Faculdade de Engenharia da Universidade do Porto

Stochastic Optimization for Home Energy Management

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Major Energy

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"Any society grows great when old men plant trees
whose shade they know they shall never sit in."

Greek proverb

Abstract

Energy demand is growing broadly across all the main sectors, mainly to meet the consumption requirements of fast-growing economies and achieve global electrification. Particularly in the residential sector, the combination of population growth and comfort parameters improvement for people in daily life and at work has been increasing the electricity consumption in buildings over the past few years.

The traditional paradigm of operation and planning the electric power system has undergone changes due to the progressive integration of distributed energy resources in the low voltage systems. After the beginning of the 21st century, there has been a significant increase in interest in distributed generation based on renewable energy sources, creating the need to develop more advanced monitoring models and new functionalities to mitigate the technical impacts of integration of these resources, while exploiting the benefits of the presence of these resources in low voltage distribution networks. Nevertheless, the smart-metering infrastructure has been enabling the transformation of the currently passive distribution networks into fully active networks by strengthening the relation between services and costumers through demand side management and demand response.

Many different works have been developed under the framework of the new operation paradigm of electrical power systems, more specifically in the scope of the energy management, in order to create solutions capable of being interoperable with the SM infrastructure, perform an optimized control of behind-the-meter resources and consumption devices, and minimize the electricity costs. Within this framework, an energy methodology for the electricity consumption scheduling is presented. It includes the internal inputs related to the home domain and the external inputs received from service providers that are interested in shaping the energy demand of certain households. The internal inputs comprise the operation of appliances according to a specific set of preferences and configurations, and the way users manage these devices will determine the flexibility of the energy used in each household.

The heuristic approach used for the optimization is the cross-entropy, which provides a simple, efficient and general method for solving complicated estimation and optimization problems, by offering a new generic approach to combinatorial optimization and rare event estimation – where very small probabilities needed to be estimated.

Resumo

A procura energética tem crescido amplamente em todos os grandes setores, principalmente para satisfazer as necessidades de consumo de economias em rápido crescimento e alcançar a eletrificação a nível global. Particularmente no setor residencial, a combinação entre crescimento populacional e aumento dos parâmetros de conforto das pessoas no dia-a-dia e no trabalho tem aumentado o consumo elétrico em edifícios nos últimos anos.

O paradigma tradicional de operação e planeamento do sistema elétrico tem vindo a sofrer alterações devido à integração progressiva de recursos energéticos distribuídos nos sistemas de baixa tensão. Após o início do século XXI, verificou-se um aumento significativo no interesse pela geração distribuída com base em fontes de energia renováveis, criando a necessidade de desenvolver modelos de monitorização mais avançados e novas formas de mitigar os impactos técnicos da integração desses recursos, explorando ao mesmo tempo os benefícios destes recursos em redes de distribuição de baixa tensão. Além disso, a infraestrutura de contadores elétricos inteligentes tem vindo a possibilitar a transformação das atuais redes de distribuição passivas em redes totalmente ativas, fortalecendo a relação entre serviços e consumidores por meio de gestão e resposta à procura de energia elétrica.

Diferentes trabalhos têm sido desenvolvidos no âmbito do novo paradigma de operação, nomeadamente no âmbito da gestão de energia, com o objetivo de criar soluções capazes de operar com a infraestrutura de contadores inteligentes, realizar um controlo otimizado de recursos domésticos e dispositivos de consumo e minimizar os custos de eletricidade. Neste contexto, é apresentada uma metodologia para a gestão doméstica do consumo de energia elétrica, que inclui os dados internos relacionados com a residência e os dados externos recebidos por serviços interessados em moldar a procura energética em certas residências. Os dados internos incluem a operação dos aparelhos de acordo com um conjunto específico de preferências e configurações, e o modo como os utilizadores gerem esses dispositivos determinará a flexibilidade da energia usada em cada residência.

A abordagem heurística utilizada para a otimização é a entropia cruzada, que fornece um método simples, eficiente e geral para resolver problemas complexos de estimação e otimização, através de uma nova e genérica abordagem para otimização combinatória e estimação de eventos raros - onde probabilidades muito pequenas são necessárias ser estimadas.

Acknowledgments

This dissertation marks the end of a long stage in my academic journey and the beginning of a new chapter in my life. The work presented here is a result from invaluable direct and indirect contributions from several people that I had the chance to meet and work with during my journey and without whom the success of this work would not be possible. I feel very fortunate for having the opportunity of studying and learning in an institution like FEUP, but most of all, I am grateful for the chance of doing my final work in such a great environment like INESC Porto, where I was welcomed since the first day and where I learned so much in the past few months.

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Leonel Duarte

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Acronyms and Abbreviations

AC	Air Conditioner
AMI	Advanced Metering Infrastructure
ANN	Artificial Neural Network
AMM	Automatic Metering Management
AMR	Automatic Metering Reading
BEV	Battery Electric Vehicle
CAMC	Central Autonomous Controller
CE	Cross Entropy
CD	Clothes Dryer
CCS	Carbon Capture and Storage
CHP	Combined Heat and Power
DER	Distributed Energy Resources
DES	Distributed Energy Systems
DG	Distributed Generation
DLC	Direct Load Control
DMS	Distribution Management System
DR	Demand Response
DSM	Demand Side Management
DSO	Distribution System Operator
DTC	Distribution Transformer Controller
DW	Dishwasher
EB	Energy Box
EES	Electrical Energy Storage
EPS	Electrical Power Systems
ETS	Electric Thermal Storage
EWH	Electric Water Heater
EV	Electric Vehicle
FCV	Fuel Cell Vehicle

GDP	Gross Domestic Product
GA	Genetic Algorithm
GHG	Green House Gas
HEMS	Home Energy Management System
HEV	Hybrid Electric Vehicle
HV	High Voltage
ICE	Internal Combustion Engine
ICT	Information and Communication Technologies
ILC	Indirect Load Control
IS	Importance Sampling
KPP	Knapsack Packing Problem
LC	Load Controller
LM	Load Management
LP	Linear Programming
LR	Likelihood Ratio
LV	Low Voltage
MC	Microsource Controller
MG	Microgrid
MINLP	Mixed-Integer Non-Linear Programming
MMG	Multi-Microgrid
MPC	Model Predictive Control
MSP	Multi-Stage Problem
MV	Medium Voltage
NLP	Non-Linear Programming
OECD	Organization for Economic Co-operation and Development
OLTC	On-Load Tap Charger
OS	Operative System
PBLM	Physically-Based Load Model
PEV	Plug-in Electric Vehicle
PSO	Particle Swarm Optimization
PV	Photovoltaic
RES	Renewable Energy Resources
RF	Refrigerator
RTP	Real-Time Pricing
RTU	Remote Terminal Unit
SA	Simulated Annealing
SCADA	Supervisory Control and Data Acquisition
SG	Smart Grid

SM	Smart Metering
SO	Stochastic Optimization
SS	Standard Shiftable
SSC	Smart Substation Controller
SSP	Single Stage Problem
TCL	Thermostatically Controlled Loads
TOU	Time-of-Use
TSO	Transmission System Operator
V2G	Vehicle to Grid
VHV	Very High Voltage
WM	Washing Machine

Chapter 1

Introduction

The current world is evolving towards a future were the energy demand tends to increase on a global scale. Under this vision, it is essential to integrate renewable sources of energy in order to minimize gradually the dependence of fossil fuels used as primary energy sources. Since the bulk of energy produced by renewable sources is converted in the electrical form and the electricity is the cleaner, sustainable and efficient way to satisfy this energy demand, one of the main goals for the next years is to achieve global electrification.

The renewable sources can be found within a wide range of types and characteristics, as well as integrated in different voltage levels of the power grid, meaning that the traditional concept of electricity production no longer fits completely in the new paradigm of operation and management of Electrical Power Systems (EPS). Thus, it is necessary to find new solutions for the integration of these sources, while at the same time creating new ways to manage the evolving smart-grids and give a greater role in the electricity management to certain users of the grid, namely the end-users.

The first step for the participation of the end-users in the management of EPS is the understanding about their electricity consumption. The consumer starts to become aware of the influence of his behaviour in his electricity consumption profile and how this can be optimized in terms of costs according to certain requisites and comfort parameters. It is in this context that this work will focus on.

The work presented in this dissertation was developed under the framework of the AnyPLACE H2020 project. The main idea behind AnyPLACE project is the development of a cost-effective solution for energy management of smart homes and residential buildings, capable to meet the requirements of the new electrical power system paradigm. Thus, an optimization algorithm for home energy management that can be implemented in this platform is proposed and tested under different operation scenarios.

1.1 Motivation

Human beings have always been more sensitive to the things that can be seen and controlled, rather than the abstract ones. In a residential context, if a consumer has its own way to produce, measure, and control energy, it is possible for him to know which the energy limits and which the main consuming appliances are, instead of knowing just a number with little significance displayed in the electricity meter.

The new paradigm of operation of EPS changed the way how different stakeholders interact with the electric grid and how different services can be exchanged among them. The consumers are now included in these stakeholders, being no longer the passive agents in the system and likely becoming active participants that play an important role in using their energy in a flexible way in order to provide new services – such as demand-response. [1]

The increasing use of technological platforms that allow the access to consumption information improves the relationship between suppliers and consumers, as end-users of energy become more empowered, educated and conscious to make decisions related to their electricity consumption profile as well as to create opportunities for energy and capital expenditure savings.

The challenge is in designing these technology platforms that allow end-users to implement energy management strategies, leveraged on dynamic services, that allow the implementation of energy efficiency strategies based on local information (preferences and configurations set by the user) and external information (dynamic price tariffs, incentives for participating in grid services, etc.).

1.2 Objectives

Many strategies have been developed within the framework of Smart Grids (SG) in order to manage the use of energy in homes and buildings. These techniques allow end users to take advantage of the flexibility in the use of certain loads and definition of dynamic comfort parameters to encourage the implementation of energy optimization actions. Moreover, these strategies rely on the use of simple and cost-effective computing and automation platforms, capable of demonstrating to the end user a set of added value in adopting more efficient behaviours. Under this context, it is particularly important to design and implement optimization algorithms that run on limited computing platforms, that are able to produce fast results and allow end users the ability to simulate various operating scenarios in an expeditious manner. Hence, this thesis has the following main objectives:

- Characterization of the context and challenges associated to the energy management in houses and buildings and modelling of the problem to be addressed;

- Analysis of stochastic techniques for optimization, based on the Cross-Entropy (CE) method, capable of producing fast solutions (optimal and sub-optimal) and be applied in limited computation platforms;
- Development and test of the proposed solution in different scenarios with real-data sets in order to evaluate its performance.

1.3 Organization of the Thesis

This work is organized in six chapters and four appendices, being this section the conclusion of the first chapter. Each chapter starts by presenting the key ideas that will be discussed and closes with a brief summary about the main conclusions.

The second chapter presents the state of art and literature review. An overview about the use of energy and electricity consumption is made, followed by the change of paradigm in the electrical power systems. Then, the home energy management systems are addressed as well as some of the optimization models that can be found in this scope.

The third chapter describes the models and considerations taken for all the internal and external inputs used in the formulation of the problem that will be solved by the optimization algorithm.

In chapter four is where the optimization methodology is detailed step by step, as well as the respective experimental validation. All the variables used in the problem are explained, as well as their influence in the algorithm.

Chapter five presents the information considered for the operation scenarios, as well as the results for the simulations performed to test the performance of the algorithm.

Chapter six discusses the conclusions about the methodology developed and some open topics and future works.

The appendices contain the graphical results for a different set of scenarios that were analysed during this work.

Chapter 2

State of the Art and Literature Review

2.1 Introduction

Everything known by man exists due to energy. *“Energy illuminates us and warms our houses, allows us to move, feeds the tools we use to produce food, and so on”*. [2] Nowadays, it is possible to identify three major purposes for the global energy use, namely heating, transportation, and electricity. To understand the relevance of these ends at the residential domain, it is important to understand the influence of energy in the present society. Hence, the state-of-art presented in this chapter is organized in a set of sections, that begins with an approach to the energy usage from a global scale and ends in the context of home energy management and the optimization solutions that can be found within this framework. The contents for each section are the following:

- The Energy Outlook – An overview on society’s current development, primary energy consumption, energy use by sector and access to electricity;
- The Electric Power System – The organization of Electric Power Systems (EPS), the change of paradigm observed in this last few years and some of the main Distributed Energy Resources (DER);
- Demand Side Management – A brief introduction on the traditional demand side and the main strategies for load management;
- Home Energy Management Systems – The HEMS concept as a gateway to improve demand response services and the AnyPLACE project;
- Optimization Models – An overview on classic and heuristic methods applied in optimization models, Stochastic Optimization (SO) and CE method. Then, related works within the scope of this dissertation are presented.

2.2 The Energy Outlook

The way in which world’s population evolves has a strong impact on the planet's natural state. In recent years, the world has witnessed an increasing prosperity resulting in the growth of the global economy. Moreover, according to [3], it is estimated that the current 7.6 billion people will increase to 11.2 billion by 2100. In the light of this evolution, energy demand tends to increase more and more, mainly to satisfy the consumption of fast-growing economies. However, with the falling energy intensity at global scale (energy used per unit GDP), the growth rate of energy demand has been decreasing.

The main driver of economic growth is increasing productivity. The Gross Domestic Product (GDP) of an economy is a measure of total production, which represents the monetary value of all goods and services produced within a country or region in a specific period. [4] As pointed out in Fig. 2.1, it is estimated that the world’s GDP will grow over the next 25 years. About 80% of this expansion is due to emerging economies in low-income countries – China and India are responsible for almost half of this expansion. Africa continues to have low levels of productivity. It accounts for almost half the world's population growth, but less than 10% GDP growth. Nonetheless, it is on the African continent that further urban growth is expected and consequently one of the major contributions to increase consumption. [5]

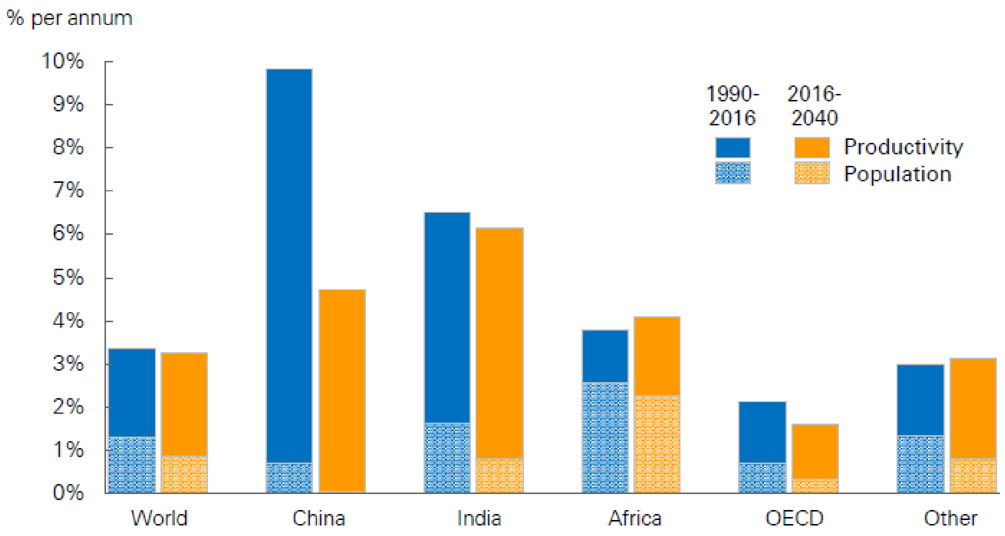

Figure 2.1: GDP growth by region and factor [1]

[1] According to Energy Transition scenario described in BP ENERGY OUTLOOK 2018 available in [4]

2.2.1 Primary Energy Consumption

Historically and until recent times, fossil fuels such as coal, gas and oil almost satisfied the total energy consumption needs of the planet. This reality will continue to be felt in some countries, at least until renewable sources become their main source of energy. Until then, huge amounts of carbon dioxide (CO_2) will continue to be emitted from the burning of these fuels.

