIFITIAL NEURAL NETWORK DESCRIPTION

The ANN approach applied in this thesis is based on [59]. To perform ANN with error backpropagation data was gathered on a 15-vehicle building. An individual analysis was performed on each of these 15 vehicles to select the one with the highest number of initial SoC on weekends. The 10th vehicle was chosen as the result of this investigation.

The network receives three input components: (1) time-step (t); (2) the initial SoC; (3) the arrival time; and (4) the departure time. To forecast the results for the next day, the model includes the values from the previous day. The case study is divided into three different samples for each uncertainty component. Each of them is decomposed into 8 different input variables, with 7 previous values from the existing value (t-1 to t-7) and one with 24 previous values (t-24), where t corresponds to the time-step. Figure 17 displays the ANN architecture used in this thesis. Table 5 shows the main ANN parameters that were utilized to forecast arrival time, departure time, and initial SoC.

The historical data is separated into two categories: training and testing. The training data is used to avoid over/under weights adjustments, while the test data is used to assess the network's performance. The training dataset corresponds to the three months with the highest initial SoC values on weekdays and weekends, whereas the testing dataset corresponds to October, which had the highest initial SoC values on weekends. Several simulations were performed varying the number of hidden layer neurons, where 5 neurons showed the best results.

Table 5 ANN parameters

ANN parameters	Arrival Time	Departure Time	Initial SoC
Number of layers	3		
Number of input variables	25		
Number of hidden neurons	5		
Training data set	July, August and September of 2019		
Testing data set	October of 2019		

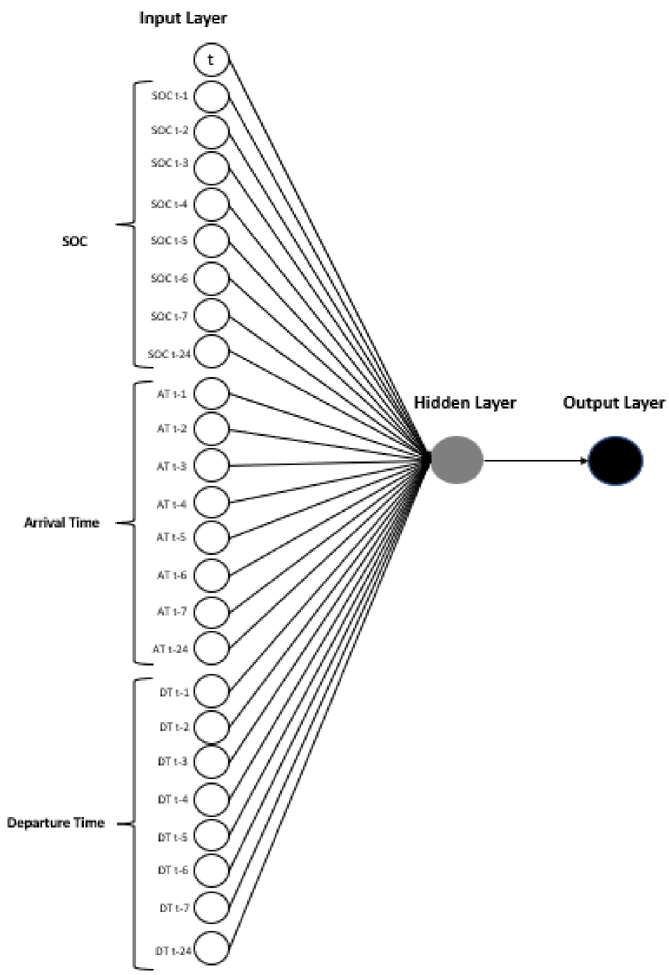

Figure 17 ANN architecture used

It's essential to determine the errors that can be used to assess the model's performance to assure the accuracy of the forecast. The Absolute error, Relative error, Mean Absolute Error (MAE), Weighted Absolute Percentage Error (WAPE), Symmetric Mean Absolute Percentage Error (SMAPE), and normalized Root Mean Square Error (nRMSE) are determined for each case [19]. Equations (37a) – (37f), describe how to calculate these errors:

$$AE = |xi - yi| . \tag{37a}$$

$$RE = \frac{|xi - yi|}{xi} . \tag{37b}$$

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |xi - yi| . \tag{37c}$$

$$WAPE = \frac{\sum_{i=1}^{n} |xi - yi|}{\sum_{i=1}^{n} xi} . \tag{37d}$$

$$SMAPE = \frac{\sum_{i=1}^{n} |yi - xi|}{\sum_{i=1}^{n} (xi + yi)} . \tag{37e}$$

$$nRMSE = \frac{\sqrt{\frac{\sum_{i=1}^{n} (xi - yi)^2}{n}}}{\max (xi)} . \tag{37f}$$

Where:

xi – Actual value;

yi – Predicted value;

n – Number of forecast periods.

4.3.2. OPTIMIZATION SCENARIOS DESCRIPTION

For both the deterministic and the robust model the same scenarios were used. The difference is that the MBLP model does not include any uncertainty. To investigate the efficiency of the optimization models, three scenarios were considered:

- Scenario 1: This scenario is considered a reference case, where a “traditional multi-unit residential building” without energy management is proposed. The electricity cost of each apartment is estimated immediately without using optimization, therefore there is no need to formulate an MBLP or RO model. Each apartment has its CP capacity with an external power grid (electricity supplier). The residential building is supplied with a PV generation and an EV per electrical facility. The EV is charged as soon as it enters the building, however, the EV discharging process is not taken into account.

- Scenario 2: This scenario has an energy management entity responsible for the building management resources such as PV and EVs. In this scenario, it is assumed that the entire building is supplied by a single CP, considering the building as a single electricity consumer. The PV generation is regulated between apartments, and the EV charging/discharging process is coordinated by the management entity, so the EV battery can charge/discharge according to the corresponding apartment consumption.

- Scenario 3: This scenario is analogous to scenario 2, where there is also an external entity considered to manage all the building energy resources. The PV-generated panels are managed between apartments, and the EV charging/discharging process is managed by the aggregator. However, BESS is implemented in the residential building. BESS is considered to ensure and further explore the management of energy resources in the residential building.

In scenarios where smart energy management is employed, an aggregator is used. This entity is economically responsible for all electrical exchanges between the building and the external power grid, as well as with each electricity customer. In addition, this aggregator has the technical responsibility for all the building’s energy management resources, including its PV, EVs, and BESS, to keep the building's energy costs as low as possible. This strategy also takes into account that all tenants must consent to be part of the management under the control of this new player. As a result, the building is perceived as a whole, rather than having numerous independent electricity units. Table 6 summarizes the main characteristics of each scenario.

Table 6 Scenarios' characteristics

Scenarios'	Optimization formulation	Management entity	PV	EV	BESS
Scenario 1	No	No	Yes	Yes	No
Scenario 2	Yes	Yes	Yes	Yes	No
Scenario 3	Yes	Yes	Yes	Yes	Yes

Since the 10th vehicle was used in the ANN model, the same vehicle was employed for the demonstration of these scenarios. It is worth noting that the uncertainty was done only for the case of this vehicle and that the other 14 vehicles will have the same uncertainty data as this one.

For the RO model, the constraints depend on the departure time being higher than the arrival time, as is the case in reality. Thus, the upper bound of the arrival time has to be higher than the lower bound of the departure time. For this to be true, it was necessary to decrease the deviation from the predicted values to 0.01%, this being the minimum value at which this condition holds. From the data for an entire year, the data for one month was extracted. Each day of this month had an arrival time, a departure time, and an initial SoC value of the respective EV. As seen earlier, each uncertainty has its upper and lower bounds. This explanation is represented in figure 18.

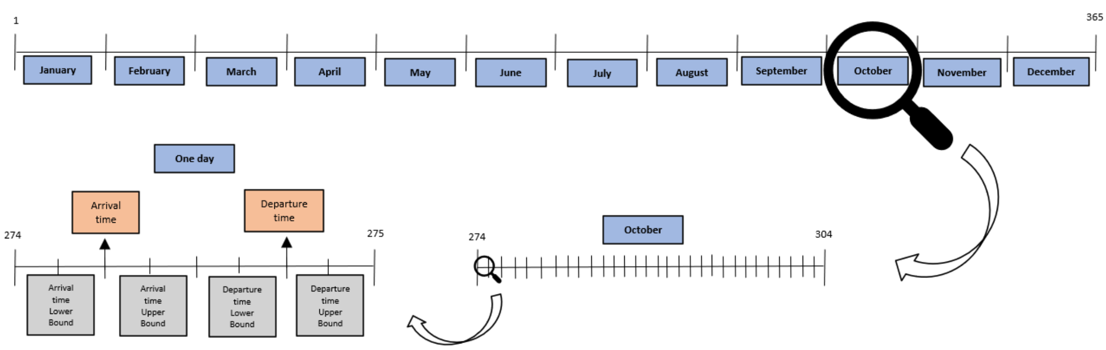

Figure 18 Data representation for one day

4.4. CONCLUSIONS

In this chapter, the case study for the implementation of the developed method is presented. First, the residential building's description was provided. The building consists of 15 apartments, where each one has an EV, and is connected to a PV generation system. To provide more effective management of energy resources, the building also has a BESS. All these energy resources are controlled by an energy management system with an aggregator that is responsible for minimizing the costs.

Subsequently, the problem is formulated. The primary issue consists in optimizing the energy schedule management system and minimizing the total electricity costs in a residential building, taking into account the uncertainties associated with EVs.

In addition, the case study is presented by considering information regarding the ANN technique and the scenarios used in the optimization for both the MBLP method and the RO model. Three different scenarios were simulated: (1) with no smart management, where the EVs are charged in an uncoordinated way; (2) with a smart energy management system, where the EVs are charged/discharged in a coordinated manner; (3) with a smart energy management system and BESS, where EVs and BESS are charged/discharged in a coordinated way.

5. RESULTS AND DISCUSSION

This section provides and analyzes the results obtained for the presented case study. First, the ANN model results are presented, then the results on the optimization, for both the MBLP and the RO model, are provided and discussed.

5.1. ARTIFITIAL NEURAL NETWROK RESULTS

In this subsection, the results of the ANN approach to deal with the EVs' uncertainty, namely the arrival time, departure time, and initial SoC, are presented. Considering the information described in subsection 4.3.1., initially, the forecasting of each uncertainty is made, and then the upper and lower bounds of each uncertainty are estimated.

5.1.1. UNCERTAINTY FORECASTING

In the beginning, the ANN model made a prediction for each of the uncertainties. The outputs of the arrival time, departure time, and initial SoC forecast for October 2019 are shown in Figures 19, 20, and 21 respectively. These Figures compare the actual and forecast data for the three uncertainties.