Global energy consumption has changed over the past few years in terms of quantity and primary source. At the beginning of the 19th century, practically entire world exploited traditional biomass (essentially with the burning of wood and other organic matter). Only a small percentage of the world (predominantly the UK) used coal. Oil was already used for several purposes, but it was only after 1870 that its true expansion in the energy market began. About two decades later, natural gas and hydroelectricity follow. In 1900, coal consumption increased significantly, meeting almost half of the world's energy demand (the other half being satisfied by biomass, since oil, gas and hydroelectricity still did not have much significance back then). In the middle of the 20th century, the energy mix was already very diversified. Consumption from coal surpassed traditional biofuels and oil accounted for about 20% of world production. By 1960, the world was already producing electricity from nuclear power, and it was not until 1980-90 that renewable resources (such as wind, sun and modern biofuels) began to be effectively exploited to produce electricity. [6]

In Fig. 2.2, the diversification of the energy mix in the last years is presented. Although the production is becoming better distributed by source, the contribution of renewables to the satisfaction of consumption still represents a very small percentage of this mix, even including production from hydro and modern biofuels. However, estimates show that by 2040 about half of the increase in electricity generation capacity is due to renewable energy sources alone. [5]

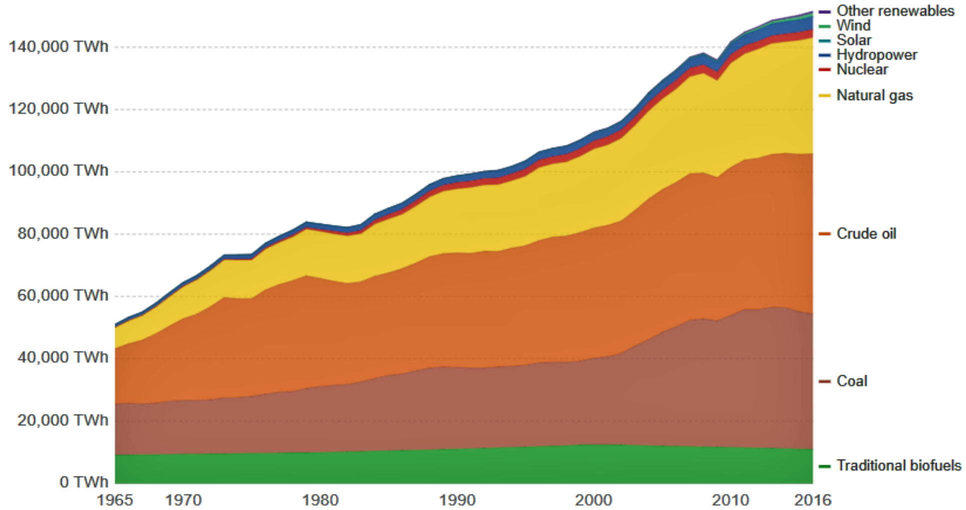

Figure 2.2: Global primary energy consumption [2]

[2] From source [6], adapted from [7]

It is important to realize that integration of renewables for electricity production goes beyond the diversification of the energy mix. It also intends to reduce the massive use of fossil fuels, that have been limiting existing primary resources and alarmingly contributing to the increase of carbon dioxide (CO_2) emissions into the atmosphere.

There is a certain amount of carbon that circulates naturally in the environment. After the industrial revolution, this natural quantity has been affected by the billions of tons of carbon removed from the soil and released into the environment, carbon that has been buried for millions of years and is no longer part of the natural cycle. This negative contribution causes CO_2 levels much higher than those that the ecosystem can absorb naturally, resulting in global warming. Due to the extreme sensitivity of the climate concerning temperature changes, irreversible damages in the atmospheric conditions may happen [8].

At the initiative of different policies and the rise of technological innovations, a gradual reduction of CO_2 emissions is expected in comparison to the past. However, this fall still falls short of the goals set by the Paris climate agreement. To solve this problem, it is required a combination of energy efficiency, increased use of renewable energy and Carbon Capture and Storage. CCS is a technology that has the potential to capture half of today's global CO_2 emissions from large power plants, large industries and refineries. With CCS technology, it is possible to capture at least 90% of the CO_2 being delivered to the atmosphere, transport it in its liquid state in aqueducts or ships and store it safely and permanently far below the earth's surface. The essence of this technology is the ability to mimic the natural cycle of oil, gas and coal storage in the soil, that nature has been repeating over millions of years [9].

2.2.2 Energy Growth by Sector

Growth in energy demand is expected to be global at all the main sectors, as presented in Fig. 2.3. The way energy is managed and consumed in these different sectors will play an important role in the future energy outlook. The current diversification in technologies and resources within the energetic sector creates a great number of opportunities, but also raises many challenges with its enlarged complexity.

The **industrial sector**, including the non-combusted use of fuels, currently consumes half of global energy and feedstock fuels. In an evolving transition scenario [10], this sector accounts for around half of the increase in energy consumption, although is expected that improving energy efficiency will cause a growth slowdown of industrial use outside non-combusted sector. In contrast, the non-combusted use of fuels is projected to be the fastest-growing source of demand, particularly as a feedstock in petrochemicals.

The slowdown in growth in the industrial sector of combusted fuels differs from region to region. Countries such as China, which has had a large energy demand in the industrial sector in the past 15 years, begin to distance their economies from energy-intensive industrial sectors (such as steel and cement industry) towards less energy-intensive services and consumer-facing sectors. In contrast, countries with developing economies (like India) and other emerging economies in Africa and Asia will be the main contributors to the growth of industrial consumption in the coming years (about 70%). All this change is accompanied by the exchange of coal for natural gas. Currently, coal accounts for about a third of the fuels used in China to supply energy demand in industry and is expected to decline to about one-quarter by 2040, meaning that by this year the increase in energy demand in industrial sector will be compensated in about two-thirds by natural gas and electricity. [10]

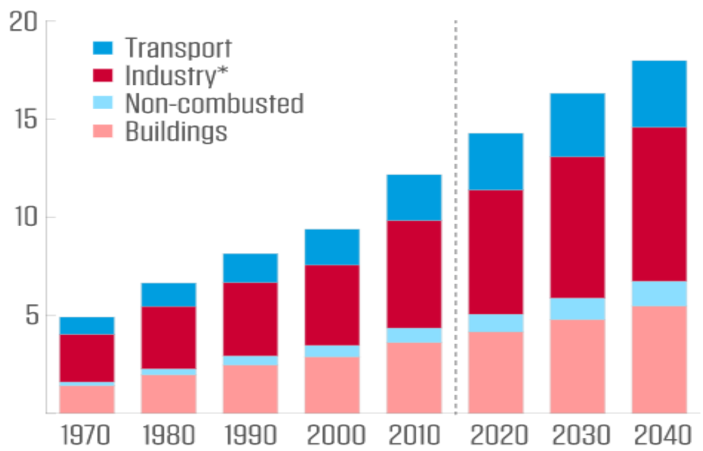

Figure 2.3: Primary energy consumption t** by end use sector [3]

It is estimated that the demand for services in the **transportation sector** will be more than double by 2040 [10]. These standards are consistent for both land, air and marine transportation. However, the impact on fuel demand is offset by gains in efficiency. Up to 2040, transport energy is expected to increase by only 25%, well below the 80% increase achieved in the last 25 years.

The growth in energy demand expected in this sector is mainly due to expansion of global GDP and industrial development. It has become easier to purchase a personal transport (such as a car or motorcycle) and there is a greater number of air and marine services available for all people at reasonable prices. At the same time, industrial development leads to an increase in the exchange of goods between regions, which are mostly transported by large trucks. [11]

Even with the integration of alternative fuels, particularly natural gas and electricity, oil remains the most widely used fuel. According to [11], the estimated decline in oil use in transportation by 2040 is only 9% from the current 94%. This fall is still far from the ideal, so it is essential to continue improving efficiency and driving range of vehicles fuelled by alternative fuels.

[3] According to Evolving Transition scenario described in [10]

* Industry excludes non-combusted use of fuels

** Consumption t in billion tonnes of oil equivalent (toe)

Approximately one-third of global consumption growth is attributed to energy in **buildings**. The increase over the years results from the combination of population growth and comfort parameters improvement for people in daily life and at work. These two trends are mainly concentrated in Asia, Africa and the Middle East, which together represent an increase of about 90% of energy use in buildings in the future. Due to the hot climate of these regions, the demand for space heating will be small. However, the demand for energy for space cooling (air conditioning) and electricity (light and electrical appliances) will be higher. It is safe to say that much of the demand on buildings will be met by electricity, as it is one of the most efficient source of energy to meet these requirements. In addition, an increase in the consumption of natural gas is estimated, to the detriment of coal and diesel usage for space heating. [10]

2.2.3 Electricity Use

Safe, sufficient and available energy constitutes one of the fundamental pillars for the welfare and economic development of any society. As all energy-related activities have a significant environmental impact, the creation of a well-organized electricity system that meets the needs of economies and preservation of the environment is indispensable. [9]

Access to electricity is essential for raising living standards. It saves time in everyday tasks (such as washing or cooking); increases productivity; improves healthcare and education services; creates digital links for local, regional or global networks. The number of people with access to electricity is an important social and economic indicator in today's world. By 1990, about 73% of the world's population had access; by 2014, this figure increased to 85%. [6] The world is increasingly electrified, and it is in the demand for electricity that is expected one of the highest growths (since its consumption grows three times faster than consumption from any other form of energy). It is estimated that by 2040 there will be an increase of about 70% of the primary energy consumption for electric power generation. [5]

A more sustainable future scenario for electricity is mainly due to the measures that are already being taken by OECD and to those that will be taken by China from 2030 onwards, on the production of electricity from coal. As a result, coal will be the resource with the slowest growth in electricity generation, with just a 13% increase expected in the future, well below the 40% seen in the last 25 years. However, it is estimated in [5] that coal will continue to be the largest source of power in 2040, with a contribution of almost 30%, as well as the main source of energy for electricity generation in the rest of the Asian countries. Natural gas, however, is projected to stabilize just above a 20% share of electricity production, after the gradual increase noticed over the last 25 years. [7]

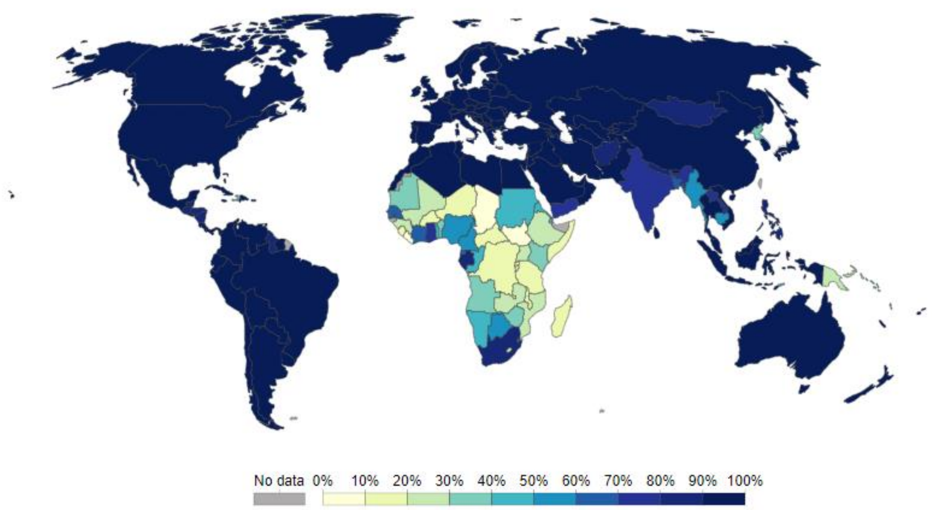

Figure 2.4: Share of people with access to electricity by 2014 [4]

Regarding the number of people with access to electricity since 1990, countries with the highest income presented in Fig. 2.4 have always remained between 95%-100%. The increase in the overall percentage is mainly due to countries with low income and high population growth, although for some of these countries (mostly in Africa) access to electricity will continue to remain a challenge in the coming decades. [6]

Everything indicates that it is essential to continue to innovate in the field of energy efficiency, whatever the sector. More specifically, in the context of this work, it is necessary to explore new methodologies for energy management in buildings, given the current state of existing technologies and expected future growth.

2.3 The Electric Power System

The power grid can be defined as a real-time power exchange system. Whenever a user of the network requests electricity, at that same instant electric power is generated, transported and distributed to the consumer. The delivery of electricity at the point of consumption is ensured by the different infrastructures that constitute the grid.