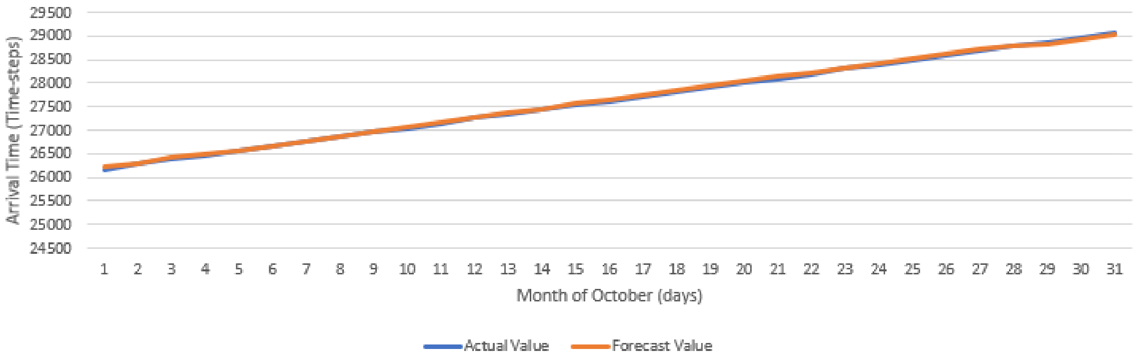

Figure 19 Comparison between actual and forecast value for arrival time

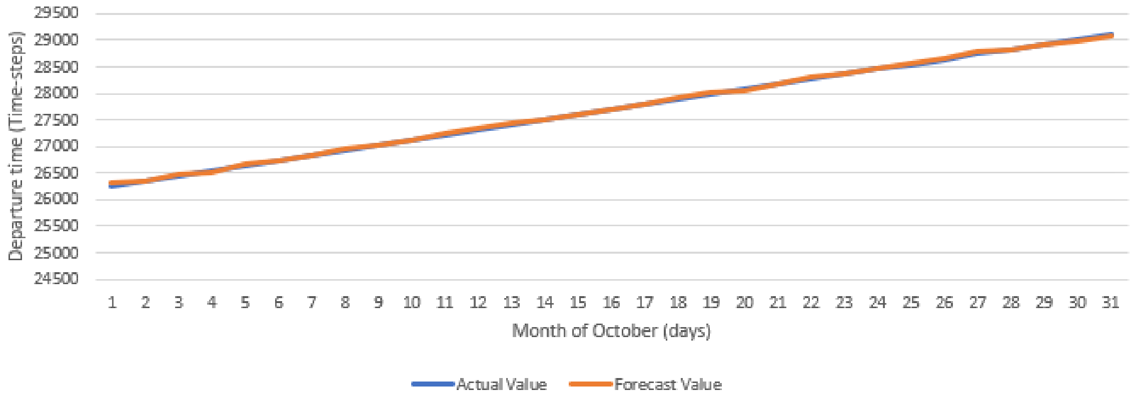

Figure 20 Comparison between actual and forecast value for departure time

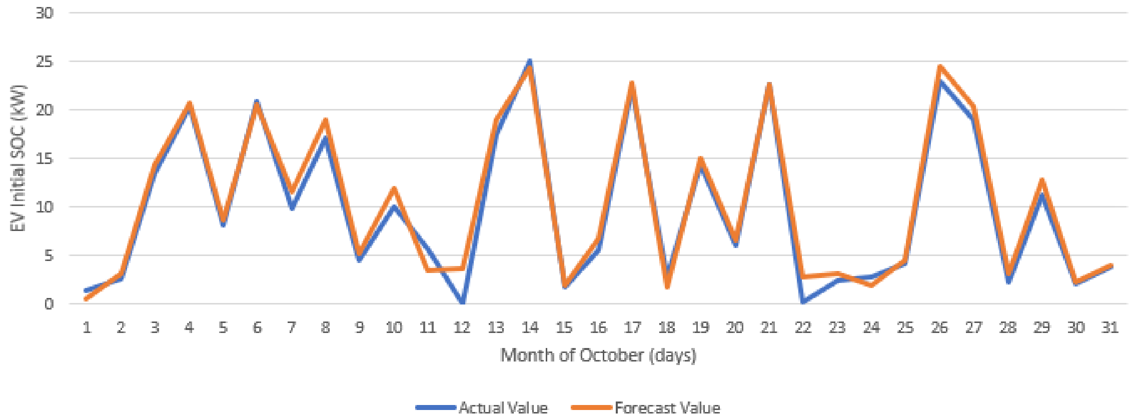

Figure 21 Comparison between actual and forecast value for EV initial SoC

It should be noted that each day in this month had only one arrival time, one departure time, and one initial SoC value of the respective EV. As for the arrival time and departure time, the data increases throughout the month as it is in time-steps. In this way, as mentioned earlier, there are 2,976 time-steps for October, so each time-step corresponds exactly to a value on a scale of 1 to 35,040 time-steps. Where for the case of this month it corresponds to a scale of 26,000 to 29,000 time-steps which can be observed on the y-axis of arrival time and departure time.

By analyzing these figures it is possible to verify that the curve of the forecasted values is highly similar to the curve of the actual values in each of the three uncertainties, indicating that the forecasting technique has a high degree of accuracy. However, the arrival time, and departure time figures depict a very similar linear trend, and it is impossible to determine their accuracy just by observing them. The most prevalent error indices have been calculated to evaluate the precision of this forecasting technique. Table 7 demonstrates the four errors calculated by Equations (37c) – (37f).

Table 7 Uncertainties error values

Umcertainties	MAE	WAPE	SMAPE	nRMSE
Arrival Time	26.3652	0.0010	0.0004	0.0026
Departure Time	24.5693	0.0008	0.0004	0.0009
Initial SoC	1.0310	0.1051	0.0508	0.0751

By analyzing the errors it is possible to verify that there is still a large difference between these values. MAE presents very high values in the case of arrival and departure time while presenting low values on WAPE, SMAPE, and nRMSE. On the contrary, the initial SoC shows a reasonable value in MAE, while revealing lower values on WAPE, SMAPE, and nRMSE as well.

Comparing the three uncertainties, it is worth noting that although the initial SoC has a lower value in MAE, it has higher values in WAPE, SMAPE, and nRMSE when compared to the other two uncertainties. Nonetheless, when excluding MAE, it is observed that the uncertainty with the lowest values is the departure time, being the most accurate for these errors.

5.1.2. UPPER AND LOWER BOUNDS ESTIMATION

After calculating the predicted values, the upper and lower bounds of each of the uncertainties were estimated. Consequently, the upper and lower bounds will differ from the predicted values by around 20%, as explained earlier in Equations (3a)-(3c). Figures 22, 23, and 24 present the upper and lower bounds of the forecasted values of arrival time, departure time, and initial SoC, respectively.

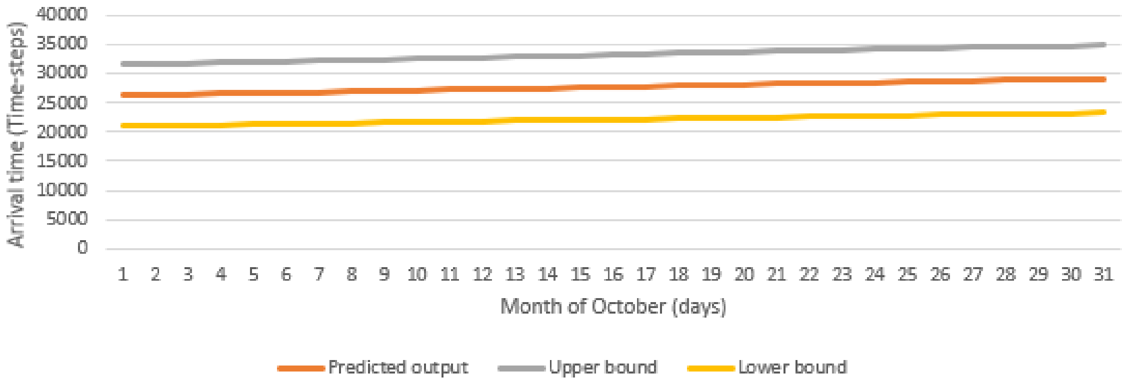

Figure 22 Upper and lower bounds of arrival time forecast

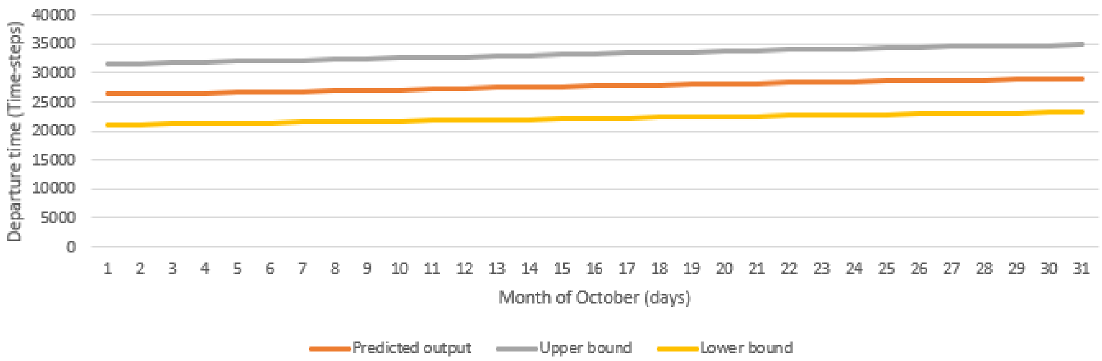

Figure 23 Upper and lower bounds of departure time forecast

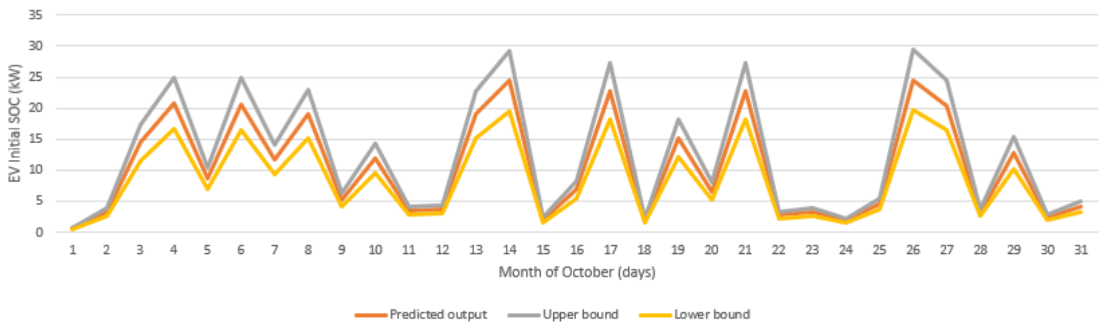

Figure 24 Upper and lower bounds of EV initial SoC forecast

As can be observed from the Figures, the upper and lower bounds of arrival time and departure time show a significant deviation from the predicted value. This is because MAE has a high value for these uncertainties, which means that the predicted value is still far from the actual value. This issue will be further improved in the RO model, where the decision-maker can rely on the upper and lower bounds of the EV uncertainties, rather than relying on a single output, which is frequently different from the actual values [60].

5.2. OPTIMIZATION RESULTS

In this subsection, the optimization results are described. Firstly, scenario 1 is presented since it does not have any type of optimization. Afterward, the results of scenarios 2 and 3 are provided for the MBLP model without associated uncertainty and for the RO model to deal with the predicted EV's uncertainty. The case study is a one-month analysis, which shows a weekly pattern. However, the one-month graph is not demonstrative, and only the example of three days 4-6 October (Friday, Saturday, and Sunday) was considered for demonstration since these days showed the highest discrepancy in values.

5.2.1. SCENARIO 1: REFERENCE CASE

The reference case consists of calculating the total consumption costs for each apartment for October, without the requirement for optimization.

The building's electricity costs were calculated assuming each customer has an energy contract with a bi-hourly tariff. The “*Entidade Reguladora dos Serviços Energéticos*” (ERSE) sets the energy costs of this tariff on an annual basis for each period. Table 8 shows the tariffs for 2019 that are considered in this case [58].

Table 8 Energy tariffs for low voltage consumers (ERSE) [58]

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

The off-peak and peak periods differ according to the season, whether it is summer or winter. The summer period covers the months from April to September, while the winter period covers the months from October to March. Since this thesis only mentions the case of October, then the winter period will be used. The duration of the off-peak and peak periods for each day of the week is shown in Table 9 [58].

Table 9 Bi-hourly tariff for the weekly cycle [58]

Weekdays and weekends	Winter		Summer	
	Off-peak hours	Peak hours	Off-peak hours	Peak hours
Monday to Friday	00h00-7h00	7h00-24h00	00h00-7h00	7h00-24h00
Saturday	00h00-9h30 13h00-18h30 22h00-24h00	9h30-13h00 18h30-22h00	00h00-9h00 14h00-20h00 22h00-24h00	9h00-14h00 20h00-22h00
Sunday	00h00-24h00		00h00-24h00	

The outcomes for scenario 1 were reported in Table 10, which demonstrates the total electricity costs for each apartment. The positive symbol denotes electricity consumed while the negative sign denotes electricity produced.

Equation 38 illustrates how the total cost of electricity for each consumer is determined in this scenario. This equation consists of adding the consumption of the apartment with the consumption of the common services and the consumption of the EVs and then subtracting the consumption of the PVs, values that can be found in Table 10. This result is multiplied by the energy price presented in Table 8, based on which period the energy is used (off-peak or peak periods).

$$\begin{bmatrix} Apartment\ consumption + Common\ services\ consumption \\ + EV\ consumption - PV\ generation \end{bmatrix} (kWh) \times Energy\ price\ (€/kWh)\ . \tag{38}$$

Table 10 Total electricity cost of each apartment

Apartment	CP (kVA)	Total EV (kWh)	Total PV (kWh)	Total Consumption (kWh)	Max load (kW)	Total Cost (€)
1	6.9	+24.1145	-158.1294	151.8743	0.9778	28.6837
2	6.9	+27.6596	-127.2000	189.5972	1.4608	33.5711
3	6.9	+26.7106	-192.0466	112.5552	0.9954	22.1078
4	6.9	+25.5192	-157.9649	955.8890	3.2782	143.1127
5	6.9	+26.0836	-127.2778	327.5913	1.4399	51.1182
6	6.9	+27.4335	-192.0620	914.5965	2.7496	134.5426
7	10.35	+23.8642	-157.9803	499.8835	2.4669	79.9082
8	10.35	+26.5847	-127.2180	491.8767	1.5364	84.8384
9	10.35	+28.5173	-191.7626	816.1496	2.3902	123.2025
10	10.35	+26.7221	-158.3194	2830.9576	4.2984	429.4525
11	10.35	+26.4896	-127.3730	1744.3525	3.0402	257.3472
12	10.35	+25.6054	-192.3924	385.0984	1.8594	65.2327
13	13.8	+27.9144	-158.3963	1866.8986	3.0255	277.7556
14	13.8	+26.6748	-127.1508	1777.6057	3.6442	284.0094
15	13.8	+27.6300	-191.7848	1195.0853	2.0037	200.6035
CS		0.0000	-192.3924	1474.4416	1.1174	419.2392
Total		+397.5233	-2579.4505	17401.2870	36.2840	2634.7250

Table 10 analysis reveals a large difference between the contracted power (10.35 kVA) and the highest peak load (4.2984 kW) for apartment 10th, indicating that the CP value for this apartment is overloaded, which also happens in the other apartments. These results show that the current CPs were not properly selected, causing the electricity cost of each apartment to increase unnecessarily.

5.2.2. MBLP RESULTS

After obtaining the results of the upper and lower bounds assigned to each of the EVs uncertainties, a deterministic model is formulated to estimate the worst-case scenario, considering the information described in subsection 4.3.2.

5.2.2.1. Scenario 2: smart management system

As mentioned earlier in subchapter 4.3.2, in this scenario, a single CP for the entire residential building and an EV charging/discharging process are taken into consideration to lower the SB electricity costs. In this scenario, an optimization method, the MBLP model is solved. In this model, the CP value of the building was chosen based on the selection made in the article [1], considering the optimization results. This CP value corresponds to 27.6 kVA and was the best value out of six different choices. The outcomes are presented in Figure 25.

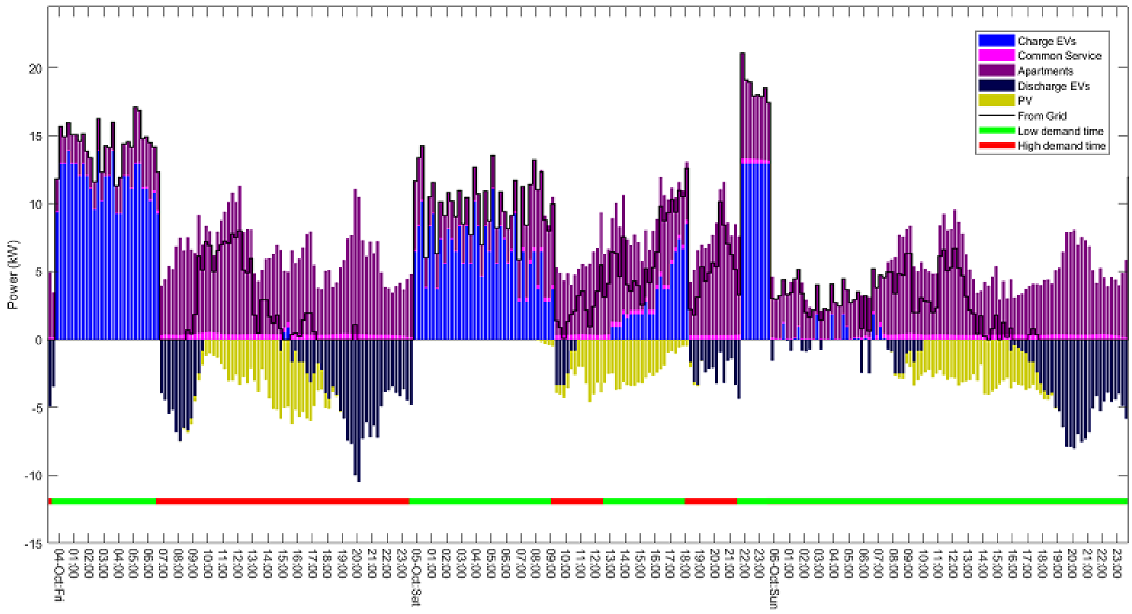

Figure 25 MBLP optimization results for scenario 2

Figure 25 depicts a three-day graph (October 4-6) of EVs charging and discharging process, common services consumption, total apartments consumption, PV generation, and the electricity used from the external power grid.

The results obtained show that on all three days EVs are often charged during periods of low demand and discharged during periods of high demand, to reduce the amount of electricity drawn from the external power grid. PV generation is also used during periods of high demand. As a result, during periods of high demand, less electricity purchased from the grid is needed, and therefore the electricity will be cheaper.

Moreover, the distinction between weekdays and weekends is apparent. It can be observed that on Friday the EVs are charged from 00h00-06h30, where there is no means of ensuring consumption, so the energy from the grid equals the consumption of the apartments, with the consumption of the CS and EV charging. Afterward, the high demand period begins and there is only consumption of the apartments and the CS, which are ensured by EV discharging and PV production. The energy purchased from the grid is null when the EVs are discharging in almost all the periods. However, PV production is not enough to ensure the total consumption and needs to purchase energy from the grid. Nevertheless, the energy from the grid decreases, which lowers the electricity cost.

On Saturday, there is less amount of EV being discharged and of PV production. Saturday can be seen as a day when consumers take the opportunity to charge more EVs, and do not need to use EV discharging and PV production as much, as there is low demand time most of the day. On Sunday there is low demand throughout the day, where EVs were charged at dawn and for a short period, and apartment consumption was lower than on previous days. In this way, the consumption is ensured by EV's discharge and PV's production, where the energy purchased from the grid decreases, being null at the end, where there is enough EV discharge to ensure consumption.

5.2.2.2. Scenario 3: smart management system with BESS

Similarly to what was done for scenario 2, in this scenario the MBLP model is also used with an EV charging/discharging process and a single CP for the building. However, this scenario includes a BESS to lower the overall cost of electricity consumption. The optimal CP value was also chosen according to the article [1]. The best CP value out of a possible six corresponds to 20.70 kVA. Figure 26 displays the results for the given CP.

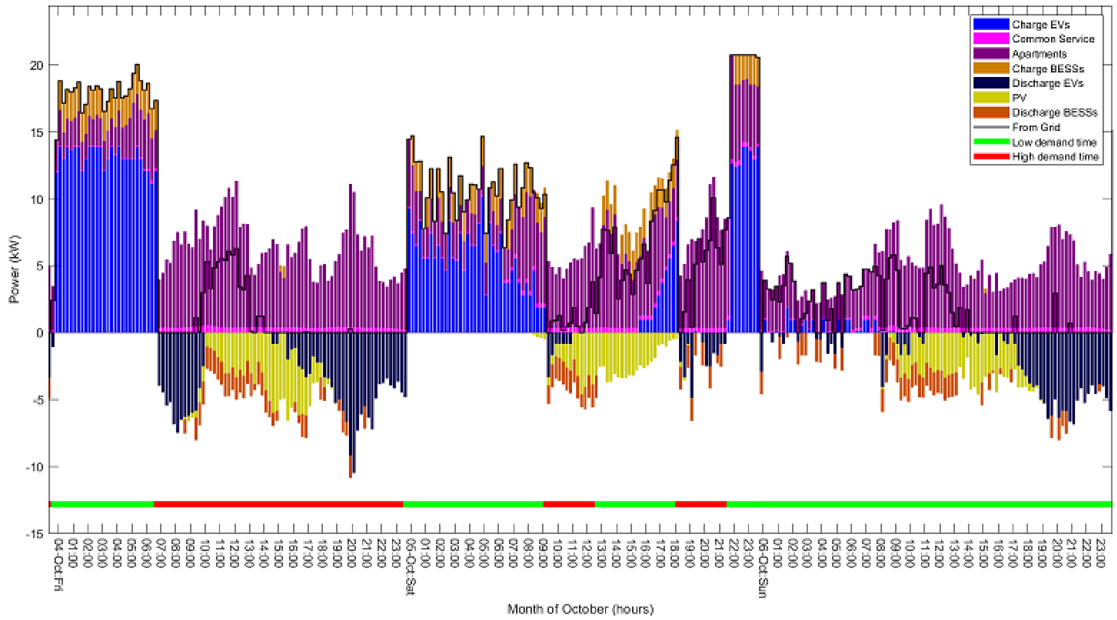

Figure 26 MBLP optimization results for scenario 3

Figure 26 shows a three-day graph (October 4-6) that depicts the results of the BESS usage in regulating building power consumption. The BESS primarily stores excess power during periods of low demand and discharges during high-demand periods, similar to EVs charging/discharging process, and PV is also employed when there is high demand. As a result, less electricity needs to be purchased during periods of high demand.

Similarly to scenario 2, this scenario also presents a difference between weekdays and weekends. On Friday, the energy purchased from the grid increased greatly since there is apartment consumption, CS consumption, EVs charging and even BESS charging with nothing to assist. However, in the high-demand period, the energy was no longer so reliant on the grid, since in addition to the EVs discharge, and PV production, there is also BESS discharge to ensure the consumption of the apartments and the CS, reducing the electricity cost.

On Saturday, there are several low-demand periods during the day, therefore consumers charge their EVs more frequently. Whereas EVs discharging, BESS discharging, and PV production are mostly used in high-demand periods, allowing to decrease the energy purchase from the grid. On Sunday there is less demand throughout the day, where the apartment consumption was lower than on previous days, and the EVs were briefly charged in the morning. On this day, consumption is mainly ensured by EVs discharge, BESS discharge, and PV production, to avoid being overly dependent on the grid's production.

5.2.2.3. Comparison of MBLP results

Regarding the results presented in the MBLP model, it can be noted that the energy purchased from the grid decreases throughout the three scenarios. Table 11 presents the objective function for each scenario implemented above.

Table 11 MBLP scenarios' objective function

Method	Objective function (Cost €)
Scenario 1	2634.73
Scenario 2	2101.71
Scenario 3	1984.98

In this way, it is possible to observe that the objective function value decreases throughout the three scenarios, which was expected. Scenario 1 did not have any type of optimization, scenario 2 had a smart management system, and finally, scenario 3 besides having a smart management system also integrated a BESS in the building. Furthermore, from scenario 2 to scenario 3, the energy purchased from the grid decreased on Friday and Sunday, where it became zero during more periods. As a result of the implementation of BESS in the residential building, the CP value has decreased from 27.6 kVA in scenario 2 to 20.70 kVA in scenario 3. This point leads to a 5.55% cost reduction as compared to scenario 2, and a reduction of 24.66% when compared with scenario 1. Hence, having an aggregator and a BESS integrated into the building helps decrease the cost of electricity.

5.2.3. ROBUST OPTIMIZATION RESULTS

This subsection displays the results of the RO model to address EV forecast uncertainty in the SB. RO considers the deterministic model previously formulated, but includes the uncertainty associated with EVs and described through the ANN model.

This optimization technique works within established uncertainty bounds. This means that the results obtained represent the robustness values achieved between the considered upper and lower bounds of the forecast values. Table 12 presents the costs of each uncertainty for each of the bounds.

Table 12 Costs of each uncertainty bounds

EV uncertainties bounds/Scenarios	Total cost for scenario 2 (€)	Total cost for scenario 3 (€)
Arrival time upper bound	2583.08	2456.74
Arrival time lower bound	2544.82	2417.72
Deaprture time upper bound	2355.93	2251.96
Departure time lower bound	2365.69	2261.10
Initial SoC upper bound	2368.29	2243.04
Initial SoC lower bound	2368.39	2243.15

When comparing the upper and lower bounds for each uncertainty, it is possible to conclude that the highest costs are at the upper bound at the arrival time, the lower bound at the departure time, and the lower bound at the initial SoC for both scenarios. This is because the upper bound of the arrival time and the lower bound of the departure time make the interval smaller, as a result, the charging/discharging of EVs decreases, and the cost increases. Hence, these bounds will correspond to the worst-case scenario of each uncertainty.

It should be noted that for each day there is only one value for arrival time, departure time, and initial SoC. When consumers are at the building they can charge/discharge several times throughout the day, and as soon as they arrive at the building the EV is connected. However, the charge/discharge process should not happen at the same time.

The same scenarios and the identical 3-days (4-6 October) that were used in the deterministic model are also considered in this situation. However, for this case, the RO model was used to consider the uncertainties of the EVs. The two scenarios' simulations were produced for the optimization scheduling of the worst-case scenario of each uncertainty.

5.2.3.1. Scenario 2: smart management system with EV uncertainty

This scenario has the same characteristics as scenario 2 of the MBLP model. The CP value corresponds to 27.6 kVA based on the selection made in the article [1]. In this scenario, RO found the best solution for the worst-case scenario for the three uncertainties.

Figures 27, 28, and 29 display the robust scheduling simulation outcomes for all the building's energy sources and the corresponding uncertainty, arrival time, departure time, and initial SoC respectively. Moreover, the energy consumption of the apartments, CS, and PV generation is equal for all uncertainties. For the case of EV charge/discharge and grid power, these have different values depending on the uncertainty.