At the beginning of the 20th century, the number of individual electric generation units was still relatively small. These units were operated in electrical islands, at low voltage (LV), and only to meet local electricity consumption through short distribution lines, resulting in an expensive system where many of the infrastructures were not properly sized. With the increased demand for electricity after World War II, electricity producers have found that interconnection between existing transmission systems would be the most efficient way to meet demand and began to build larger generation plants to meet their combined electricity consumption at the lowest cost,

[4] From source [6]

avoiding the construction of duplicate power plants. Better management of transport infrastructure increased the reliability of the service, and with the need to transport large amounts of energy over long distances, high voltage (HV) interconnections have begun to be explored. The traditional concept of electrical network was established, which came to solve the problem of geographical separation between production and consumption centres. [12]

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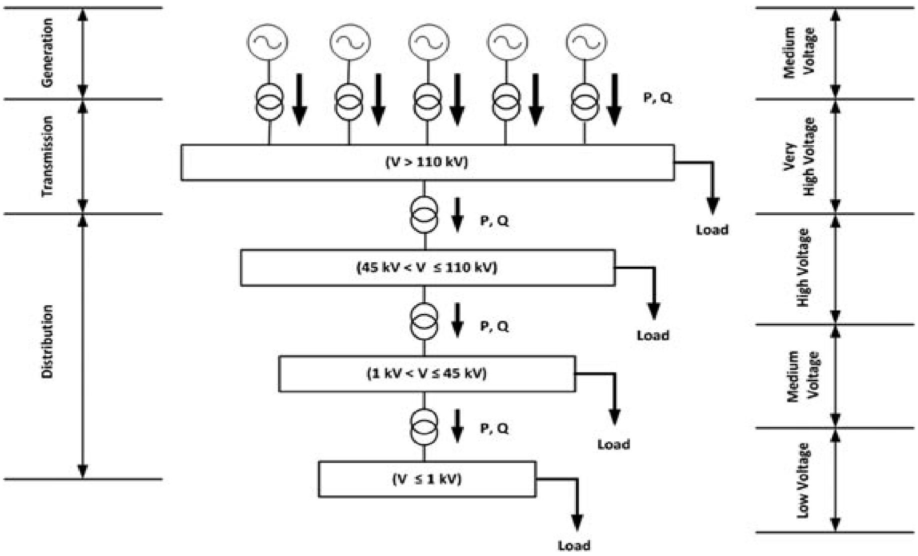

Figure 2.5: Organization of conventional electrical power systems [5]

In the last 50 to 60 years, the organization (design and operation) of the electrical power systems has followed a traditional hierarchical structure. In this classical paradigm, shown in Fig. 2.5, energy flows from higher to lower levels:

- Electricity is produced in large power plants. The main technologies used for this purpose are hydro units, thermal units (burning of fossil fuels such as coal, oil and natural gas) and nuclear units;

- Connection of the plant to the grid is done through a substation, where a step-up transformer is located to increase the electrical voltage - to very high voltage (VHV) to minimize the amount of losses in the transportation of electricity;

- Interconnected transmission lines transport electricity over long distances from the first substation (next to the power plant) to another substation, where a step-down transformer lowers the electrical voltage to a value appropriate to the distribution lines. The transmission network can supply VHV consumers;

[5] From source [13]

- Finally, the distribution network provides electricity to the different consumers of the grid according to their needs, being the respective voltage lowering done through transformers. Typically, industry consumption is made in HV, commercial buildings in medium voltage (MV) and residential buildings in LV.

2.3.1 The Change of Paradigm

In recent years, the traditional paradigm of operation and planning the electric power system has undergone changes due to the progressive integration of distributed energy resources in the LV systems. After the beginning of the 21st century, there has been a significant increase in interest in distributed generation (DG) based on renewable energy sources (RES), creating the need to develop more advanced monitoring models and new functionalities to mitigate the technical impacts of integration of DERs, while exploiting the benefits of the presence of these resources in LV distribution networks. With this, arises the opportunity to make the current merely passive networks in fully active networks. [13]

According to [14], the primary drivers behind the grow of DG can be classified into three main categories, namely environmental, commercial and national/regulatory.

Environmental drivers - At present, society is much more aware of the environmental impacts resulting from industrial activity for electricity production. Following the Kyoto protocol, governments began to play a more active role in policies to reduce greenhouse gas emissions. The increase in DG reduces the electricity dependence of large conventional plants, which in turn leads to a reduction of CO_2 emissions into the atmosphere and losses associated with electricity transmission. In addition, it increases the use of RES based technologies and the use of more efficient applications (such as CHP) in electricity production.

Economic and commercial drivers - the electricity industry has witnessed the transition from a vertically integrated structure to a more deregulated environment with access to the distribution network, favouring DG integration and increasing the variety and capacity of the products traded. In a highly competitive market, consumers will seek the solution for the most appropriate electricity supply to their situation. In addition, the increase of DG creates investment alternatives in the expansion and reinforcement of the network and has created a new range of opportunities for the different agents of the electric system, which were interested in developing solutions for safely integrating these new elements in the grids.

National / regulatory drivers - the system operation begins to have a more sustainable basis and a more diversified energy mix for electricity production. The external dependence of fossil fuels, located mainly in regions facing political instability, decreases. The increase of DG next to consumption centres can be the solution to mitigate the problems of consumption growth and capacity for generation, transmission and distribution. DG integration encourages electricity production from RES in a supporting act to raise environmental awareness and allows the system to have a greater reliability, safety, reserve capacity and provision of ancillary services.

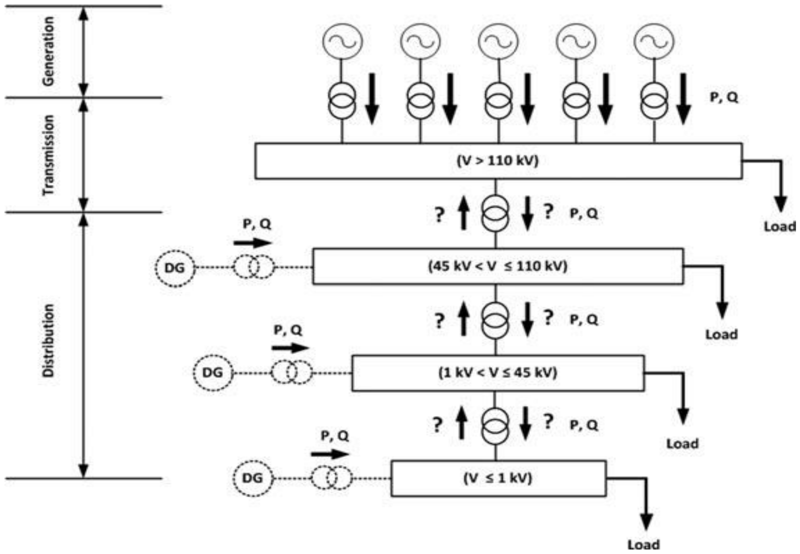

Figure 2.6: Integration of distributed generation in electrical power systems [6]

Fig. 2.6 shows the new organization of the electric power system. Within this new paradigm, *active distribution network management is considered as a key factor in achieving cost-effective solution*s in the planning and operation of distribution networks, given the increasing DG integration and the improved control solutions by means of information and communication technologies (ICT) [13]. However, this approach must be carefully revised, since the total amount of DG integration can be severely limited by the challenges that arise in the system operation.

Impacts on system operation - the existence of large (conventional) generating units and their intended amount of production are known to the system operator. In most cases, if production levels jeopardize the operational safety of the system, the operator can change the production of these units (dispatchable units - production can be adjusted, switched on or off according to demand). The same does not happen with DG (non-dispatchable), where the operator must accept production regardless of its quantity. In addition, the production levels of RES based DG are constantly changing over time and are difficult to predict. The presence of different DG technologies, with different variations in production, makes it even more difficult to plan and operate EPS.

Impacts on the transmission network - the main concern of the transmission system operator (TSO) is the increased uncertainty caused by the fluctuations and unpredictability of DG

[6] From source [13]

based on RES. Although the level of uncertainty is not a recent problem, the introduction of these generation sources creates even more and new types of uncertainty. A network that has a strong penetration of renewables to meet consumption can be seriously affected by a simple atmospheric change (*e.g.*, wind or solar). Another factor that may hinder the TSO is the behaviour of small or novel generators in the face of major disturbances, which until now is still relatively unknown. With DG integration, the following transmission impacts may occur: (i) power ramps, which oblige TSO to have to cut or increase the generation to satisfy the variation of electricity in a given time period; (ii) over-supply, when electricity production is greater than its real-time consumption; (iii) frequency degradation and voltage control, due to a greater unavailability of resources to control the network.

Impacts on the distribution network - while transmission systems have been designed in such a way that power can be transported in both directions, distribution systems were designed to transport power in only one direction: towards the consumers. Although the distribution network was not designed to receive production, the introduction of DG does not immediately result in a total collapse of the power supply. However, there are potential impacts associated with this integration: (i) overload of feeders and transformers may occur due to large amounts of production in periods of low consumption; (ii) the losses profile can be significantly modified, mainly due to the inversion of the energy flows; (iii) the risk of overvoltage increases due to the presence of DG in remote locations of the distribution feeder; (iv) the level of power quality may become inadequate for certain consumers; (v) an incorrect operation of the protections may occur, such as failure to operate or unwanted operation. [13], [14]

2.3.2 Distributed Energy Resources

In recent years, technological development has made it possible to create a wide variety of technologies that can be associated with DG. These technologies can vary according to many parameters such as power rating, application type, electric conversion efficiency, fuel type, investment and operating costs, greenhouse gas (GHG) emissions, type of resource that the technology exploits, among others. According to Lopes [14], nowadays it is more common for DG to be considered in a wider context of DER, which includes not only DG but also energy storage and responsive loads. In addition, Akorede [15] describes DER as electric power generation resources (including both generation units and energy storage technologies) that are directly connected to MV or LV distribution systems, rather than bulk power transmission systems.

In the new paradigm of EPS, distributed systems come in different forms and shapes, and can be tailored to meet the specific needs of each user [16]. Fig 2.7 intends to show some of the main DER that can be found in distributed energy systems (DES) within the scope of this new paradigm. The following is a brief introduction on three of the DER types where there has been the highest growth in recent years and where further growth is expected in the future.

Figure 2.7: Distributed energy systems [7]

2.3.2.1 Distributed Generation

The exact definition of DG (also referred to in the scientific literature as Dispersed Generation, Decentralized Generation or Embedded Generation) varies somewhat between sources and capacities. According to Jenkins [17], there is no consistent and unified definition for DG: some countries use a definition based on voltage level or on maximum power rating, while others consider that DG comprises the generation sources connected to circuits from which consumer loads are supplied directly; certain definitions rely on the type of prime mover (*e.g.*, renewable or CHP), while other definitions are based on the generation not being despatched. However, as pointed out in [15] and [17], some common ground can be found in order to define or categorize DG: (i) it is not centrally planned or dispatched; (ii) it is normally based on small scale generators, where capacity depends on connection voltage and grid characteristics; (iii) it is typically connected to the distribution grid, but depending on the size, it can be connected to the transmission grid; (iv) it can be based on RES to locally exploit a given energetic resource, but it is not limited to renewables (as in the case of CHP based applications). It can be powered by micro-turbines, combustion engines, fuel cells, wind turbines, geothermal, photovoltaic system, etc. Therefore, DG definition is quite broad in terms of technologies that can be connected to the grid. Nevertheless, the size of the DG units is generally below a few tens of kW due to the technical limitations of LV grids to accommodate high power injections.

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[7] From source [16]

Small DG units connected to LV networks are usually referred to as microsources or microgenerators [13], depending on their capacity. In the last decade, government initiatives have been promoting the use of these units. The goal is to encourage less intense consumers (typically connected to the LV network, such as households and condominiums) to produce electricity from locally available resources to satisfy part or all of their consumption, and therefore, becoming a prosumer (producer and consumer).

Table 2.1: Main DG technologies [8]

Technology	Typical Capacity Ranges	Controllability
Solar PV	A few W to (tens) MW	Non-controllable
Wind	A few hundred W to (hundreds) MW	Non-controllable / Partially controllable *
Combined Heat and Power	A few tens of kW to (hundreds) MW	Controllable
Microturbines	A few tens of kW to a (hundreds) MW	Controllable
Fuel Cells	A few tens of kW to a few (tens) MW	Controllable
Internal Combustion Engine	A few kW to (tens) MW	Controllable
Combined Cycle Gas Turbines	A few tens of MW to several (hundreds) MW	Controllable
Hydro	A few W to (hundreds) MW	Non-controllable / Partially controllable **

2.3.2.2 Electrical Energy Storage

EES is one of the technologies with the greatest potential to solve the challenges inherent to the new paradigm of operation and planning EPS, namely in the development and integration of RES-based generation. However, the variety of options and complexity of the characteristics of these technologies makes it difficult to choose the right technology for a specific application.

According to Luo [18], EES refers to the process of converting a form of energy (mainly electrical energy) to a storable form (in a given state, according to its technology), so when it is necessary be converted to electrical energy and used. The various EES technologies can be categorized by different methods. One of the most common methods of doing this is based on how energy is stored in the system, as shown in Fig. 2.8. Some considerable value applications for EES technologies have been proposed by Luo in [18], such as:

Helping in meeting peak electrical demands – a low-cost generator can produce and store electricity in off-peak demand periods for later use in peak demand periods. In addition, it can provide support in following load changes with electricity demand, offering greater flexibility in the way energy is produced and consumed.

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[8] From source [19]

* Depending on the type of technology used (conventional asynchronous generator, doubly-fed induction generator, synchronous generator with gearbox…)

** Depending on the existence of some type of reservoir associated

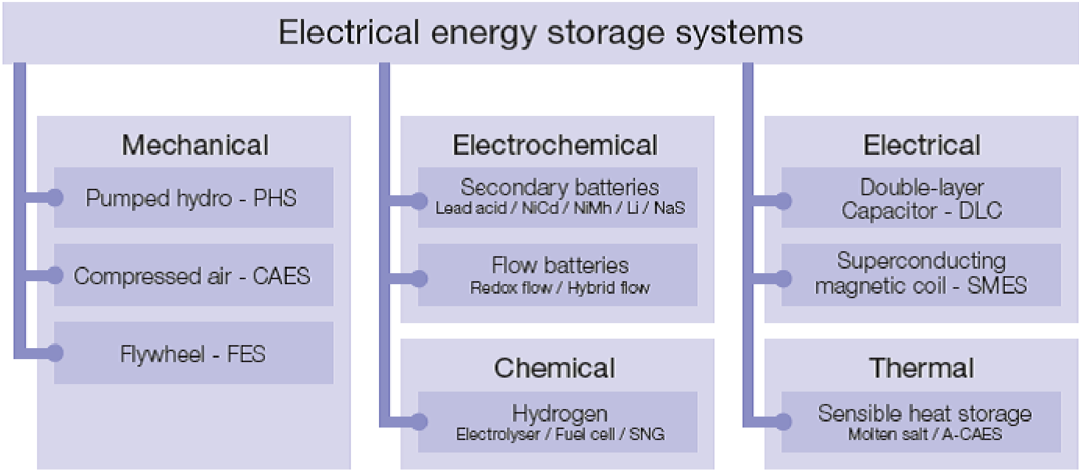

Figure 2.8: Classification of EES technologies by the form of stored energy [9]

Providing time varying energy management - energy storage plays an important role in the energy management and use optimization, as it allows the decoupling between periods of electricity production and consumption. Typical EES applications in energy management can be the storage in times when it is cheaper, to be later used or sold during periods of peak demand (time shifting), and peak shaving.

Alleviating the intermittence of renewable sources for power generation – electricity is the result of a process of converting primary energy into electrical energy. The use of fossil fuels as primary energy in this process allows the electric production profile to be adjusted according to consumption needs. However, the same does not happen when the primary energy have renewable origin, since the generation profile fluctuates over time according to the availability of the exploited resource. EES allows to overcome this fluctuations in energy supply and avoid discrepancies between supply and demand of electricity. Renewable surplus production is stored at times when production is higher than consumption, so that it can be used in periods when there is no production and that was necessary to rely on the grid. [15]

Improving power quality / reliability – storage units contribute to improve EPS operation and security, providing support for ride-through power and fault recovery.

Meeting remote and vehicle load needs – power supply for transportation applications, such as HEVs and EVs. EES units used for this end must have high energy density, small dimension, light weight and fast response. In these applications, batteries can be charged according to the grid capacity.

Supporting the realization of smart grids – some power electronic, information and communication systems in the grid / network are highly sensitive to power related fluctuation.

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[9] From source [20]

EES facilities can provide the function to protect these systems by suppressing these fluctuations. In addition, it also helps in the management of distributed / standby power generation and reduces the import of electricity during peak demand periods.

"Currently, applications are emerging where specific technologies fit specific applications" [9]. Size of storage devices is an important factor for many applications. For a given amount of energy, the higher the power and energy densities are (which represent the total energy and power per unit weight), the smaller the volume of the required energy storage system will be. Currently, size can range from very small (*e.g.*, battery storage for domestic PV installations of a few kW) to very large (*e.g.*, pumped hydro of several hundred MW), and from very short-duration (frequency response services for grid operators) to very long (seasonal storage in hydro reservoirs). [9] In this way, the location for installation can be quite flexible, either housed inside a building or close to the facilities where needed. Other important EES features are: (i) cycle efficiency, also named the round-trip efficiency, which is the ratio of the whole system electricity output to the electricity input; (ii) discharge efficiency, which represents the energy transmission ability from the energy-storing phase to the energy-releasing phase and contributes to the overall cycle efficiency achieved; (iii) self-discharge, which is related to energy dissipation in the forms of heat transfer losses in thermal storage, air leakage losses in compressed air storage, electrochemical losses in batteries, among others. The level of self-discharge of an EES system is one of the major factors in deciding the associated suitable storage duration. Further information about this topic can be found in [18].

The maturities of EES technologies are linked to the level of commercialization, the technical risk and the related economic benefits. Energy storage systems have traditionally been very expensive and not economically viable on a commercial scale. Lifetime and cycling times are two factors which affect the overall investment cost. Low lifetime and low cycling times will increase the cost of maintenance and replacement, and currently have been considered as the main barriers to implementing large-scale facilities. However, drastic improvements in energy storage technologies have led to decreases in costs and improved technology applications, and there is reason to believe that costs will fall as production volumes increase, reducing market barriers and increasing investor confidence.

Many projects have been exploiting the benefits of EES in the operation of EPS, such as in Évora, the first smart city chosen by the *InovGrid* project led by *EDP Distribuição* (main Portuguese DSO) [21]. The storage system is based on electro-chemical energy, and is connected to the distribution grid, with also the islanding capacity to self-supply the University campus for 30 minutes, at nominal load. Field results have shown that Li-Ion batteries for EES can significantly improve energy quality and enhance renewable integration at distribution level, providing at the same time an "online" lab to understand the new possibilities and challenges of batteries interconnection with EPS and off-grid applications. [9]

2.3.2.3 Electric Vehicle

As mentioned earlier in *Energy Growth by Sector*, energy consumption in the transport sector tends to increase in the future. Although much of this consumption continues to be met by fossil fuels, significant changes in energy consumption are expected in the automotive sector. Interest in the electric vehicle (EV) arose with the increasing search for solutions capable of mitigate the dependence on fossil fuels and contribute to the reduction of the environmental impacts associated with its use. Currently, the interpretation of EV extends to the context of the supporting elements of the grid, being more and more the studies on the potential benefits of the integration of EVs in the planning and management of the new paradigm of distribution networks.

EVs are vehicles with an electric-drive motor powered by batteries, a fuel cell, or a hybrid drivetrain. In other words, EVs are vehicles that use an electric motor to provide all or part of the mechanical drive power. EVs are intrinsic to the concept of vehicle-to-grid power or V2G power, as they can generate or store electricity when parked, and with appropriate connections, can feed power back to the grid. With this concept, the EV battery can charge during low demand times and discharge when power is needed. According to Kempton [22], three elements must be verified in a EV: (i) a grid connection for electrical energy flow; (ii) control or logical connection for communication with the grid operator; (iii) controls and metering on-board the vehicle. These elements vary somewhat with the business model. Kempton also divide EVs in three major types relevant to the V2G concept, namely battery electric vehicles (BEV), hybrid electric vehicles (HEV) and fuel cell vehicles (FCV). A comparison between these three types is presented below.

Table 2.2: Comparison between the main characteristics of the three EV types [10]

Types of EV	BEV	HEV	FCV
Propulsion	• Electric motor drives	• Electric motor drives • Internal combustion engines (ICE)	• Electric motor drives
Energy storage subsystem	• Battery • Supercapacitor	• Battery • Supercapacitor • Fossil or alternative fuels	• Hydrogen tank • Battery/supercapacitor needed to enhance power density
Characteristics	• Zero local emissions • High energy efficiency • Independent of fossil fuel • Relatively short range • High initial cost • Commercially available	• Low local emissions • High fuel economy • Dependence on fossil fuel • Long driving range • Higher cost than ICE • Commercially available	• Zero local emissions • High energy efficiency • Independent of fossil fuels • High cost • Under development
Energy source infrastructure	• Electrical grid charging facilities	• Gasoline station • Electrical grid charging facilities	• Hydrogen
Major issue	• Battery sizing and management • Charging facilities • Cost • Battery life time	• Battery sizing and management • Control, optimization and management of multiple energy sources	• Fuel cell cost, life cycle and reliability • Hydrogen production • Cost

[10] From source [23]

Battery and fuel cell EVs are driven only by electric power while current available HEV have also an internal combustion engine (ICE). The major difference between BEVs and FCVs is the way energy is stored. While BEVs store energy electrochemically in batteries, FCVs typically store energy in molecular hydrogen (H_2), which feeds into a fuel cell along with atmospheric oxygen, producing electrical energy with heat and water as by-products. Operationally, BEVs plug in to charge their batteries and unplug to drive, and they must have grid connections for charging, so that can be possible to minimize the incremental costs and operational adjustments to add V2G.

With respect to current HEV, batteries are charged by the vehicle engine and by energy recovered from braking. In a conventional hybrid, the battery is used to boost the ICE as the vehicle is driven and allows the vehicle to go further on the same amount of gas. Savings in fuel consumption can be achieved with reduced energy during braking, downsizing of the engine, operating engine more efficiently and shutting the engine off when it is not moving.

Since EVs require the use of batteries with large storage capacities and large electric load charging requirements, the massive integration of the EV will cause considerable impacts on the design and operation of EPS as well as changes in energy demand. According to [24], the large deployment of EVs will involve: (i) evaluation of the impacts that battery charging may have in system operation; (ii) identification of adequate operational management and control procedures in relation to battery charging periods; (iii) identification of the best strategies to be adopted in order to use preferentially RES to charge EVs; (iv) assessment of the EV potential to participate in the provision of power systems services.

The level of impact caused in EPS will depend primarily on the technologies and charging modes used. The bulk of electric car charging will take place in homes and businesses or in public charging facilities, meaning that it is likely to have an impact on LV distribution grid in residential or commercial areas first. As pointed out in [25], depending on the electric car usage patterns, higher shares of electric cars could have a sizeable impact on the capacity required at certain times and locations, with consequences for both adequacy and quality at different levels: (i) at the generation / wholesale market level, where high demand and scarce capacity could increase prices; (ii) at the transmission / system operator level, where stress on the system during peak times requires more system services, such as frequency control, and the need to maintain reserve power capacity; (iii) at the distribution level, where the overloading of power lines and transformers and voltage drops could occur.

Most plug-in EV drivers do more than 80% of their charging at home, because is convenient and inexpensive. [26] It allows consumers to take advantage of low and stable residential electricity rates (cheap off-peak electricity), sometimes with specific tariff plans for EV charging, and some governments can even offer fiscal benefits. Just like diesel or gasoline cars, the consumption costs of EVs will rely on the model and manufacturer, as well as the driving range.

Currently, due to the improvements in the EES field, the autonomy range already broke the 600 km barrier (Tesla Model S 100D, 2018). [27]

2.4 Demand Side Management

This section presents a brief literature review about electricity Demand Side Management (DSM). Firstly, it will be presented within the context of a vertical organization of EPS, a paradigm where programs were launched by integrated public utilities that were responsible for the whole system management, operation and security of supply, and due to the strategic nature of EPS, were also at the same time viewed as instruments to achieve macroeconomic and political targets. After, an introduction on Load Management (LM) and the three main types of strategies that can be found in LM programs are presented.

2.4.1 Traditional Demand Side

The definition of DSM was first presented in [28]. According to the author, "*Demand side management is the planning, implementation, and monitoring of those utility activities designed to influence costumer use of electricity in ways that will produce desired changes in the utility's load shape, i.e., changes in the time pattern and magnitude of a utility's load"*. Back in the days, DSM was considered appealing from the technical point of view and made economic sense, so electric utilities start applying simple measures to incentive efficiency in consumption and promote waste reduction. Currently, DSM actions taken by either electrical utilities or regulators and policy makers have both the goal of saving electricity costs and provide peak power through consumption efficiency and flexibility. Fig. 2.9 illustrates the DSM objectives [28]:

- Peak clipping – Reduction of the peak load using direct load control, as it happens in the interruption and curtailment rates applied to commercial and industrial loads;
- Valley filling – Load increase during off-peak periods. Preferred when generators have high starting costs and the benefits from keeping it running during valley hours are greater than stop and start them later;
- Load shifting – Change in the load profile by shifting power demand from peak hours to off-peak hours, avoiding major variations in the loads diagram;
- Strategic loads growth – Increase in the load shape. Consists in an overall demand increase by the influence of utilities programs;
- Strategic conservation – Decrease in the load shape. Consist in an overall load shape decrease due to incentives for energy conservation by utilities programs;

- Flexible load shape – Consideration for load curtailment or interruption availability instead of its magnitude, therefore related with the load flexibility characteristics.

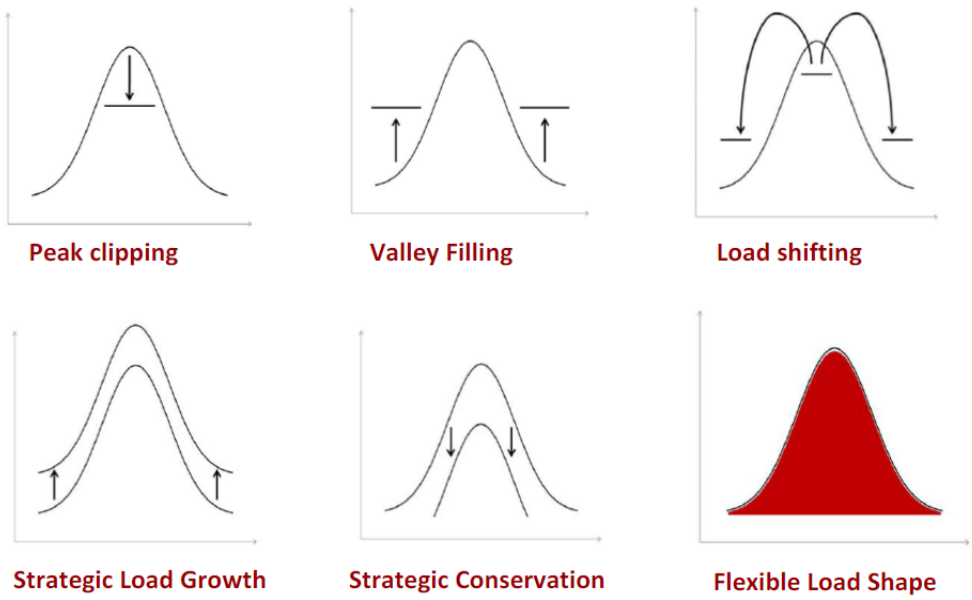


Figure 2.9: Demand side management objectives regarding load shape [11]

In [29] a set of traditional DSM measures are described from the implementation point of view – presented in [30] – relevant to achieve the load shape objectives proposed by Gellings:

1. Appliance upgrade – procedures that improve appliance efficiency and reduce the total load. Two types of measures can be applied towards this end, through electromagnetic efficiency and environment and equipment usage;

2. Distributed generation – the implementation of power sources next to the load that can be used to provide electricity in a regular basis, minimizing energy losses associated with the transmission;

3. Building insulation – benefit electricity savings and peak power reduction by changing the building envelope;

4. End-use storage – energy storage that can be used to shift loads from peak to off-peak hours;

5. Fuel-switching – switch of electrical energy to other types of fuel to reduce the electrical peak-load, and in most cases reduce substantially the energy losses;

[11] From source [29]

6. Interlocking – load control mechanism that avoids the operation of two or more appliances at the same time, thereby reducing peak power; (vii) Light efficiency and motors/equipment upgrade – measures implemented to minimize electricity losses (related to appliances upgrade);

7. Load control – direct and indirect control of residential, commercial and industrial loads performed by the utilities;

8. Uninterruptable power supply devices – small automation devices used to disconnect appliances during peak periods;

9. Conservation voltage reduction – measures taken by utilities programs that consist in a voltage decrease on the distribution system to reduce total load power.

2.4.2 Load Management

The first LM programs were established with the goal for lowering the average cost of electricity by managing the consumption of appliances. Considering the existing vertical integrated structure of EPS at that time, different strategies and methods were developed for this purpose, such as the LM addition to the economic dispatch formulation.

LM is the capability to perform a deliberate shifting in time of the loads electrical power or its associated energy. From the implementation point of view, three types of strategies concerning LM programs can be found: Electric Thermal Storage (ETS); Indirect Load Control (ILC); and Direct Load Control (DLC). These strategies represent alternative ways of provoking changes in the demand consumption profile.

LM activities within the SG context can be interpreted as permanent DER that can be traded in the wholescale energy and ancillary services markets. More specifically in the residential sector, where the capacity of individual LM resources pales in insignificance when compared with the total demand, load aggregators and flexibility agents play an important role by facilitating the demand side integration into this markets. [29]

2.4.2.1 Electric Thermal Storage

The ETS strategy consists in storing heat during off-peak hours to be used during peak hours for space and water heating. This strategy is performed without utility intervention and do not consider any economic incentives. Although ETS involves appliances control, it does not affect the end-user comfort, since its management procedures are integrated in the appliance design and it is the user that gives the control orders. Hence, the behaviour of these devices can be easily predicted due to its conception, that is made in such a way that avoids consumption during typical peak periods.