Figure 27 presents the results of robust scheduling for the worst-case of arrival time, which considers the upper bounds of arrival time forecasting values.

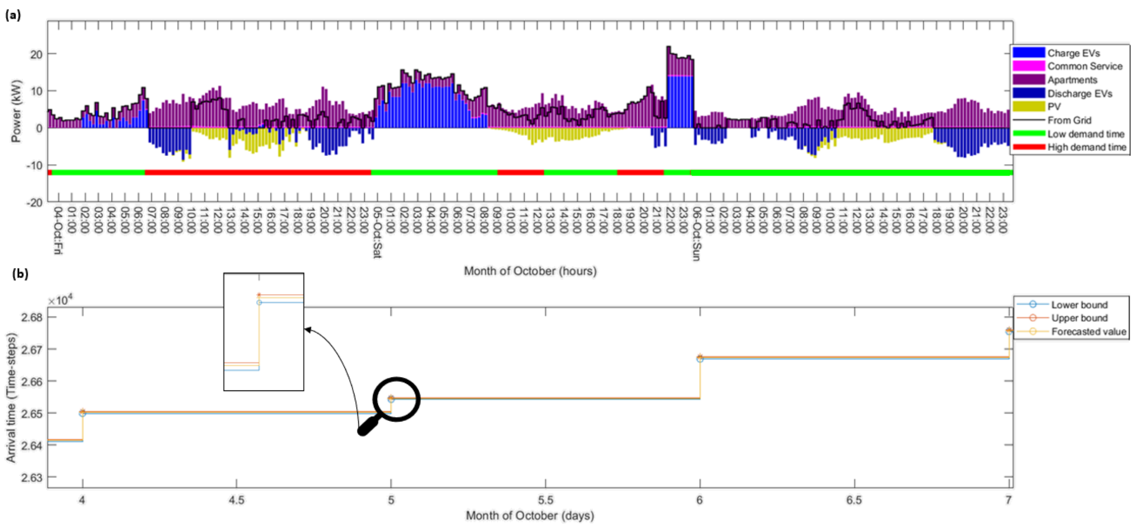

Figure 27 RO results in scenario 2 for (a) Energy consumption and RES (b) upper and lower bounds of arrival time

Two graphs are depicted in Figure 27: (a) the consumption of the apartments, the charging/discharging process of EVs, the consumption of CS, the PV generation, and the grid power; (b) the arrival time uncertainty, where the forecasted value, as well as the upper and lower bounds, can be highlighted. These values are quite close because the deviation value was only 0.01%. The worst-case scenario for this uncertainty is the upper bound because it corresponds to the worst-case situation with the higher uncertainty.

Regarding figure 27(a), Friday shows different values when compared to the weekend. EV charging was done in the off-peak period (00:30-06:30), charging little. However, there are no resources to ensure the total consumption, so the energy acquired from the grid will correspond to the aggregation of the consumption of the apartments, with the CS and the charging of the EVs. In the peak period (6:30-23:30), the EV takes the opportunity to discharge. During the first hours (6:30-10:00), since the discharge power of EVs could meet the demand, there was no need to purchase power from the grid. In the remaining periods, the demand was assured by PV power generation and some EV discharge. However, the amount of PV generation and EV discharge, was not sufficient, requiring grid power, and increasing the cost. In any case, the energy purchased from the grid was reduced in this peak period.

Regarding the weekend, on Saturday, EVs are scheduled to charge during the off-peak periods (00:00-09:30) and on (21:30-23:30). Nonetheless, during these periods the power purchased from the grid equals the building's total consumption. Afterward, there is a high demand period (09:00-12:30) where the PV generation starts to meet the demand for apartments and CS. In the following low-demand period (12:30-18:00), the PV generation decreases but continues to meet demand and reduce the electricity cost. When the PV generation ends, the period (18:00-21:30), corresponds to high demand where the EV discharges to assured the demand and reduce the energy purchased from the grid.

On Sunday, there is an off-peak period throughout the day, so the energy price is cheaper. In addition, the total consumption is lower, since there is no EV charging. Even so, the consumption is assured by EV discharge and PV generation, although they are not enough to satisfy the total consumption, they allow for a decrease in the amount of energy that comes from the grid. There is an exception during the last hours of the day (17:30-23:30) when the EV discharging process meets the demand, and there is no need to buy energy from the grid, reducing the electricity price.

In this situation, the arrival time uncertainty proves to be very network-dependent since there are only two periods when there is no dependence on the grid energy, on Friday (06:30-10:00) and Sunday (17:30-23:30). However, on the other days the EV discharging and PV generation were able to reduce the power purchased from the grid.

Figure 28 displays the outcomes of robust scheduling for the worst-case of departure time, similar to what happened with the arrival time. For this case, the worst-case is to consider the lower bounds of departure time forecasting values.

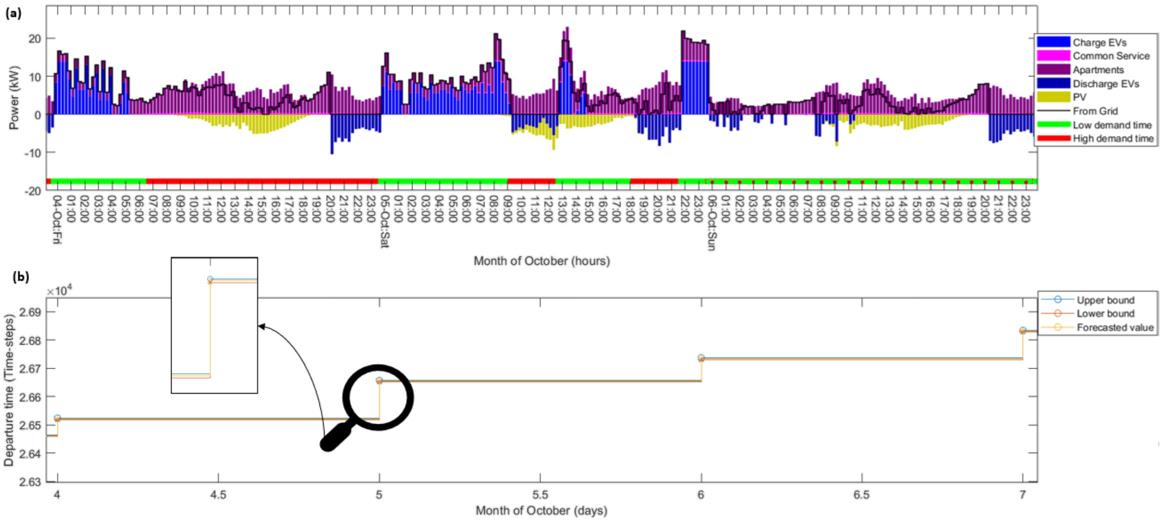

Figure 28 RO results in scenario 2 for (a) Energy consumption and RES (b) upper and lower bounds of departure time

Figure 28 features two graphs: (a) apartments consumption, EVs charging/discharging process, CS consumption, PV panels production, and the power grid; (b) the departure time uncertainty, where the predicted value and upper and lower bounds can be noted. It's possible to note that these values are pretty close because the deviation value is only 0.01%. The lower bound represents the worst-case scenario for this uncertainty because it corresponds to the worst-case scenario with the higher uncertainty.

Regarding figure 28(a), on Friday the EVs are scheduled to charge during the night (00:00 - 06:30), which represents low-demand periods where the price of energy is cheaper. However, the energy purchased from the grid is equal to the total consumption of the building, and the cost is the same. Afterward, there is a period of high demand (6:30-23:30) where initially only PV generation occurs and can reduce the energy purchased from the grid. In the last hours (20:00-23:30), EV takes the opportunity to discharge. During this period, since the power of EVs' discharge could meet the total demand, the electricity price reduces.

Concerning the weekend, on Saturday, EVs are scheduled to charge three times during the day, early morning (00:00-09:00), early afternoon (13:00-15:00) and during the night (21:30-23:30) representing moments of low demand, where the price is cheaper. However, only the afternoon period has PV production to ensure the consumption of the apartments, the CS, and the charging of EVs, reducing the cost. During the high demand period (09:00-12:30) the EV is discharged and there is PV generation, which allows the total demand to be met. When the PV generation ends, the period (18:00- 21:30), corresponds to a peak period where the EV discharges to ensure the demand. However, in this period the EV discharging process is not enough and it is necessary to buy energy from the grid. Sunday represents a low-demand period throughout the day, where the price is lower. Moreover, there are fewer apartments and CS consumption when compared with the previous days. As a result, the energy purchased from the grid is lower, being null during the last hours of the day (20:30-23:30), where consumption only depends on EV discharge.

The departure time uncertainty appears not to be to much dependent on the power grid. There are three periods when the energy acquired from the grid was zero, on Friday (20:00-23:30), on Saturday (09:00-12:30), and Sunday (20:30-23:30). Moreover, there are periods when the PV generation and EV discharge process was available where the dependency on the electric grid has decreased. However, neither the EV discharge nor the PV generation are sufficient to guarantee that consumption is not entirely dependent on the power grid.

Figure 29 shows the results of robust scheduling for the worst-case of initial SoC uncertainty. For this case, the worst-case consists of considering the lower bounds of initial SoC forecasting values.

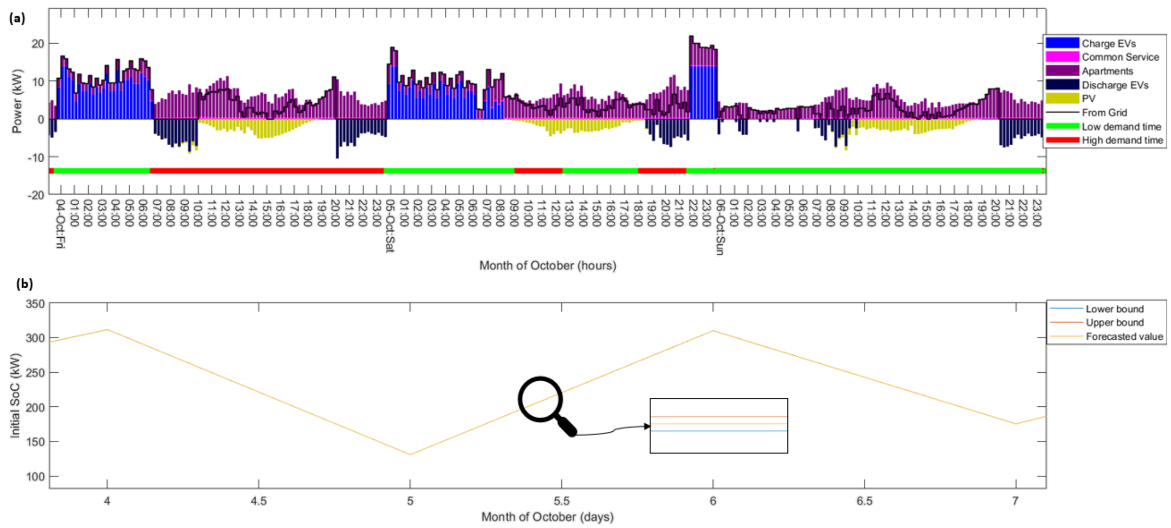

Figure 29 RO results in scenario 2 for (a) Energy consumption and RES (b) upper and lower bounds of initial SoC

Figure 29 presents two graphs: (a) relative to the consumption of the apartments, the EV charging/discharging schedule, the CS consumption, the PV generation, and the energy from the grid; (b) initial SoC uncertainty, in which it is possible to highlight the predicted value, as well as the upper and lower bounds. For this uncertainty, the worst-case scenario considered is the lower bound, which is similar to the predicted values, these values are very close due to the deviation value being only 0.01%.

Regarding figure 29(a), on Friday, the EVs are scheduled to charge during the night (00:00 - 06:30), which represents low-demand periods where the price of energy is cheaper. However, since there are no energy resources to satisfy the total consumption the energy purchased from the grid equals the total consumption of these services. Afterward, there is a period of high demand (06:30-23:30) where the EV takes the opportunity to discharge. During the period when EVs are discharging, this resource allows to ensure the total demand, therefore it was not necessary to purchase energy from the grid. In periods when EVs were not discharging, the demand was assured by PV generation. However, when there is only PV generation, this resource only allows for a reduction in the amount of energy that comes from the grid.

On the other hand, there is a difference on the weekend. On Saturday, EVs are scheduled to charge during moments of low demand (00:00 - 09:00). In this period the energy that comes from the grid equals the total consumption. Afterward, there is a period of high demand (09:00-12:30), where the consumption was assured by PV generation, and the power purchased from the grid decreases. During the low demand period of (12:30-18:00), the PV generation decreases but continues to ensure the consumption and decrease the amount of energy coming from the grid. When the PV generation ends, the EV discharging process starts to ensure the total demand during the period of (18:00-21:30), which corresponds to a peak period. However, this resource is not enough to fully ensure consumption, being able to only reduce the energy purchased from the grid. During the night, namely between (21:30-23:30), which corresponds to a low-demand period, the EV is charged again.