For some years, ETS was only performed at the costumer metering side through time-clock control of air-conditioner and water heaters, but despite the success of this programs in the load shifting capability for thermal appliances, the strategy as sole was not enough for the potential implementation in large scale. Therefore, a combination with other strategies could result in a more cost-effective solution, namely if the local control of ETS is performed directly by the utility company or through price signals and Time-of-Use (TOU) rates.

2.4.2.2 Indirect Load Control

The ILC strategy consists in the use of economic incentives (or disincentives) to encourage voluntary changes in the end-user consumption patterns. Normally, the main point of this strategy is to influence consumers to shift the use of appliances from peak to off-peak hours using price signals and the electricity rate, thereby reducing demand during the expected daily peak hours.

Several utilities began to explore this strategy during the 70's and 80's, especially in the US. Back then, economists and engineers participated in an intense debate over the electricity rates supporting the developing of these programs. Some decades later, this debate is being recovered due to its relevance in the establishment of a regulatory framework for the new era of DER management in the SG context.

2.4.2.3 Direct Load Control

The DLC strategy consists in the control or postponement of load activation during peak hours or emergency situations. This can be achieved through an active control of electrical devices by an electricity utility, aiming for an efficient use of resources that can minimize energy delivery costs. [31] Typical residential loads considered for DLC include air conditioners systems and space and water heaters. Since the utility will perform an intrusive direct control management, this strategy may provoke some discomfort situations to the end-users by restricting their appliances use. Therefore, economic incentives may by envisaged in order to incentive consumers' participation in these programs and compensate unpleasant situations.

DLC strategies required a significant knowledge about the devices to manage, so that utilities can estimate the number of appliances that are operating in each period and calculate the available interruptible power capacity. This pushed forward the development of load models for DLC programs, contributing to the decrease of generation costs and system peaks, improved load factors and a high-speed load shedding that contributes to the reserve capacity. [29]

2.5 Home Energy Management Systems

The HEMS concept started to appear by the time that models were being developed to better understand the dynamics of the evolving smart grids. At that time, HEMS emerged under the name of a gateway interface designated in some studies by Energy Box (EB). The initial idea for HEMS was the creation of a central unit located in the residential building, capable of being interoperable with the SM infrastructure and perform an optimized control of behind-the-meter resources and consumption devices, in order to minimize the electricity costs. Besides that, the unit need to be capable to consider weather conditions, local generation units, the thermal model of the house and the outdoor temperature [32].

In [33] optimization functionalities are extended to advanced services to the grid, such as Demand Response (DR).

An automated response model for the EB was developed and conceptualize based on Real-Time Pricing (RTP). In the author's work, the EB is capable of performing an optimized control in order minimize electricity costs, and it is demonstrated how a single residence's hourly power profile might change via enabling technology's automated response to different pricing systems and local weather-dependent sources of electricity, such as rooftop wind turbines and/or solar panels. The generic view of the EB simulation process proposed by the author is presented in Fig. 2.10.

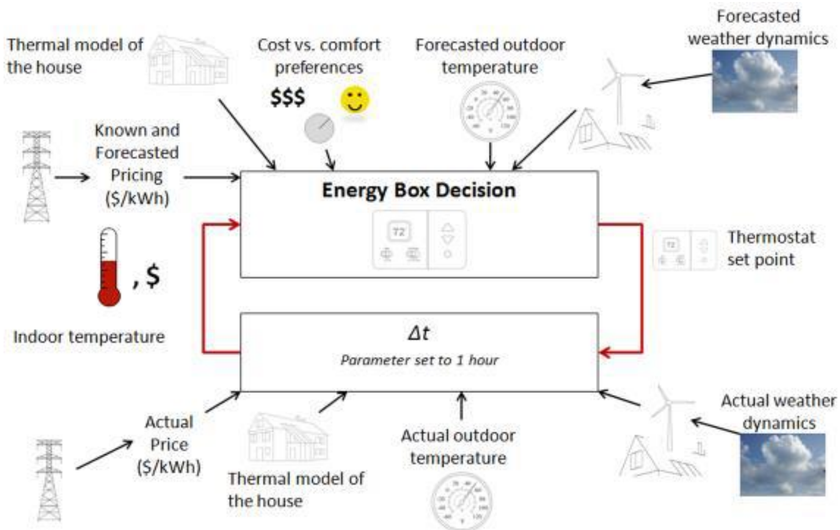


Figure 2.10: Energy Box model proposed by Livengood [12]

Recent advances in communication and modulation methodologies, as well as in the adaptive digital signal processing and error detection and correction, have allowed the development of sophisticated communication capabilities in many appliances (*e.g.*, send commands remotely to adjust AC temperature or shut it down; activate AC with previously defined comfort parameters when the user is in the house premises). [34]

In general, communications in the home domain between the HEMS and the consuming appliances and/or generation devices is established via Power Line Communication (PLC) or Wireless. A widely used PLC protocol to perform communications between HEMS and smart

[12] From source [33]

appliances is the *HomePlug*. [35] PLC technologies work as a medium that enables the bidirectional data exchange by exploring the use of electric power lines (LV, MV or even HV). More information about PLC and Wireless communication can be found in [36] and [34].

Currently, many commercial solutions exist in the market for home energy management. However, many of these solutions are very expensive, are not able to integrate recent SM technologies and are often limited to support devices of a single vendor. [1] Nevertheless, available and affordable commercial solutions such as EDP remote energy dynamics (re:dy) [37], Cloogy [38] or SMA home system [39] are a great departure point to start reducing electricity costs, improve end-user comfort and raise energy efficiency awareness.

2.5.1 Demand Response

The exchange of advanced services with the grid, such as DR, is the main reason why certain technologies stand out from others, since most of existing HEMS are primarily designed to improve energy efficiency and comfort standards within a single residential building and do not take into consideration the utility data for the schedule of appliances. Ozturk [32] defines DR as a *"change in electricity usage by the end-use costumers from their normal consumption patterns in response to a change in the price of electricity over time"*. Ozturk also states that DR strategy coordinates the requirements and needs between electricity suppliers and consumers, by encouraging the consumer to reduce the peak demand in response to incentives.

Traditionally, domestic Thermostatically Controlled Loads (TCL) such as HVAC systems and Hot Water Heaters (HWH) have been a valuable resource for DR by utility companies. Nonetheless, improvements in the smart appliances field and the recent expansion of the Internet-of-Things (IoT) have been providing a greater degree of control that allows these loads to report real-time consumption and receive possible set-points [40]. In [41] a study is presented about the use of real-time data (*e.g.*, report current temperature or on/off state to the house controller) to control heterogeneous populations of residential TCL in order to deliver services in the EPS and participate in short time scale energy markets – such as respond to real-time electricity prices and participate in ancillary services market. Their study showed that TCL aggregations are able to provide reliable services, significant electricity cost savings and the storage capacity desired in EPS with high penetrations of renewables. In this context, HEMS will be the interface that enables the conversion of appliances control into actual services exchange with the retailers.

Besides providing external services, HEMS load control capabilities can be also applied on more internal purposes, namely in the control of behind-the-meter flexible resources to maximize Photovoltaic (PV) self-consumption. A multi-period optimization model considering PV generation forecasts as well as inflexible load was presented in [42]. The HEMS module is based on the flexibility estimation methods for TLC and is capable of scheduling Electric Water Heater (EWH) appliances for the day ahead, aiming self-consumption optimization. In [43] the flexible demand of an EWH is exploited to maximize PV self-consumption in the residential domain. The author presents a predictive control model strategy that uses both PV generation and hot water consumption forecasts in order to predict the on/off state of the appliance.

The increasingly interest in PV self-consumption currently observed in Europe follows the promotion of renewable generation that has been taking place in the past few years. As mentioned before, the massive deployment of DG next to consumption centres may cause grid disturbances, therefore, in order to avoid disturbances like voltage rise during PV generation peak periods some regulatory measures had to be taken. In some countries (*e.g.*, Belgium, Denmark and Netherlands) the balance between endogenous generation and local consumption is ensured by PV self-consumption measures encompassed by net metering schemes for large time periods. In contrast, a policy that encourages instantaneous consumption is implemented in countries like Germany and Portugal. In the Portuguese case, the recent legislation [44] ended the previously high feed-in tariff and announced lower remuneration for PV generation injected into de grid – when compared with electricity price for the consumption –, making self-consumption always more profitable than inject energy into the grid. [42]

2.5.2 AnyPLACE Project

The *Adaptable Platform for Active Services Exchange* – AnyPLACE – is an European H2020 project [45] that developed a modular, adaptable, and cost-effective solution for energy management of households and similar buildings. The AnyPLACE platform integrates all smart devices in the user property, connects they to electricity suppliers and external services linked to SM – such as retailers or system operators –, and has interfaces that provide information and control to the user regarding electricity consumption. The system is capable of advanced monitoring and control schemes for local devices, allowing the end-users to better manage the electricity usage according to their preferences and comfort standards. The main contribution of this project and the reason why this platform stands out from others with the same features is because it offers a flexible and extendable architecture that combines existing communication protocols and SM regulations that can be applied in several EU countries. [1]

A set of goals for this project is presented in [45] focused on building a set of prototypes with different combinations of modules under different scenarios of application, tested in a smart grid laboratory environment and in a field trial, in order to provide a real-world assessment of their performance.

2.5.2.1 Modular Architecture

In order to support the interactions among different stakeholders – such as ancillary services, retail market and costumer management – a set of requirements and functionalities was established under the groups of energy management, end-user interaction, ICT, and maintenance and support. The set of services that can be supported by the AnyPLACE platform within this groups is the following:

- Energy management – Data analytics and energy awareness, tariff selection management, local energy management and DR;
- End-user interaction – Preferences, configurations and media presentation management;
- ICT – Local device management, interaction with stakeholders, metering management, system integration and management, cloud services, and secure access and exchange;
- Maintenance and support – Maintenance services, reporting and alarms, and storage management.

The proposed modular reference architecture is presented in Fig. 2.11. It is an approach that enables the development of a modular and adaptable infrastructure, that is likely to be suited for a large group of different end-users.

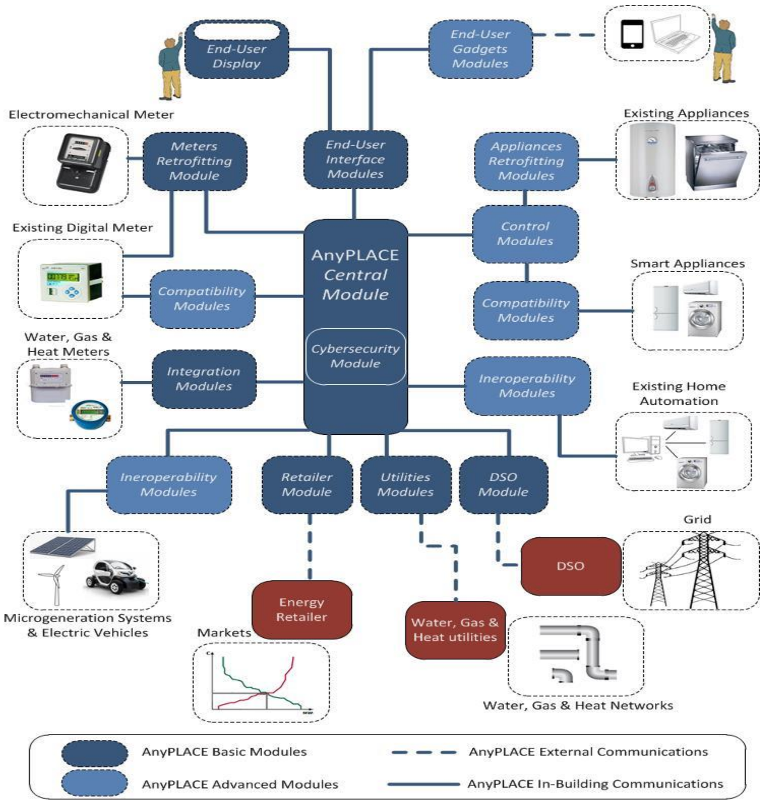


Figure 2.11: Initial design of the modular architecture for AnyPLACE [13]

[13] From source [46]

The *AnyPLACE Central Module* is the core of the architecture and provides the main functionality of the identified requirements. The interaction between different devices and stakeholders, as well as with the end-users, are provided by basic and advanced modules. The basic modules are expected to be available in all AnyPLACE installations, while the advanced can depend on the availability of devices in the end-user premises, services provided by different stakeholders, or available budget for the platform. More detailed information about this subject can be found in [1].

2.6 Optimization Models

The field of optimization has grown rapidly in the past two decades. Many new theoretical, algorithmic, and computational contributions in this field have been proposed to solve problems in different areas, such as finance, allocation and location problems, engineering design, system and database design, chemical engineering design and control, and molecular biology. [47]

Optimization methods can be divided into classic and heuristic. The differentiation factor between these two approaches is the existence or not of randomness – if an algorithm does not use randomness, the method is classic.

The classic approach can provide general tools for solving optimization problems in order to obtain a global or an approximately global optimum. This approach takes advantage of the analytical properties of the problem to generate a sequence of points that converge to the global optimal solution. Classical optimization assumes that perfect information about the loss function is available and uses that information to determine the search direction in a classic manner at every step of the algorithm. [48] A review of classic optimization methods used in engineering and management can be found in [47].

Heuristic approaches can be more flexible and efficient, but the quality of the obtained solution cannot be guaranteed. Like classic optimization, there is no single solution method that works well for all problems. Therefore, structural assumptions – such as limits on the size of the decision and outcome spaces, or convexity – are needed to make problems tractable. [49] Moreover, the probability of finding the global optimum solution is inversely proportional to the size of the problem. Some known examples of optimization heuristics are the Genetic Algorithms (GA), Particle Swarm Optimization (PSO) and Simulated Annealing (SA). More information about heuristic optimization can be found in [50]

Fig. 2.12 presents an overview of the major problem types related to classic optimization problems. These types can be classified in Linear Programming (LP), Non-Linear Programming (NLP), and Mixed-Integer Non-Linear Programming (MINLP). Then, the Stochastic Optimization (SO) and the CE method are addressed in separated sub-sections due to their specific relevance to this work.

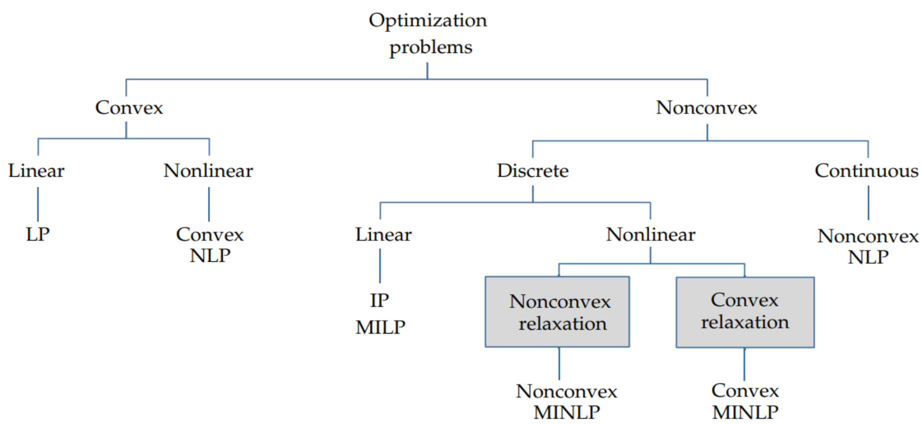


Figure 2.12: Problem types related to classic optimization problems [14]

2.6.1 Stochastic Optimization

According to [49], "S*tochastic optimization refers to a collection of methods for minimizing or maximizing an objective function when randomness is present*", being the randomness usually introduced through the cost function or through the constraint set.

The great advantage of SO is its capability to cope with inherent system noise and models or systems that are highly non-linear, highly dimensional or not appropriated for classic optimization methods. Over the last few decades, SO methods have been broadly explored in the resolution of different practical application problems and field works, such as statistics (*e.g.*, design of experiments and response surface modelling), science (*e.g.*, designing laboratory experiments to extract the maximum information about the efficacy of a new drug), engineering (*e.g.*, running computer simulations to refine the design of a new technology), and business (*e.g.*, making short- and long-term investment decisions in order to increase profit). [48]

Two types of optimization problems can be solved using SO methods, namely problems with a single period – Single Stage Problem (SSP) – and problems with multiple time periods – Multi-Stage Problem (MSP). A SSP aims to find a single and optimal solution (*e.g.*, find the best set of parameters for a statistical model of a given data) and is usually solved with modified classic optimization. A MSP tries to find an optimal sequence of decisions (*e.g.*, scheduling different home appliances for the next day's operation) and is more reliant on statistical approximation and strong assumptions about problem structure, such as finite decision and outcome spaces. [57] Currently, multi-objective optimization is used to solve a wide range of MSPs associated with real-world applications involving multiple and conflicting objectives. [51] Some typical stochastic algorithms are presented in [52].

A SSP will be presented later for the experimental validation of a CE method algorithm, as well as a SO algorithm to solve a MSP – scheduling different home appliances for the day ahead operation, aiming cost minimization or PV maximization.

[14] From source [47]

2.6.2 Cross Entropy

Cross entropy is a heuristic that provides a simple, efficient and general method for solving complicated estimation and optimization problems, by offering a new generic approach to combinatorial and multi-external optimization and rare event simulation – where very small probabilities are needed to be estimated (*e.g.*, reliability analysis, or performance analysis of telecommunication systems). [53] Hence, CE method can be applied to two types of problems:

1. **Estimation** – Estimate $\ell = \mathrm{E}[H(\mathbf{X})]$, where $\mathbf{X}$ is a random object taking values in some set $\mathcal{X}$, and H is a function on $\mathcal{X}$. An important special case is the estimation of a probability $\ell = P(S(\mathbf{X}) \geq \gamma)$, where S is another function on $\mathcal{X}$.

2. **Optimization** – Optimize (*i.e.*, minimize or maximize) a given objective function $S(x)$ over all $x \in \mathcal{X}$, where S is either a known function or a noisy one. In the latter case, the objective function needs to be estimated (*e.g.*, via simulation).

The CE method was first proposed by Rubinstein [54] as an adaptive Importance Sampling (IS) or Likelihood Ratio (LR) procedure for the estimation of rare-event probabilities, that uses the CE or *Kulback-Leibler divergence* as a measure of closeness between two samples. [55] At that time, Rubinstein presented an adaptive algorithm capable of estimating probabilities of rare events in complex stochastic networks, involving variance minimization. Following his work, It was later realized by Kroese and Rubinstein [56] that many optimization problems could be translated into a rare-event estimation problem, *i.e.*, use adaptive IS (such as CE method) in randomized algorithms for optimization.

The main idea behind CE method is the association of the rare-event probability with the probability of locating an optimal or near optimal solution using naïve random search. The method can be used to gradually change the sampling distribution of the random search in order to make the rare-event more likely to occur. Moreover, by using the CE distance, the method can estimate a sequence of sampling distributions that converge to a distribution with probability mass concentrated in a region of near-optimal solutions. [55] Once the problem is defined, the method involves the following two phases [56]:

1. Generation of a random data sample (*i.e.*, vectors, trajectories, etc.) according to a specified mechanism (*e.g.* Bernoulli distribution for the discrete case and normal distribution for the continuous case);

2. Updating the parameters of the random mechanism, based on the data, to produce an improved sample in the next iteration. These parameters are usually related to a probability density function.

The CE method has been successfully applied to a variety of problems of combinatorial optimization and rare-event estimation. Typical application fields include control and navigation, DNA sequence alignment, neural computation, reinforcement learning, scheduling, vehicle routing, systems reliability, signal processing, buffer allocation, queueing models of telecommunication systems and project management. References and more details on applications and theories can be found in [53] and [55].

2.6.3 Overview of Related Works

Many works have been exploiting the benefits of optimization models in the context of energy management. For instance, a classic approach is made in [40] for the algorithm of the AnyPLACE platform in order to achieve cost savings and PV self-consumption maximization. The optimization criteria for cost savings is performed to minimize the total daily cost and considers dynamic price tariffs, peak-power limit, shiftable appliances with different durations, power consumption and number of activations, as well as the models and external data for thermal appliances – Air Conditioner (AC) and EWH. For the PV self-consumption maximization, the PV production forecast is considered.

In [32] an energy management solution is proposed that learns and adapts to the residential electricity usage patterns. The model consists in an adaptive neuro-fuzzy learning algorithm that makes decisions based on peak load, dynamic electricity prices, customer usage patterns and electricity budget, as well as on social and environmental factors and available PV production. The learning of this algorithm is implemented in two stages. The first is a neural network that provides the learning machine that permits to identify the unknown or the changing power plant and the latter is a fuzzification component that compensates the uncertainties or inaccuracies related to the plant or the environment.

In [57] and [58] a multi-scale multi-stage stochastic optimization model is presented for HEMS formulated as a Model Predictive Control (MPC) algorithm that minimizes costs and peak-power constraints. The model includes plug-in HEV charging, thermal dynamics, temperature measurement and RTP signals. In both works, a partition of the energy management into slow and fast time scales is made to reduce computation complexity.

In [59] a stochastic dynamic programming framework is proposed for the optimal management of a smart home with Plug-in Electric Vehicle (PEV) energy storage. The model aims to minimize electricity ratepayer cost while satisfying home power demand and PEV charging requirements.

In [60] a combination of a GA with LP is proposed to reduce the electricity consumption costs of a smart home. Besides the energy scheduling problem, their study also includes the modelling of the battery of a PEV and the economic and technical constraints for PV production, thereby resulting in a non-linear, dynamic (time-varying) and stochastic optimization problem (MINLP).

Their approach separates the discrete variables from the continuous variables by addressing the non-linearity of the problem with the GA (discrete) and boosting the search for the global optimum with LP (continuous). Later, Rahmani and Shen [61] extended their work [60] to the cooperative distributed energy scheduling between smart homes using stochastic MPC. The gist of the idea is the electrical connection among smart homes for energy transaction, *i.e.*, each smart home can provide electricity to the others and purchase electricity from them.

In [62] an appliance's commitment algorithm is presented that schedules thermostatically controlled household loads based on price and consumption forecasts. The model considers user's comfort settings to meet an optimization objective such as minimum payment or maximum comfort. The EWH is considered, being its operation over the scheduling time horizon predicted by the physical model. The author transforms the user's comfort parameters in a set of linear constraints and use a linear sequential optimization multiloop algorithm to solve the appliances commitment problem based on price and consumption forecasts.

In [63] an optimal and automatic residential electricity consumption scheduling framework was developed based on simple LP computations. The model aims to achieve a trade-off between minimizing the payment and minimizing the waiting time for the operation of each household appliance based on the needs declared by users. A price prediction filter is used to improve the algorithm results.

In [64] a MINLP technique is presented that minimizes electricity costs and reduce peak demand. The optimization is formulated based on physical load model for load scheduling and the general model incorporates the nonlinear characteristics of the industrial loads, being able to analyse the industry's response to different TOU tariffs.

In [65] a PSO algorithm that optimizes electricity services provision by enabling end users to first assign values to desired electricity services, and then scheduling their available DER to maximize net benefits. The basic formulation of cooperative PSO was improved with stochastic repulsion among the particles in order to introduce more randomness in the particle trajectories at the initial iterations and prevent premature convergence.

2.7 Summary and Main Conclusions

Energy demand is growing broadly across all the main sectors, mainly to meet the consumption requirements of fast-growing economies. Particularly in the residential sector, the combination of population growth and comfort parameters improvement for people in daily life and at work has been increasing the electricity consumption in buildings over the past few years. Under this vision, today's society is becoming more and more aware about the importance of electricity efficiency and renewable's integration for electricity production, changing the way how electricity is produced and consumed.

Many different works have been developed under the framework of the new operation paradigm of EPS. Although the challenges are greater, the range of solutions is increasing at fast rate in different sectors of the grid, particularly in distribution systems due to the advent of the SG concept. Nevertheless, the SM infrastructure has been enabling the transformation of the currently passive distribution networks into fully active networks by strengthening the relation between services and costumers through DSM and DR. However, despite the proven economic and social value of controlling DER behind-the-meter, there is still no disruptive technological solution for home energy management in the market capable of causing a large-scale impact and lead to a massive deployment of these systems.

Chapter 3

Model for Home Energy Management

3.1 Introduction

This chapter focuses on the models and deliberations considered in the algorithm that was implemented for an optimized scheduling of appliances for the day ahead. The integration of microgeneration was regarded as well, namely through PV self-consumption and remuneration from the energy injected into the grid. As mentioned before, the algorithm was developed under the framework of the AnyPLACE project, and therefore, the configurations and preferences associated with the energy management system platform of this project are also considered.

The energy methodology presented in this work includes the internal inputs related to the home domain and the external inputs received from service providers that are interested in shaping the energy demand of certain households. The internal inputs comprise the operation of appliances according to a specific set of preferences and configurations, and the way users manage these devices will determine the flexibility of the energy used in each household. To understand the behaviour of the appliances and their influence on the end-user's consumption, a characterization of the ones that are suitable to be reschedule is made. Two different categories of appliances are considered – shiftable and thermal appliances –, and each category is classified in two types, as presented in Fig. 3.1.

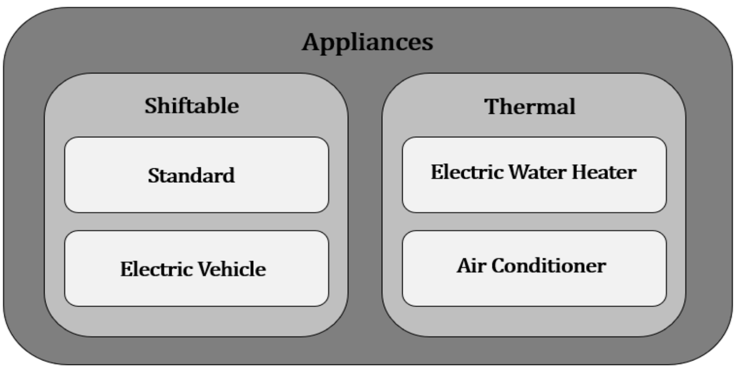


Figure 3.1: Classification of the appliances being considered

3.2 Shiftable or Deferrable Appliances

This category includes the appliances that operate on a predefined cycle with a known duration and consumption. The term deferrable (or *shiftable*) is used because the operation of these type of devices can be shifted along the considered timeframe (24h of the next day) in order to be scheduled for low-priced periods. Two types of shiftable appliances are considered – Standard Shiftable (SS) and EV. The EV was included in this category because the scheduling of the charging is similar to the scheduling of a SS. The model of these appliances is based on historical data retrieved from the house or based on default consumption patterns. The smart shiftable appliances can be controlled and monitored through direct communication and the manual ones through a smart plug[15].

3.2.1 Standard Shiftable

The SS model is very simple and is based on three parameters: power (kW), duration (h) and number of times to operate during the day (#). The number of timeframes for the appliance will be determined according to how many times the appliance operates. For example, if the SS only operates once, there is only one timeframe; if it operates four times, four timeframes will be considered. Within each timeframe it is possible to define a time interval for operation, during which the control method will decide the best time for activation. Nonetheless, some points must be considered concerning timeframes:

- If there is only one timeframe, the user can define an interval for the operation (*e.g.*, between [9 am - 6 pm]) or an interval to exclude operation (*e.g.*, [18 am – 11 pm] meaning that it can operate between [0 am – 11 am], cannot operate between [11 am - 6 pm], can operate again between [6 pm – 12 pm]);

- If there is more than one timeframe, an interval to exclude operation cannot be defined and the starting time of the next operation cannot overlap the previous one (*e.g.*, two timeframes, if the first has a deadline at 9 am, the second only can start after 9 am, including).

Fig. 3.2 presents an example of two SS appliances operating more than one time during the day. As can be seen, *Load 1* operates three times and each starting time is defined by the previously deadline. The same happens with *Load 2*. Nevertheless, it is important to stress out that the second starting time does not have to be necessarily at the same time as the previous deadline, as illustrated in the figure, it only has to be afterwards.

[15] A smart plug is a device that can be remotely controlled to connect or disconnect a power socket

In terms of algorithm, this type of appliances is the only one that can be freely added by the user, since only three parameters are required. The algorithm was tested with ten SSs, EV, AC and EWH, and despite the extra time to run, it still has reached the expected optimal results.