On Sunday there is an off-peak period during the whole day, therefore lower costs. On this day the consumption of apartments was lower than the previous days, and there are no EVs charging. Consequently, it is not necessary to employ PV generation and EVs discharge as much as on the other days, which are only utilized when the consumption is higher. Additionally, there is less electricity coming from the grid, and there is none between the period of (20:00-23:30) when EV discharge is the only resource of energy and can ensure the total demand.

Just as departure time, the initial SoC uncertainty also shows not to be to very network dependent, since there are several periods where there is no dependence on grid power, on Friday (06:30-10:00) and from (20:00-23:30), and on Sunday (20:00-23:30), which decreases the electricity cost.

5.2.3.2. Scenario 3: smart management system with EV uncertainty and BESS

The primary goal of scenario 3 is the same as scenario 2. The key difference between this scenario and the previous one is the addition of a new energy resource, BESS. The CP value corresponds to 20.70 kVA based on the selection made in the article [1].

Figures 30, 31, and 32 present the robust scheduling simulation results for all the building's energy sources and the corresponding uncertainty, arrival time, departure time, and initial SoC respectively. In addition, the energy consumption of the apartments, CS, and PV generation remains the same in all figures. The EVs scheduling charge/discharge process and the grid power are adjusted, depending on the uncertainty, as well as the introduction of BESS scheduling.

Figure 30 displays the outcomes of robust scheduling for the worst-case arrival time uncertainty. The worst-case considers the upper bounds of arrival time forecasting values.

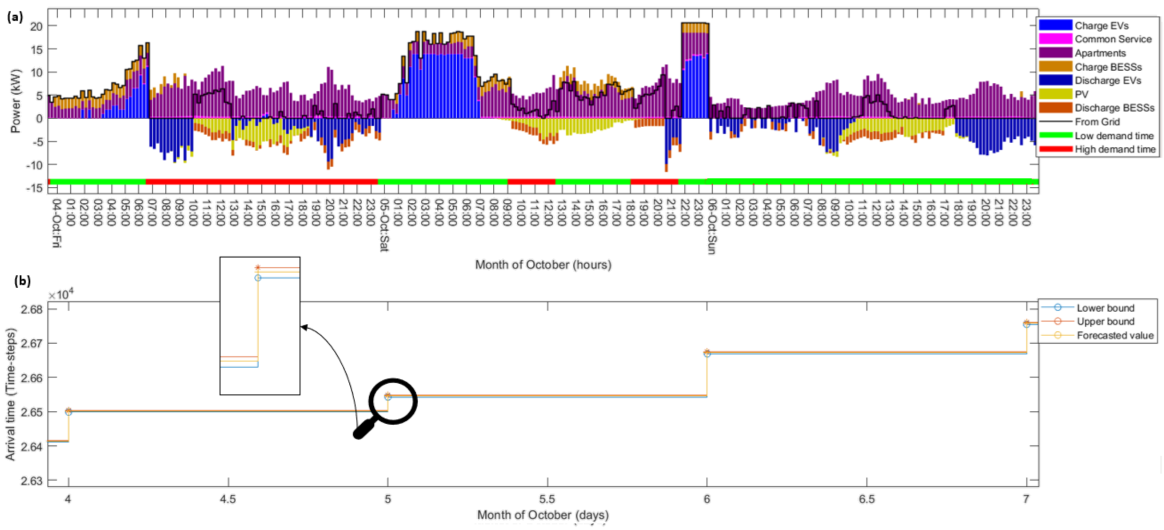

Figure 30 RO results in scenario 3 for (a) Energy consumption and RES (b) upper and lower bounds of arrival time

In Figure 30, two graphs are shown: (a) the consumption of the apartments, EVs scheduling charging/discharging process, CS consumption, PV production, and the power grid; (b) the arrival time uncertainty, where the predicted values, as well as the upper and lower bounds, can be emphasized. At the moment these values are very close since the deviation value is 0.01%. The lower bound represents the worst-case scenario for this uncertainty because it corresponds to the worst-case scenario for the higher uncertainty.

Concerning Figure 30(a), on Friday, EVs and BESS were charged at high-demand periods (00:00-06:30), where the energy purchased from the grid is equal to the total consumption of the building. Later in the high demand period (6:30-23:30), the cost of electricity is higher. In the early period from (06:30-10:00), the EVs discharging process was sufficient to satisfy the total consumption of the building. During the rest of the time, there is a variation between the EVs discharging, BESS discharging and PV production to reduce the grid energy as much as possible, often reaching zero values, and reducing the energy cost.

As for the weekend, on Saturday, EVs and BESS are scheduled to charge during low-demand periods (00:00 - 09:00), where the price is lower. Afterward, there is a period of high demand (09:00-12:30) where the cost is high. At this moment, the energy consumption from the apartments and the CS is being assured by the PV generation and BESS discharge, which lowers the power from the grid and the cost of electricity. In the period (12:30-18:00), where the cost is low, BESS is charged again. During this period, only the PV generation meets the load demand, being insufficient to meet the total demand, but being able to reduce the power grid. The period from (18:00-21:30) represents a peak period where PV production no longer exists. At this moment, there is only consumption made by the apartments and the CS, which demand is assured by discharging the EVs and BESS, reducing the energy purchased from the grid. The EVs and BESS are charged once more overnight, specifically between (21:30-23:30), at a cheaper rate. Nonetheless, during this period there is a surge in the amount of energy drawn from the grid, raising the cost of electricity.

On Sunday, there is an off-peak period throughout the day, with a low energy cost. On this day there are only apartments and CS consumption, where neither the EVs nor the BESS are charged. Therefore, the total consumption is lower compared to the previous days. This consumption is ensured through the EVs and BESS discharging process and the production of PV, thus reducing the power grid, as well as the cost of electricity. When EVs and BESS are discharging, there is practically no need to get power from the grid. However, when only PV production and BESS discharging are employed in periods of higher consumption they are not able to ensure total consumption and are more dependent on the power grid. Except for the (13:30-16:30) period when the consumption was lower and the PV production and BESS discharging process managed to ensure the total consumption. During the last hours of the night (17:30-23:30) it is verified that the EVs discharge ensures the total demand, reducing the electricity cost.

Regarding the arrival time uncertainty, there were several periods when the energy purchased from the grid was zero. Nonetheless, when there is EV charging, BESS charging, apartments consumption, and CS consumption without any energy resource to meet the demand, the building needs a lot of energy to satisfy them all. As a result, the arrival time proves to be grid-dependent and greatly increases the energy cost.

The outcomes of robust scheduling for the worst-case scenario of departure time uncertainty are shown in Figure 31. The worst-case considers the lower bounds of departure time forecasting values.

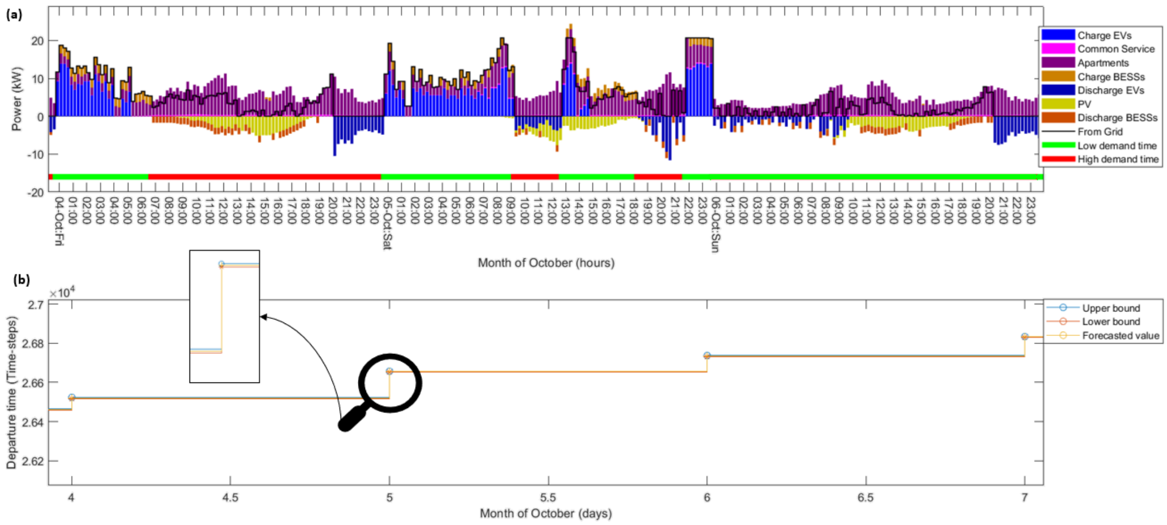

Figure 31 RO results in scenario 3 for (a) Energy consumption and RES (b) upper and lower bounds of departure time

Two graphs are shown in Figure 31: (a) apartments consumption, CS consumption, EVs charging/discharging scheduling process, PV generation, and the power grid; (b) the departure time uncertainty, where it is possible to specify the forecasted value as well as upper and lower bounds. At the moment, these values are very close, since the deviation value is 0.01%. Since the worst-case scenario with the highest uncertainty corresponds to the lower bound, it serves as the worst-case scenario for this uncertainty.

Regarding Figure 31(a), on Friday, EVs and BESS are scheduled to charge between the period of (00:00-06:30), where the energy purchased from the grid is equal to the total consumption of the building. Afterward, there is a period of high demand (06:30-23:30), in which there is only consumption from the apartments and the CS. To ensure this consumption, initially, PV generation and BESS discharging processes are employed, reducing the energy purchased from the grid. There is a period from (18:00-20:00) when the total consumption was not assured, and the energy purchased from the grid equals this consumption. Subsequently, the total demand is ensured by the EVs discharging process, thus decreasing the cost of energy.

On the weekend there are different values. On Saturday, EVs and BESS are scheduled to charge from (00:00 - 09:00) at a time when the price is lower, where the energy purchased from the grid is equal to the total consumption of the building. Later, there is a period of high demand (09:00-12:30) where total demand is being ensured by photovoltaic generation, EVs discharge, and BESS discharge, which annuls the energy purchased from the grid and lowers the cost of electricity. During the period (12:30-18:00), when there is apartments consumption, CS consumption, and also EVs and BESS charging, this consumption is provided only by PV generation. However, this energy resource is not sufficient, ensuring only for the BESS charging process. At the end of the period, the amount of PV produced decreases, so it no longer ensures the discharge of BESS. In the period of (18:00-21:30), which represents a higher cost, there is no more PV generation. However, the total consumption is ensured through EVs and BESS discharge, which decreases the cost. In the period of (21:30-23:30), the EVs and BESS are charged again. However, here the consumption is not ensured, leading them to draw power from the grid, which increases the cost of energy.

On Sunday there is something different. Throughout the day there is low demand, with low-cost energy. Consumption is lower, so there is no need to rely heavily on energy resources. However, there are times when the consumption produced by the apartments and the CS is higher, which are ensured by EVs discharge, BESS discharge, and PV production, reducing the energy purchased from the grid. Except for the period (20:00-23:30) when the energy purchased from the grid is null, and the total consumption is assured by the discharge of EVs.

Regarding the departure time, there are three periods where the energy from the grid was null, on Friday (20:00-23:30), on Saturday (09:30-12:30), and on Sunday (20:30-23:30). In addition, it appears that the introduction of BESS helped to reduce dependence on energy from the grid, thus reducing the cost of energy. However, energy resources are not sufficient to ensure consumption does not depend on the network.

The results of robust scheduling for the worst-case of initial SoC uncertainty are shown in Figure 32. The worst-case considers the lower bounds of initial SoC forecasting values.