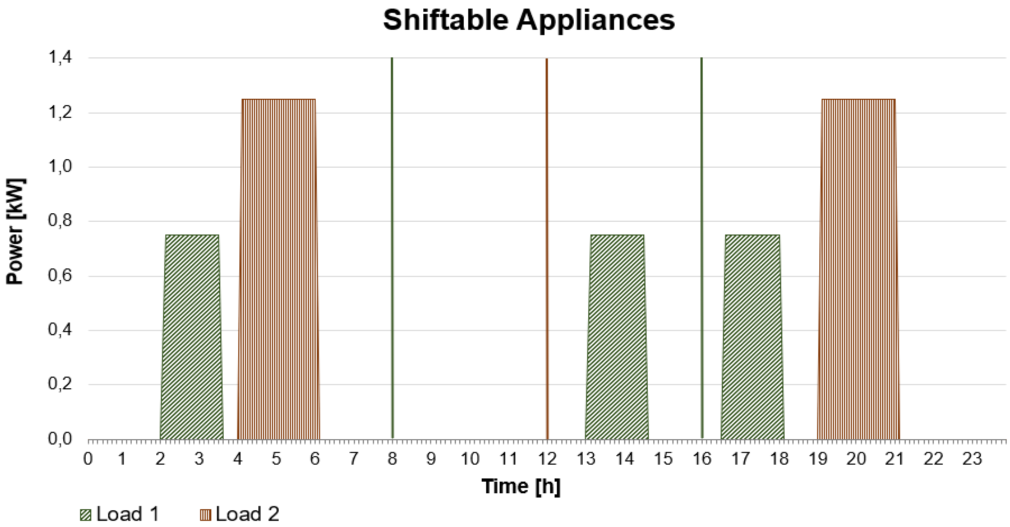


Figure 3.2: Example of loads with deadlines

3.2.1 Electric Vehicle

The EV is included in the shiftable category of loads because it also requires the same three parameters used in the SS. However, these parameters are not directly defined by the user, but rather determined according to the user's intended driving range. Hence, the user needs to define two preferences: the expected range in km, and one unique timeframe for operation. The duration of the charging is always the same, and the number of activations determined by the user's driving range, *i.e.*, the duration of the charging is always in gaps of 15 min (can be any number multiple of 0,25 hours, such as 30, 45, 60 min) and the number of times for 15 min charging periods is calculated with the following equation:

$$D_{times} = roundup(\frac{A_{Input} * P_{cons}}{P_{charger}}) \tag{3.1}$$

Where:

- A_{Input} – User's range input $[km]$
- P_{cons} – Power consumed during the charging $[kWh/km]$
- $P_{charger}$ – Power of the charger $[kW]$
- D_{times} – Duration of the activations represented by the number of times to be activated $[h]$

Therefore, the number of times will depend on the type of charger that is being used, and on the power consumed by the EV during the charge as well. The idea of this approach is to divide the total duration of the charging in smaller fractions, so that it can be possible to shift the charging for low-priced periods or, if some power limit is considered, expand the range of options for the appliances' activation. In order to successfully apply this model, only one timeframe can be considered, being the previous established rules for one unique timeframe applied to the EV as well. This methodology is illustrated in Fig. 3.3. As can be seen, the charging is divided in two distinct fractions as a result from the chosen dynamic price tariff.

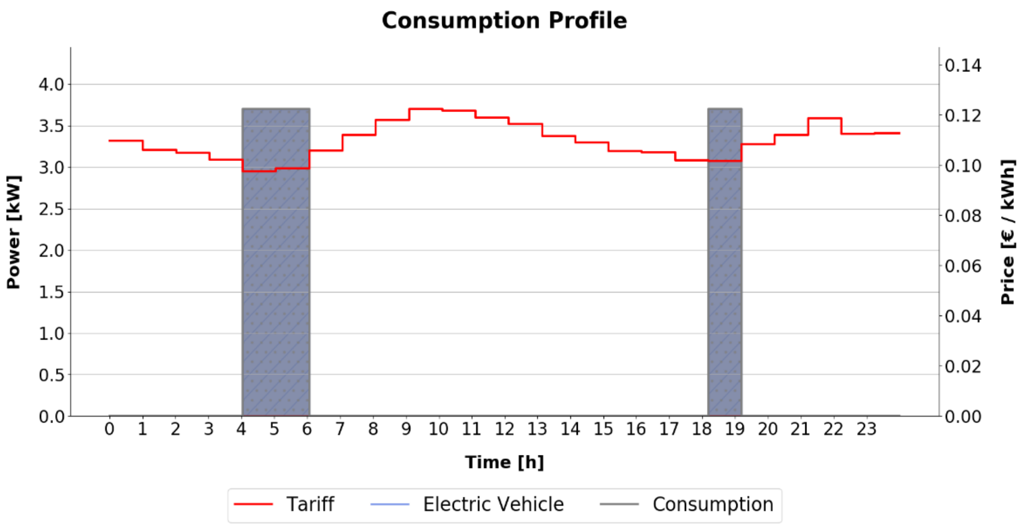


Figure 3.3: Charging of the EV

The number of times is rounded up because of the conversion of hours into periods (time step). As a result, the final range will differ from the user's input, as shown in Fig 3.4.

$$A_{Final} = \frac{1}{P_{cons}}[P_{charger} * D_{times}] \tag{3.2}$$

Where:

- A_{Final} – Final range of the EV $[km]$

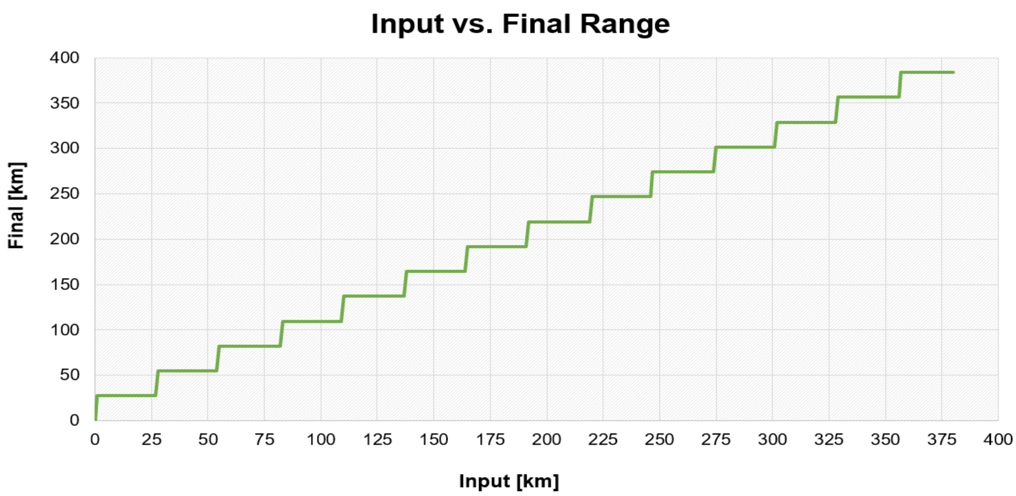


Figure 3.4: Range rounding

3.3 Thermal Appliances

There are several works proposed in the literature to model the behaviour of the thermal appliances. Although many of these models were developed under traditional DSM programs, they can still be applied to current load control methods in the SG paradigm.

The modelling for the domestic TCLs presented in this sector is based on the Physically-Based Load Models (PBLM) developed in [29]. PBLMs for thermal loads are based on energy balances that occur inside a thermal chamber, which can be a room – in case of space heating devices –, a refrigerator (RF) cavity or the cylinder for the hot water. Two different models are considered, one for the AC and another for the EWH. Each model is detailed in its respective sub-section, as well as other considerations taken in the scope of this work.

The model for the AC can also be applied to the RF, and therefore, this appliance was considered in the beginning of the work as well. However, when the code was first implemented and tested, the algorithm showed more difficulties in converging to optimal results when considering the RF than without it. Since the energy scheduling is aiming for the minimization of costs, and the RF have tight limits in terms of temperature and fast variations when powered, it is difficult to change the times for activation considering cost minimization without violating the limits sometimes. Moreover, these devices hardly consume power when compared to the other appliances and are currently being conceived to consume as less energy as possible (since practically every home needs to have a RF to conserve food supplies). In any case, the model was testes in this appliance to show its behaviour, as presented below.

The linearized formulation proposed for the AC and RF temperatures is given by:

$$\theta_t = \theta_{t-1} + \frac{\Delta t}{R \cdot C}[\theta_{t-1} - \theta_e + \eta \cdot R \cdot P] \tag{3.3}$$

The negative right-hand side of (3.3) means that when the power of the appliance increases, the temperature inside the room decreases – space cooling. The values of the variables used for the RF in (3.3) are presented in Table 3.1, and the respective illustration in Fig. 3.5.

Table 3.1: Variables to apply in the model for the RF

	Variable	Value	Unit
Time step	ΔT	0,25	h
Thermal capacity	C	0,05	$kWh/°C$
Thermal resistance	R	286	$°C/kW$
Electric power	P	0,09	kW
Coefficient of performance	H	3,7	–
House indoor temperature	θ_e	21	$°C$
Set point temperature	θ_{SP}	5	$°C$
Maximum temperature	θ_{max}	7	$°C$
Minimum temperature	θ_{min}	3,6	$°C$

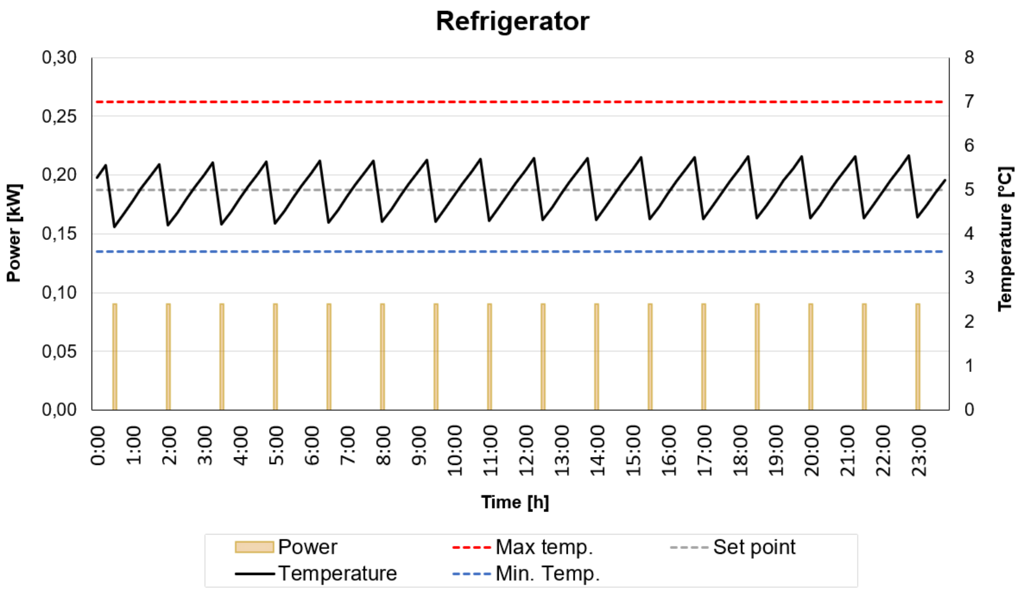


Figure 3.5: Illustration of the PBLM applied to the RF

As can be seen in Fig. 3.5, the appliance has a similar behaviour over time to maintain the temperature within the limits. The external temperature is considered constant.

It is important to mention that the external temperature can be both referred to as house indoor temperature – for the RF and EWH – and as ambient temperature – for the AC. This variable represents the average exterior temperature during the time step.

3.3.1 Air Conditioner

The air conditioner can be used for space heating or cooling, depending on the external temperature or user preferences. If the external temperature is higher than the set point, the AC will operate in cooling mode (3.3); if is lower, the AC operates in heating mode (3.4). Notice that a change of signal in the right-hand side of (3.3) is enough to switch the AC from one mode to the other.

$$\theta_t = \theta_{t-1} + \frac{\Delta t}{R \cdot C}[\theta_{t-1} - \theta_e - \eta \cdot R \cdot P] \tag{3.4}$$

In [29] it is stressed out that, depending on the time step used and on the magnitude of the temperature required for the AC operation, the estimated temperature error for a linearized representation of an AC is around 3% (less than 1°C).

Table (3.2) contains the values for the variables used to test the model with the AC in cooling mode. Like in the RF, the model is tested assuming an external temperature constant over time, and therefore, is being powered in a symmetrical way. The illustration of the model is shown in Fig. (3.6).

Table 3.2: Variables to apply in the model for the AC

	Variable	Value	Unit
Time step	ΔT	0,25	h
Thermal capacity	C	2,72	$kWh/°C$
Thermal resistance	R	4	$°C/kW$
Electric power	P	3	kW
Coefficient of performance	η	3,6	$-$
Ambient temperature	θ_e	30	$°C$
Set point temperature	θ_{SP}	21	$°C$
Maximum temperature	θ_{max}	24,2	$°C$
Minimum temperature	θ_{min}	17,5	$°C$

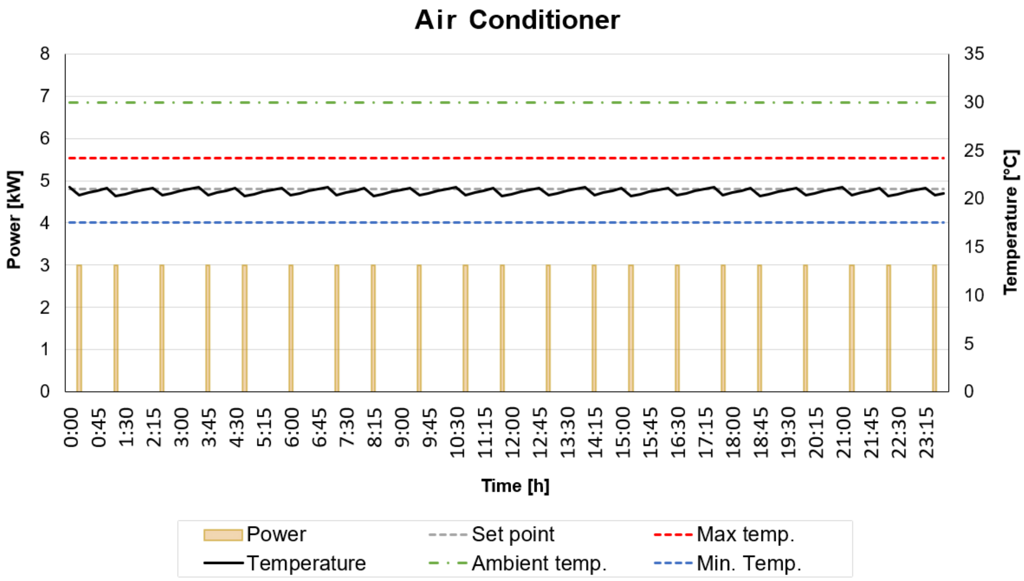


Figure 3.6: Illustration of the PBLM applied to the AC

In terms of controllability of the AC according to the user's preferences, the algorithm is capable of optimize the scheduling considering the set point, maximum and minimum temperatures, as well as a start time and/or deadline, *i.e.*, define a timeframe where the room temperature is the one defined by the user. Hence, the user can have three different approaches: (i) define a start time in order have the expected temperature after that time; (ii) define a deadline and the AC must be turned-off from that time onwards; (ii) define a period along the day where the AC is not needed (*e.g.*, the temperature must correspond to the user's preferences between [0 am – 9 am], is not considered between [9 am – 6 pm], and the temperature must be again inside the limits between [6 pm – 12 pm]). The latter approach is useful if, for example, the user only wants the house temperature inside the limits before going to work and when arrives from work. In order to illustrate this feature, the first approach is presented in Fig. 3.7, with the AC temperature requirements starting at 6 pm. The idea is to have the temperature within the limits from that hour until the end of the day.