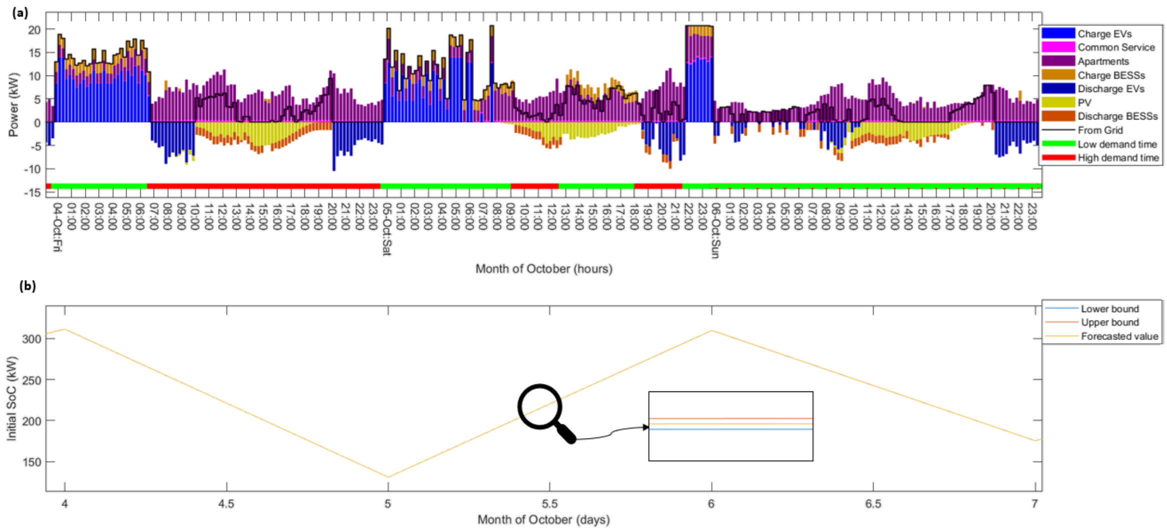

Figure 32 RO results in scenario 3 for (a) Energy consumption and RES (b) upper and lower bounds of initial SoC

There are two graphs in Figure 32, as in scenario 2: (a) apartments consumption, EVs charging/discharging process, CS consumption, PV generation, and the power grid; (b) initial SoC uncertainty, where the predicted value, as well as the upper and lower limitations, can be highlighted. These values are very similar due to the deviation value being only 0.01%. The worst-case situation for this uncertainty is represented by the lower bound since it corresponds to the worst-case scenario with the highest uncertainty.

Concerning Figure 32(a), on Friday, the EVs and BESS charging process starts during the periods (00:00-06:30), which represent off-peak periods, where the price is lower. In this period there is a higher dependency on the grid power because there is no power source to satisfy the total consumption of apartments, CS consumption, EVs, and BESS charging processes. Subsequently, there is a high demand period from (06h30-23h30), where the price is higher. However, during this period EVs and BESS discharging processes and PV generation occur to ensure the consumption of the apartments and the CS. Nonetheless, the EVs discharging process is the only one that fully supports the demand and does not need to resort to grid power.

Regarding the weekend, on Saturday the EVs and BESS start charging during the (00:00-09:00) period, and during the night, namely between (21:30-23:30), when the price is lower. However, in these periods the power grid equals the total consumption. Afterward, there is a period of high demand (09:00-12:30) when the cost is high and there is only PV generation and BESS discharging to partly ensure the total consumption, thus reducing the grid power cost. In the period from (12:30-18:00), where the cost is low, the BESS is charged again. In this period, photovoltaic generation reduces the cost of grid power. When the PV generation ends, the period from (18:00-21:30), corresponds to a high demand where the EVs and BESS discharge to ensure the consumption of the apartments and the CS, reducing the cost of energy purchased from the grid.

On Sunday the price is lower throughout the day. Thus, PV generation, EV discharge, and BESS discharge processes are not as required as on other days. These are only used when consumption is higher to decrease the energy purchased from the grid. Moreover, it can be observed that the energy bought from the grid is zero during the period (13:30-17h00) where PV production and BESS discharged were able to meet the total demand and on the last hours of the day (20:00-23:30) where consumption only depends on EV discharge.

It's possible to confirm that the initial SoC proves not to be highly grid-reliant. It is observed that there are 4 periods where there is no dependence on the network, on Friday morning (06:30-10:00) and night (20:00-23:30), on Sunday early afternoon (13:30-17:00), and during the nigh-time (20:30-23:30). Furthermore, in periods that present energy resources this dependency decreases.

5.2.3.3. Comparison of RO results

Regarding the results presented in the RO model, it can be noted that the energy purchased from the grid decreases throughout the three scenarios. The objective function for each of the aforementioned scenarios is shown in Table 13.

Table 13 RO scenarios' objective function

Method	Arrival time objective function (Cost €)	Departure time objective function (Cost €)	Initial SoC objective function (Cost €)
Scenario 1	2634.73	2634.73	2634.73
Scenario 2	2583.08	2365.69	2368.39
Scenario 3	2456.74	2261.10	2243.15

Similar to what happened for the MBLP model, also in the RO model the cost decreased throughout the scenarios, which was expected. However, this model already includes uncertainty. The simulation results for scenario 2, present a cost decrease of 1.96% for arrival time, 10.21% for departure time, and 10.10% for initial SoC when compared to the traditional scenario. Additionally, scenario 3, illustrates a significant reduction of 4.89% in arrival time, 4.42% in departure time, and 5.28% for initial SoC when compared to scenario 2. The same scenario 3, presents a cost reduction of 6.75% for arrival time, 14.18% for departure time, and 14.86% for initial SoC when compared to scenario 1. As a result, it was found that employing ESS (such as EVs and BESS) serves as examples of how intelligent scheduling and management of various energy resources can result in a decrease in electricity costs.

Moreover, Table 13 shows that the uncertainty with the highest cost corresponds to the arrival time. As a result, the arrival time is considered to have the most uncertainty and therefore the most volatile in the energy consumption in the building.

5.2.4. Evaluation of the outcomes

In this subchapter a comparison was performed between the results of the MBLP model and the robust optimization model, namely for the uncertainties of arrival time, departure time, and initial SoC. Figure 33 presents the total electricity costs for the three uncertainties in each of the scenarios and the total electricity costs regarding the MBLP model in each scenario.

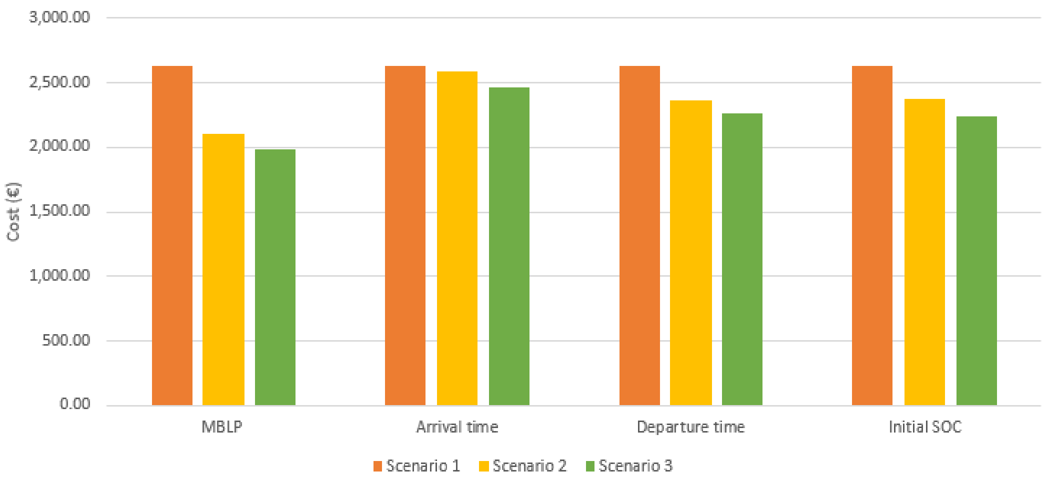

Figure 33 Total electricity costs of all uncertainties on each scenario

When comparing the robust optimization model through the three uncertainties with the MBLP model, it is possible to notice that the MBLP presents lower values in all scenarios, which was expected since the MBLP model does not present any type of uncertainty. Regarding the MBLP model, as expected, the cost decreased throughout the three scenarios. As a result, scenario 3 presented the lowest cost since not only the schedule of the EV and BESS charging and discharging process were optimized but also the electricity bill of the smart building was significantly reduced.

Concerning the RO model, it is clear from comparing the three uncertainties for each scenario that the cost of electricity decreases from one scenario to the next. As expected, scenario 1 without intelligence management and any kind of optimization represents higher costs. On the other hand, both scenarios 2 and 3 have optimization. Nonetheless, scenario 3 has lower electricity costs when compared with scenario 2, due to the introduction of BESS. Hence, it can be verified that a good optimization of energy resources and the introduction of BESS significantly reduces the cost of electricity, despite uncertainties.

As for uncertainty, it appears that the one with the highest cost is the arrival time in all scenarios. That's because this uncertainty presents higher values of energy consumption, in contrast with the two other uncertainties. As a consequence, the aggregator needs to buy more energy from the grid to meet the load demand, increasing the cost.

5.2.5. BUDGET OF UNCERTAINTY ANALYSIS

The budget of uncertainty is a parameter used to balance the robustness of the method against the degree of conservatism of the solution. The value of the budget of uncertainty is not an integer, varying between 0 and 1. The maximum value depends on the number of uncertain variables and the minimum value corresponds to the minimum number of uncertain variables [51].

When the budget of uncertainty is zero, the actual values are equal to the predicted ones because there is no uncertainty taken into account. Additionally, this value corresponds to the lower level where the model can be viewed as deterministic, and the scheduling problem does not take into account the uncertain constraint. On the other hand, when the budget of uncertainty is equal to 1, the worst-case scenario is considered, representing the maximum uncertainty. In this example, each uncertainty has a possibility of approaching either its upper or lower bounds [52], which corresponded to scenarios 2 and 3 present in the RO model.

As seen earlier, the worst-case for initial SoC is the lower bound, for arrival time is the upper bound, and departure time is the lower bound which results in increased energy expenses. Besides the fact that a higher value leads to more conservative solutions and therefore higher economic costs, it provides better risk performance and guarantees full protection against EV uncertainties.

According to equations 1(a), 1(b), and 1(c) concerning the uncertainty set, a new value for each uncertainty can be calculated according to the budget level of uncertainty. For the budget of uncertainty analysis, scenario 2 and 3 were considered, since it was in these scenarios that robust optimization was used. This analysis is done considering the three uncertainties, namely arrival time, departure time, and initial SoC. However, there is only one uncertainty considered at each time. Table 14, Table 15, and Table 16 show the energy management system scheduling costs for six distinct values of each uncertainty.

Table 14 Optimization costs under the budget of uncertainty for arrival time

Scenarios/Budget of uncertainty	0	0.20	0.40	0.60	0.80	1.00
Scenario 2	2562.70	2563.60	2569.65	2571.42	2577.37	2583.08
Scenario 3	2436.56	2437.41	2443.56	2445.18	2451.13	2456.74

Table 15 Optimization costs under the budget of uncertainty for departure time

Scenarios/Budget of uncertainty	0	0.20	0.40	0.60	0.80	1.00
Scenario 2	2360.42	2361.14	2361.81	2362.37	2364.39	2365.69
Scenario 3	2256.08	2256.56	2257.27	2257.67	2259.80	2261.10

Table 16 Optimization costs under the budget of uncertainty for initial SoC

Scenarios/Budget of uncertainty	0	0.20	0.40	0.60	0.80	1.00
Scenario 2	2368.34	2368.35	2368.36	2368.37	2368.38	2368.39
Scenario 3	2243.09	2243.10	2243.12	2243.13	2243.14	2243.15

It should be noted that the uncertainty does not influence the cost too much since this thesis used random data values, and the variance deviation is very small.

As seen earlier in the results of the MBLP model and the RO model, when comparing the two scenarios, scenario 3 has the best results, with lower costs. Furthermore, it can be verified that as the budget uncertainty value increases, the total energy costs of each of the uncertainties also increase for both scenarios.

Regarding each of the uncertainties, the uncertainty that presents the highest variation through the budget of uncertainty values is the arrival time since it is the one that presents the greatest uncertainty, as seen previously. As a result, it is the uncertainty that presents the highest cost for the entire set of budget uncertainty values.

The uncertainty budget may be employed to model all uncertainties that impact the scheduling results. Figure 34, Figure 35, and Figure 36 demonstrate the results of arrival time, departure time, and initial SoC respectively, considering different values of budgets of uncertainty. For these figures only scenario 3 was considered since the scheduling costs were more promising than in scenario 2. As was the case in the optimization model, the apartments consumption, the CS consumption, and the PV generation remain the same in all figures. However, the charging/discharging of the EV and BESS changes, due to the variation of the uncertainty values determined by the budget of uncertainty level.

To regulate the conservative degree of the solution and, as a result, to modify the robust energy schedule, the aggregator can select an appropriate value for the budget of uncertainty. A higher budget of uncertainty leads to conservative solutions and higher costs, while at a lower value there is no uncertainty considered. As a result, the aggregator must select a reasonable value from the uncertainty budget's range of possible values.

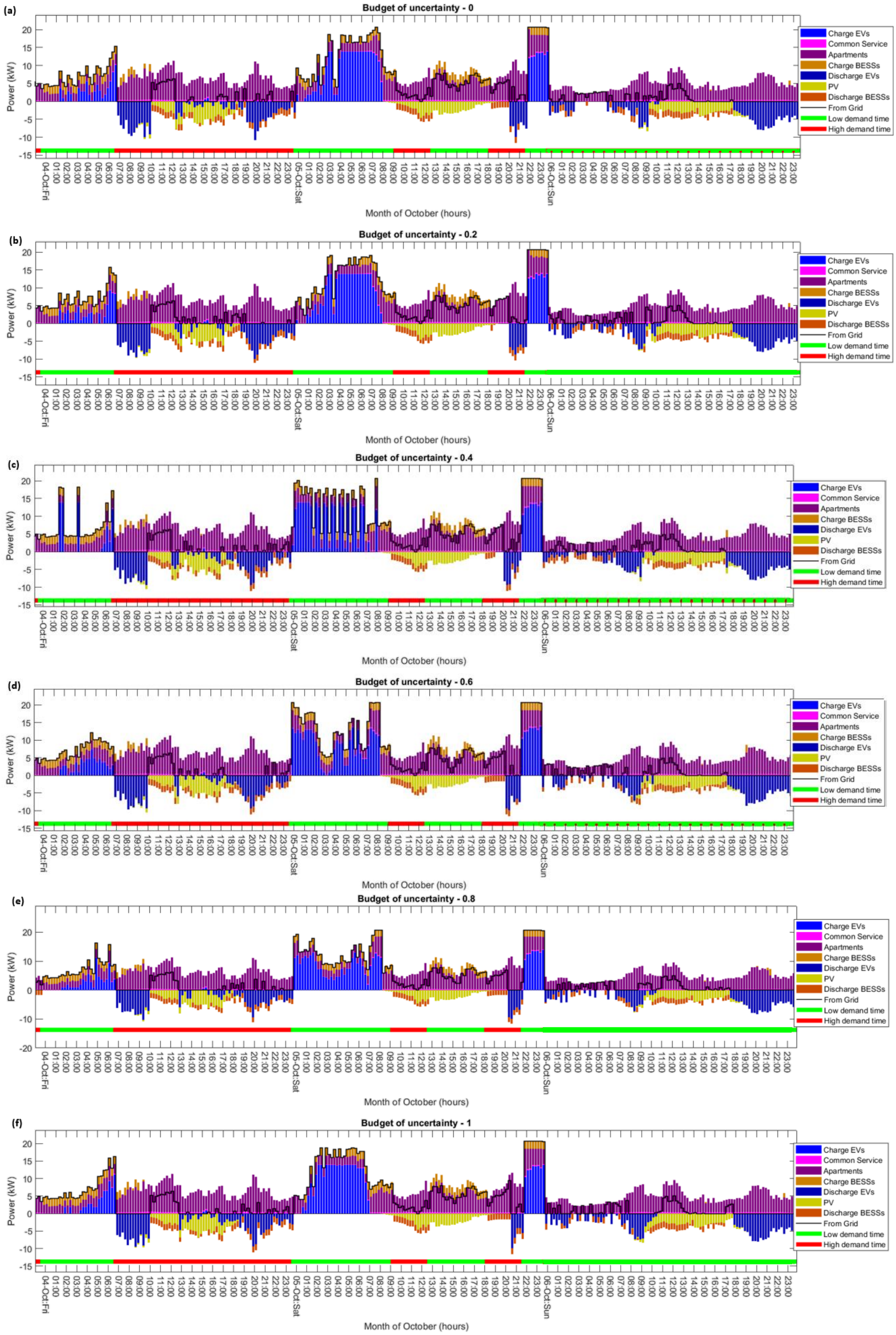

Figure 34 RO consumption results of arrival time for the different budgets of uncertainty (a) 0.0, (b) 0.2, (c) 0.4, (d) 0.6, (e) 0.8, (f) 1.00

As seen before, the worst-case scenario for the arrival time corresponds to an upper bound, therefore, by increasing the value of the budget of uncertainty, the value of arrival time increases, and the level of uncertainty increases, hence the cost increases with a higher amount of energy purchased from the grid. As a result, the worst-case scenario occurs when the budget of uncertainty is the highest and represents a maximum increase in the arrival time.

By analyzing Figure 34, it is possible to notice that the results of charge/discharge of EVs and BESS are different throughout the different levels of the budget of uncertainty, thereby representing the uncertainty with the highest cost.

There is a big change in the charging level of EVs on Friday and Saturday. On these days this charge increases throughout the increase of the budget of uncertainty. Although, when the budget of uncertainty is 0.4 shows high peaks, these do not occur continuously, presenting only a large variation in cost in comparison to the previous one. Furthermore, it is observed that with the increase of EVs charged in low-demand periods, the total consumption equals the consumption of the apartments, CS consumption, EVs, and BESS charging processes, since there is no resource to ensure this consumption. As a result, it can be noted that when the budget of uncertainty is one, needs more energy from the grid, increasing the electricity costs.

Among these budget of uncertainty values, the aggregator chooses the best value, which depends on the objectives of the decision maker. However, a budget of the uncertainty of 0.4 corresponds to a reasonable value as it presents some uncertainty along with a low cost.

Figure 35 shows the results of departure time uncertainty considering different values of budgets of uncertainty. In this situation, the worst-case scenario for the departure time corresponds to a lower bound. As a result, by increasing the value of the budget of uncertainty, the value of the departure time decreases, and the level of uncertainty increases, hence the cost increases with a higher amount of energy purchased from the grid. Therefore, the worst-case scenario occurs when the budget of uncertainty is the highest and represents a maximum decrease in the departure time.

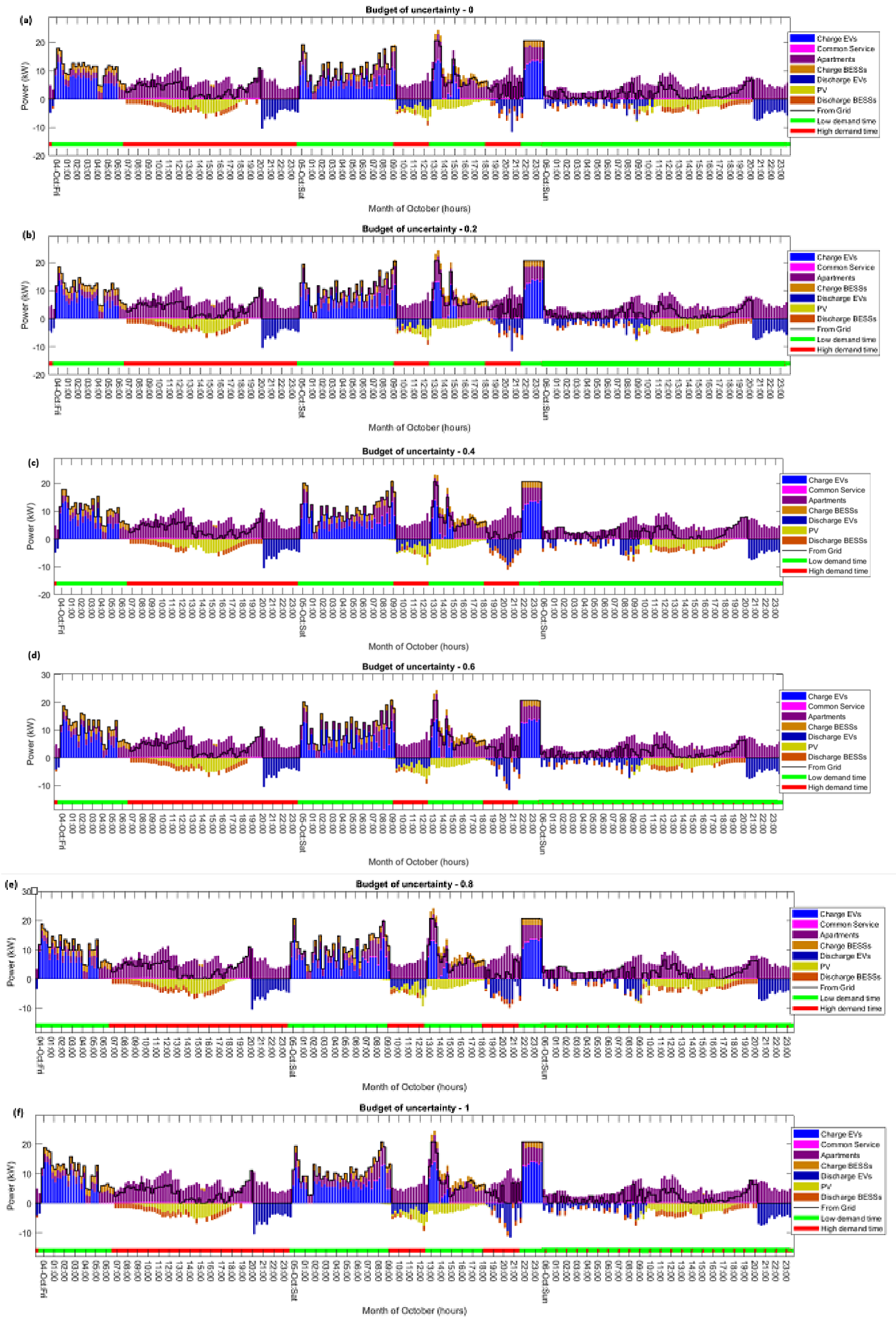

Figure 35 RO consumption results of departure time for the different budgets of uncertainty (a) 0.0, (b) 0.2, (c) 0.4, (d) 0.6, (e) 0.8, (f) 1.00

In this case, the departure time uncertainty modifies slightly, as predicted in Table 15. The departure time has lower values than the actual values when the uncertainty budget is at its maximum since it represents the worst-case scenario.

In figure 35, it can be noticed that there are more changes at the grid level due to the slight differences in EVs charging/discharging process. When the budget of uncertainty is one, during the low-demand periods the total consumption is higher compared with the other values. On the other hand, when demand is high, despite the PV generation, EV discharging and BESS discharging, the building is more dependent on the grid, increasing the electricity cost.

The aggregator selects the best budget of uncertainty value, which corresponds to a budget of uncertainty value of 0.4 for departure time uncertainty. On average, this value presents a lot of uncertainty and has a reduced cost.

Figure 36 shows the results of initial SoC uncertainty considering different values of budgets of uncertainty. This case is similar to the departure time uncertainty since the difference between the costs is minimal, presenting slight differences with the increase of the budget of uncertainty. Furthermore, the initial SoC is the least expensive uncertainty in this scenario.

Since the worst-case scenario for the initial SoC corresponds to a lower bound, by increasing the value of the budget of uncertainty, the value of initial SoC decreases, and the level of uncertainty increases, hence the cost increases. In addition, it is noted that a decrease in the initial SoC results in a greater amount of energy purchased from the grid, which increases costs. As a result, the worst-case scenario occurs when the budget of uncertainty is the highest and represents a maximum decrease in the initial SoC.

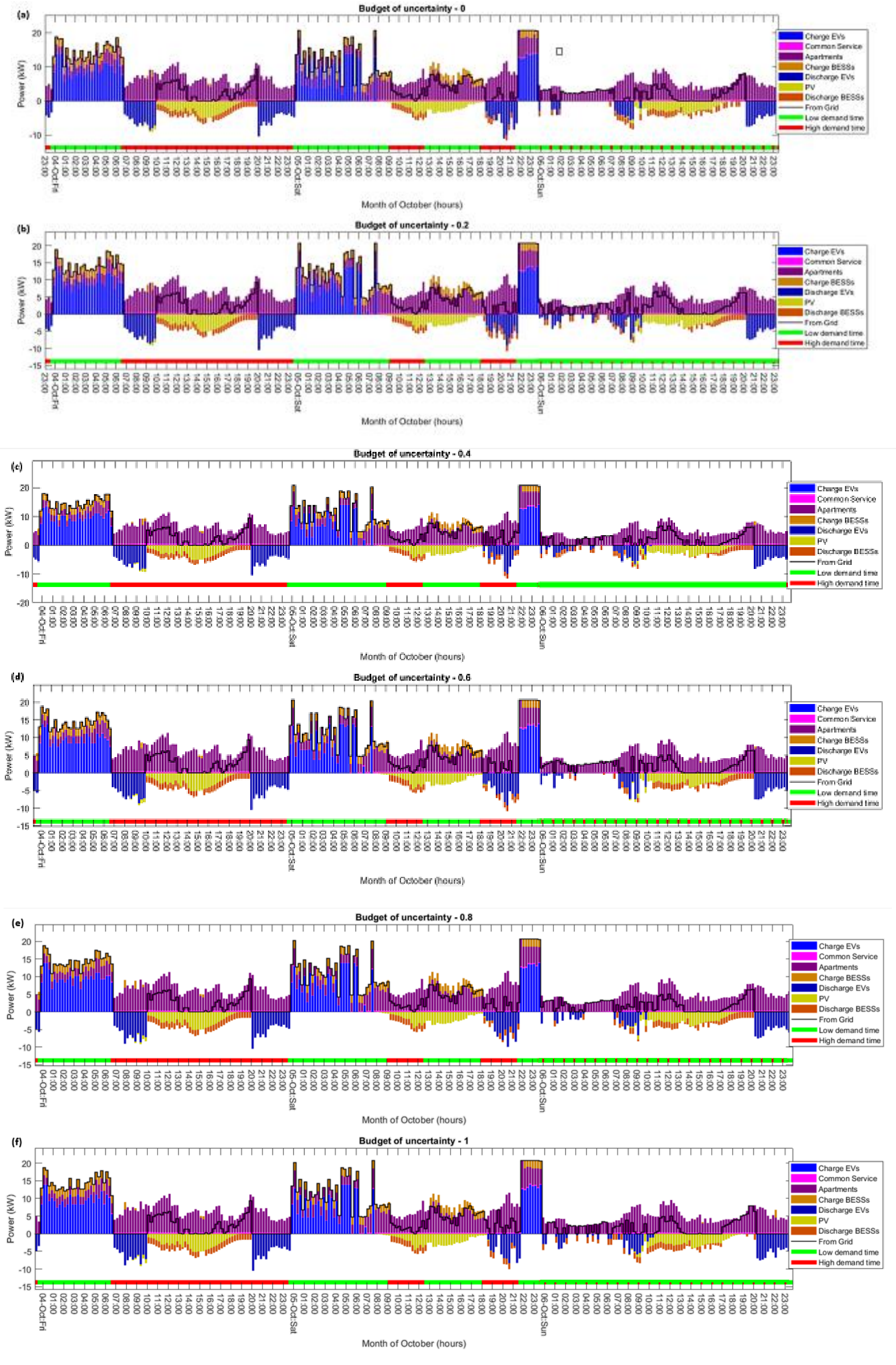

Figure 36 RO consumption results of inital SoC for the different budgets of uncertainty (a) 0.0, (b) 0.2, (c) 0.4, (d) 0.6, (e) 0.8, (f) 1.00

Analyzing Figure 36 it is possible to observe that by increasing the budget of uncertainty, the charge/discharge of EVs and BESS is very similar, presenting only slight differences, as predicted through Table 16. Therefore, the initial SoC uncertainty changes slightly, thus representing the uncertainty with the lowest cost. The grid power as well as the charging/discharging of the EVs and the BESS, are the variables that change the most throughout the budget of uncertainty values, although they do it so slightly. Similarly, the grid power increases and becomes equal to the total building consumption, including the apartments consumption, the CS consumption, the EVs charge, and the BESS charge.

For the initial SoC uncertainty, this value corresponds to a budget of uncertainty of 0.4 since this value is almost half of the total value of uncertainty and also has a low cost.

5.3. CONCLUSIONS

This chapter presents the results and discussion of each implemented model. The ANN model results show that the proposed forecast model has a high degree of accuracy, however, the MAE error presents high values in all three uncertainties, with the arrival time presenting the highest value. Therefore, the arrival time uncertainty will present the highest uncertainty.

The results of the MBLP model show that the costs decrease throughout all three scenarios. The simulation results of scenario 2 illustrate that coordinated charge/discharge of EVs can reduce the total cost by about 20.23% compared to the uncoordinated charging mode, scenario 1. Also, the results of scenario 3 present a reduction of 5.55% compared to scenario 2, and 24.66% compared to scenario 1. This reduction is due to the smart EV management scheduling in scenarios 2 and 3, and the implementation of BESS in scenario 3.

Finally, the results of the RO model prove to be similar to those of the MBLP model, as the total electricity costs also decrease throughout the three scenarios. The simulation results of scenario 2, with coordinated charging/discharging, present a cost decrease of 10.10% for initial SoC, 1.96% for arrival time, and 10.21% for departure time when compared with the traditional scenario. Additionally, scenario 3, illustrates a significant reduction of 5.28% for initial SoC, 4.89% in arrival time, and 4.42% in departure time when compared to the coordinated charging/discharging scenario, scenario 2. The same scenario with smart management of EVs and BESS presents a cost reduction of 14.86% for initial SoC, 6.75% for arrival time, and 14.18% for departure time when compared to the uncoordinated charging mode, scenario 1. As a result, both the use of EVs and BESS serve as examples of how smart scheduling and management of various energy resources can result in a decrease in electricity costs.

Additionally, the effects of different values of the budget of uncertainty on the scheduling management system for scenario 3 are also analyzed. As the value of the budget of uncertainty increases, the total energy costs also increase. Accordingly, when there is no uncertainty, the value of the budget of uncertainty is zero and the model can be considered deterministic. On the other hand, when the budget of uncertainty is one, it represents the worst-case scenario, corresponding to the highest cost of uncertainty, and most conservative. In this way, each uncertainty varies according to the budget of uncertainty, being the arrival time uncertainty the one that most modifies the results because it is the one that presents the highest uncertainty, and highest costs. Following the chosen robustness level, the RO approach adapts the energy schedule.

6. CONCLUSIONS

This chapter provides a final overview of this thesis and summarizes the main conclusions concerning the implemented methodology. The main contributions accomplished within this work are outlined. Additionally, some limitations are identified as well as some recommendations for future work considering the model described.

6.1. FINAL CONCLUSIONS

The introduction of RES in electric grids has increased in recent years, leading to a transition in the energy system. Therefore, a coordination method had to be developed to ensure affordable energy, such as a building energy management system, which reduces energy costs and improves efficiency, through energy scheduling. However, the deployment of BEMS has led to a major problem due to the unpredictability of EVs.

The main goal of this thesis was to develop optimal scheduling of energy resources in the SB by considering the uncertainties in EVs. Robust Optimization is very effective when dealing with uncertainty. This optimization model consists in finding the worst-case scenario in the building energy scheduling and minimizing its impact by obtaining the best solutions among the worst ones.

Initially, the Artificial Neural Network technique was formulated to deal with EVs uncertainties. Subsequently, a mathematical model based on a deterministic model (MBLP model) was developed to deal with the energy scheduling problem and reduce the building energy costs. Then, the deterministic model is transformed into a robust problem, ensuring immunity against the worst-case scenario within the uncertainty bounds. Lastly, the RO solution is adapted by finding the appropriate value of the uncertainty budget.

Three scenarios were implemented to evaluate the performance of the proposed approach. These scenarios consisted of a three-day energy scheduling, where the first one considers a non-smart energy management system, where EVs are charged in an uncoordinated way. The second scenario represents a smart management system with a single CP, where EVs are charged in a coordinated manner, and the third scenario presents a smart management system with EVs and BESS scheduling the charging/discharging process.

When comparing these three days, it was noticed that Sunday is the day when energy does not depend so much on the grid and is, therefore, the cheapest. Regarding uncertainties, the ANN results demonstrated that the arrival time uncertainty was the one that presented the largest error in MAE, as well as higher costs when compared to the other uncertainties. In this way, it may be concluded that arrival time is the most uncertain parameter which further increases the costs.

On the simulations of the MBLP model, scenario 1 was reduced by 20.23% in scenario 2, and 24.66% in scenario 3. Concerning the introduction of BESS in scenario 3, it showed a reduction of 5.55% compared with scenario 2. The RO results proved that the model can provide immunity against the worst-case scenario, which differs from uncertainty. However, the best uncertainty protection also happens to be the most conservative, which results in higher energy costs but better risk performance. In this optimization model, scenario 1 had a 1.96% reduction for the arrival time, 10.21% for the departure time, and 10.10% for the initial SoC in scenario 2. The last scenario had a reduction of 4.89% for arrival time, 4.42% for departure time, and 5.28% for initial SoC when compared with scenario 2, and a reduction of 6.75% for arrival time, 14.18% for departure time, and 14.86% for initial SoC when compared with scenario 1. In this way, the results proved that the smart management system and the integration of ESS, such as EVs and BESS, significantly decrease the price of electricity, as well as the adjustment of the robust optimization technique according to various levels of robustness.

In summary, it can be concluded that the robust optimization model not only reduces the total electricity costs of the residential building but also reduces the problems associated with the uncertainty of EVs.

6.2. CONTRIBUTIONS

With the development of this work, there was a need to highlight the importance of using optimization methods capable of managing the existing energy resources in residential buildings in dealing with the uncertainties of EVs.

This dissertation has contributed to the formulation of a methodology based on the robust optimization method. In this way, the first analysis was made in the scientific literature on what already existed regarding this theme, having concluded that it is not yet a widely studied theme when it comes to the uncertainties of EVs. Furthermore, an analysis was made of what methods were the best for the proposed theme, as well as what was the best technique to predict the uncertainties. The ANN model was implemented to predict the uncertainties by using the Python language in the Colaboratory program, which obtained favorable results despite still having a high MAE.

Another contribution of this dissertation was to highlight an algorithm that presented good results when dealing with BEMS and uncertainty. This algorithm was adapted for this case study and was implemented on a programming and numerical computing platform, Matlab. This adapted algorithm was used in the MBLP and RO models, where both showed good results. In this way, the effectiveness of the proposed model is verified, providing reductions in the problems associated with the EVs uncertainties, as well as reductions in electricity consumption costs.

The work developed in this dissertation led to the publication of some papers. The papers are as follows:

- J. Chavez, J. Soares, Z. Vale, B. Canizes, and S. Ramos, "A Review of Unpredictable Renewable Energy Sources through Electric Vehicles on Islands," in: Innovations in Bio-Inspired Computing and Applications. IBICA 2021. Lecture Notes in Networks and Systems, vol 419, pp.751-760. Springer, 16-18 December 2021. Cham. doi: 10.1007/978-3-030-96299-9_71 (published);

- Alexander Van Waeyenberge, Bruno Canizes, João Soares, Sérgio Ramos, Simon Ravyts, Juliana Chavez, Zita Vale. “Simulation and Operation Analysis of a Smart Grid using Simulink”. Electrimacs 2022: 14th International Conference of TC-Committee, 16-19 May 2022, Nancy, France (accepted);

- Bruno Canizes, João Soares, Sérgio Ramos, Juliana Chavez, Zita Vale, Zahra Foroozandeh. “Optimal Location of Normally Closed Switches in Medium Voltage Distribution Networks”. ICEEE 2022, 9th International Conference on Electrical and Electronics Engineering, 29-31 March 2022, Antalya, Turkey (published);

- J. Chavez, J. Soares, Z. Vale, B. Canizes and S. Ramos, “Survey on grid flexibility solutions to deal with unpredictable renewable energy sources and high penetration of electric vehicles on islands”, in International Journal of Computer Information Systems and Industrial Management Applications, pp. 1-13, Accepted: 25 March, 2022, ISSN 2150-7988 (accepted);

- J. Chavez, Z. Foroozandeh, S. Ramos, J. Soares, and Z. Vale, “A Short Review on Optimization Approaches when Dealing with the Uncertainty Associated with Electric Vehicles”, in IEEE Saudi Arabia 2022 Conference (submitted);

- J. Chavez, Z. Foroozandeh, S. Ramos, J. Soares, and Z. Vale, “Electric Vehicle Uncertainty Forecast through a Machine Learning Approach”, in IEEE Saudi Arabia 2022 Conference (accepted);

- J. Chavez, Z. Foroozandeh, S. Ramos, J. Soares, and Z. Vale, “Energy Resource Management in Smart Buildings considering EV Uncertainties” (to be done).

6.3. LIMITATIONS AND FUTURE WORK

During the development of this work, some limitations were encountered. The robust optimization model is not yet widely used in building energy management systems, especially when considering the uncertainty of EVs.

For future work, some concerns can be explored in further detail and improved. In the ANN model it is found that the MAE error is still high, so modifying some parameters such as the number of hidden layers or the number of input variables could improve this value. In the MBLP model, the CP value of each scenario could be changed to further decrease the building electricity cost and rely less on the grid. The RO model should be improved since this work uses one month as a case study, not making much difference between weekdays and weekends. Improving this aspect by predicting each uncertainty for the weekend and another prediction for the weekdays would be something to consider. In addition, another improvement would be to implement actual data values in the uncertainties instead of random ones to compare if the EV uncertainty becomes more apparent. Explore other uncertainty modeling techniques, such as the robust model predictive control (RMPC), and compare it with the robust optimization model to determine which method is better to implement. Concerning building uncertainty, other uncertain factors related to building energy management systems, such as the uncertainty in PV and energy consumption could be considered. Furthermore, an analysis including all three uncertainties together would be something to consider to compare how much the cost of electricity decreased.

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