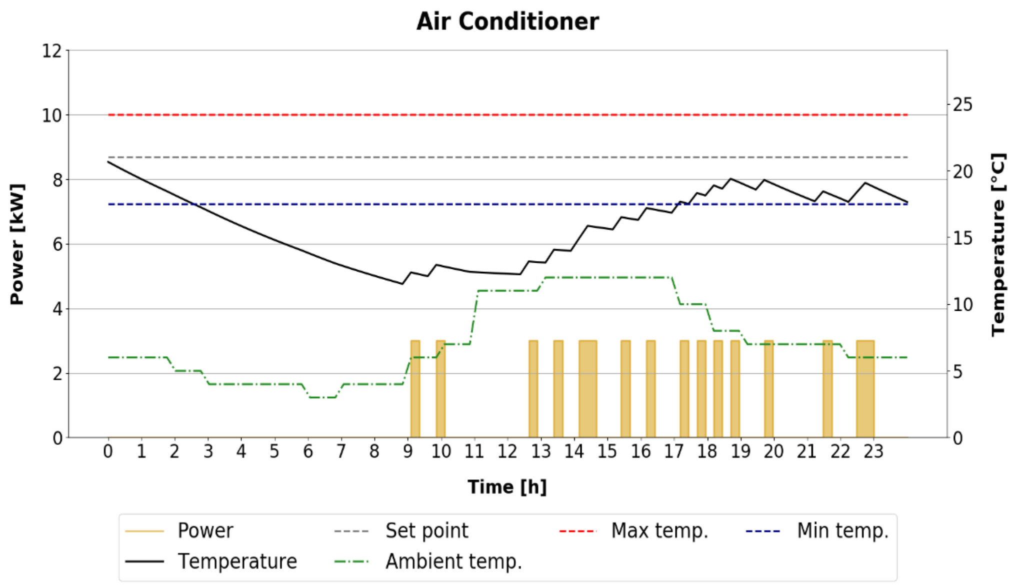


Figure 3.7: Example of AC with start time

Excepting the ambient temperature, the AC was tested under the same conditions applied to test the model – presented in Table 3.2. The considered temperature respects a winter day in a warm Mediterranean climate region (Portugal – Alentejo), and the price tariff used to run the algorithm is the Portuguese by-hourly electricity rate – TOU tariff. Notice that the AC is activated before the start hour to have the expected temperature after the start hour. The times for activation will depend on the objective function.

3.3.2 Electric Water Heater

Since the hot water consumption also affects the energy balance, the model for the EWH differs from the one applied to the AC. The variable v is added to represent the water demand, which is associated with the difference between the desired temperature for hot water usage (θ_d) and the water inlet temperature (θ_{in}) of the cylinder. Some considerations have been pointed out in [29] concerning this term for the model:

- It is not accurate from the thermal energy balance point of view consider v as a "real hot water consumption rate". Since the arithmetic multiplication of water consumption (litres) by the temperature range $(\theta_d - \theta_{in})$ is not equivalent to the thermal energy loss, the water specific heat constant (c_p) is added to the multiplication;

- The temperature of the water in the cylinder is not homogenous and is influenced by the height of the water in the tank. Therefore, the average temperature is assumed in the model;

- v is normally referred to as the water usage (*e.g.*, amount of water demand for a shower) and θ_d as the desired mix temperature. These parameters are only acceptable in the model if the water inlet temperature of the EWH is the same as the cold-water temperature of the mix, which happens in most of the EWH installations.

$$\theta_t = \theta_{t-1} + \frac{\Delta t}{C}[-\alpha(\theta_{t-1} - \theta_e)] - c_p \cdot v_t(\theta_d - \theta_{in}) + P \tag{3.5}$$

The values of the variables used for the EWH in (3.5) are presented in the Table 3.3, and the respective illustration of the model in Fig. 3.8.

Table 3.3: Variables to apply in the model for the EWH

	Variable	Value	Unit
Time step	ΔT	0,25	h
House indoor temperature	θ_e	21	$°C$
Water specific heat capacity	c_p	1,16E-03	$kWh/\ (Ltr.°C)$
Water consumption (normal shower)	v	0,05	$Ltr./s$
		180	$Ltr./h$
Water consumption (power shower)		0,15	$Ltr./s$
		540	$Ltr./h$
Thermal capacity of cylinder	C	0,117	$kWh/°C$
Thermal losses constant	α	9,42E-04	$kW/°C$
Electric power	P	2	kW
Coefficient of performance	η	3,6	$-$
Water inlet temperature	θ_{in}	17	$°C$
Set point temperature	θ_{SP}	64,3	$°C$
Maximum temperature	θ_{max}	80	$°C$
Minimum temperature	θ_{min}	45	$°C$
Desired temperature	θ_d	38	$°C$

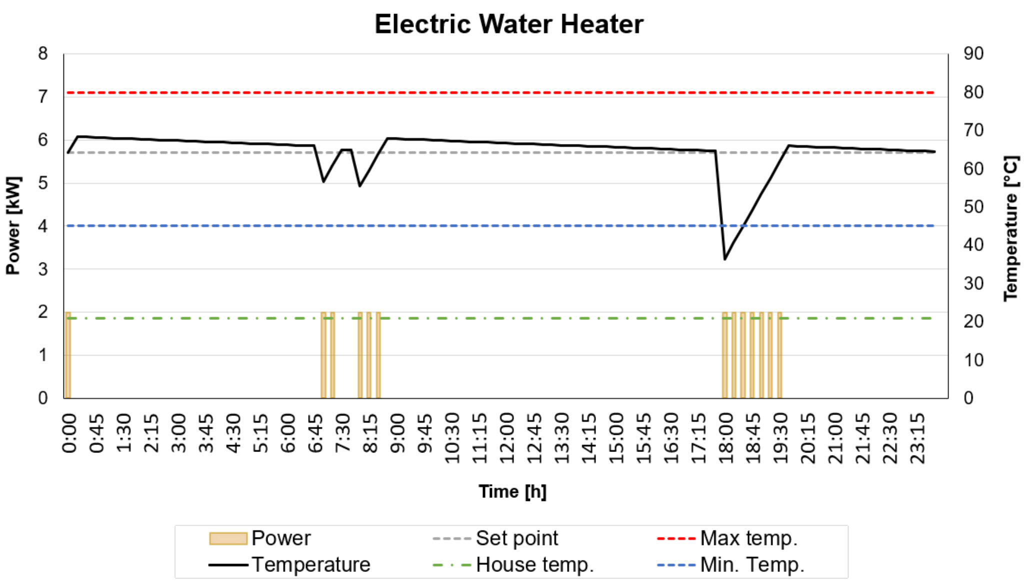


Figure 3.8: Illustration of the PBLM applied to the EWH

As can be seen in Fig. 3.8, two types of showers can be defined by the user – the normal shower, and the power shower. These two types differ in the amount of water being consumed during the shower. It is also prominent that the lower limit for the temperature was violated when the model was being tested. However, the same does not happen in the algorithm when tested under the exact same conditions, as shown in Fig. 3.9.

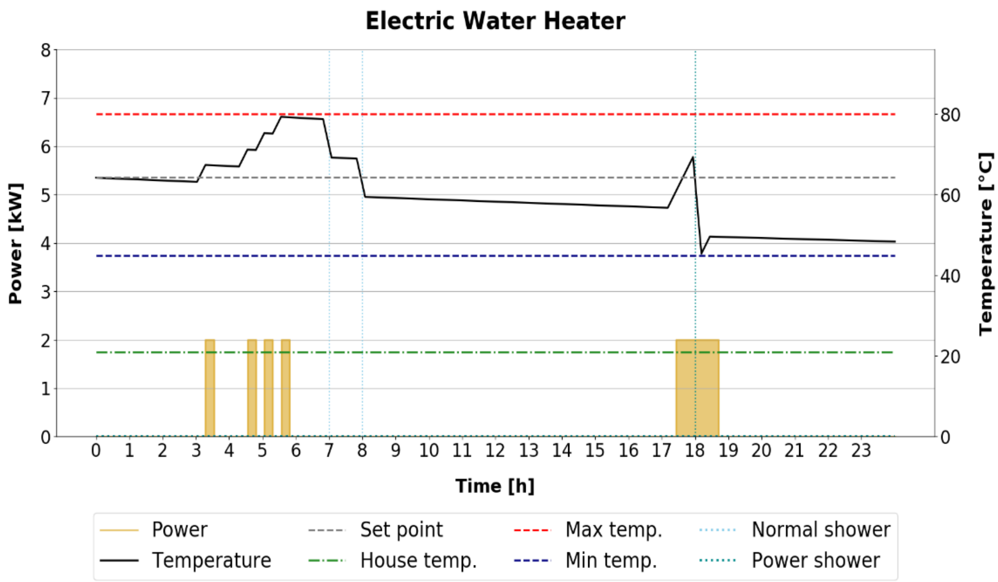


Figure 3.9: Results for the PBLM applied to the EWH with the algorithm

In terms of preferences, the user can define the set point, maximum and minimum temperatures for the EWH cylinder, as well as the desired hot water temperature for shower, number of baths and the respective type of shower (normal or power shower) to determine the amount of water demand.

3.4 PV Self-Consumption

As mentioned earlier, besides providing external services, HEMS load control capabilities can be also applied on more internal purposes, namely in the control of behind-the-meter flexible resources to maximize PV self-consumption. Since a great part of users are not at home consuming energy during the times when PV is producing energy, it is necessary to modify their consumption profile by shifting the loads for periods with higher PV generation. Therefore, PV generation is also considered in this work.

The maximization of PV self-consumption is not achived directly through a specific objective function, but rather indirectly through the goal of minimizing electricity costs, *i.e.*, by increasing the PV self-consumption, there will be less power being consumed from the electric grid, and consequently the energy costs will be minimized. This means that if the appliance's operation costs in a period without PV generation are cheaper than in a period with PV production, the algorithm will choose the first option. The remuneration for PV production injected into the grid is also considered, adding one more criterion to the minimization of costs in the algorithm. The idea for the integration of PV self-consumption in this work is illustrated in Fig. 3.10.

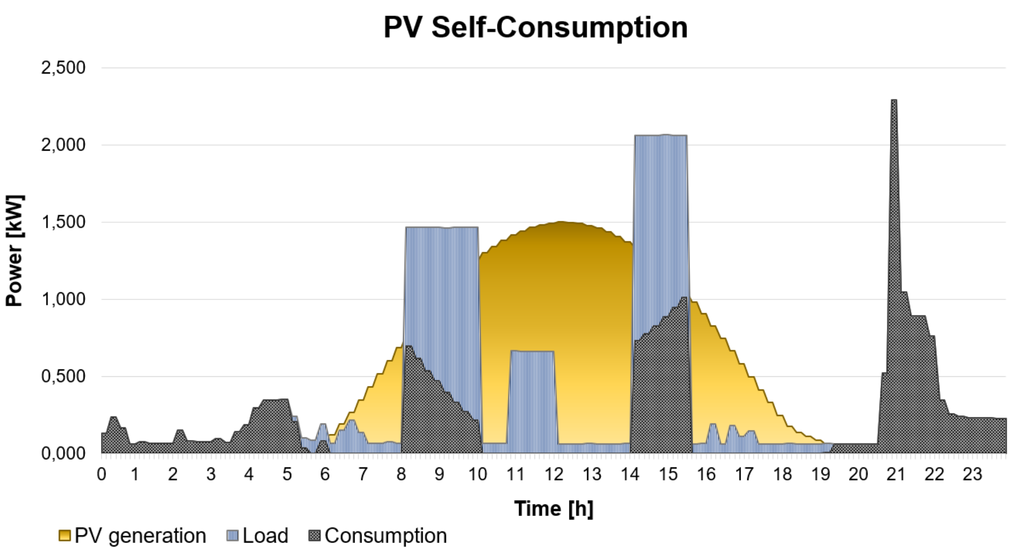


Figure 3.10: Illustration of the model for solar generation [16]

3.5 External Data

The energy management algorithm is capable of incorporate functions to deal with external information as well. This information includes tariff publishing (load and generation) and other online services that can provide local forecasts for the day ahead. Hence, three sets of data are included in the algorithm, namely: (i) price tariffs from energy providers and remuneration for the PV production injected into the grid; (ii) temperature for the next day; (iii) PV forecast, that includes the expected PV production and sun irradiance.

3.6 Summary and Main Conclusions

The models and considerations included in the energy scheduling problem are presented in this chapter. The implementation of these models will be further detailed in the next, while explaining the algorithm architecture and objective function.

The proposed model for the EV only considers the EV as a load that consumes power and can be shifted along the day, being the losses associated with the charging and discharging rates neglected. Other models could be included in the algorithm, such as the battery model, since its architecture is quite flexible for the problem being addressed.

[16] PV curve estimated from PVGis [66]

Chapter 4

Optimization Methodology

4.1 Introduction

This chapter intends to show the methodology used for the optimization behind the energy scheduling problem as well as the general algorithm architecture and the respective experimental validation. Since this methodology is applied in two different problems (one for the validation and another for the energy scheduling), it is first presented a simplified architecture that is common to both problems, and then the algorithm more detailed in the subsequent sectors of the chapter.

The optimization heuristic is a natural result from the CE method for estimation. Depending on the state space $\mathcal{X}$, the heuristic can be applied to solve *continuous optimization problems* or *combinatorial* (*discrete*) *optimization problems*. For example, $\mathcal{X}$ could be the finite space of combinatorial objects such as binary vectors, trees, paths through graphs, permutations, etc. To explain how the CE method works, let's first assume that the goal is to find the minimum value of a function $S(\boldsymbol{x})$ over a set $\mathcal{X}$:

$$S(\boldsymbol{x}^*) = \gamma^* = \min_{\boldsymbol{x} \in X} S(\boldsymbol{x}) \tag{4.1}$$

Where:

- S – Real-value function to minimize
- γ – Limit, threshold or level parameter
- γ^* – Minimum (optimal) limit
- $\boldsymbol{x}$ – Values in the finite state space $\mathcal{X}$
- $\boldsymbol{x}^*$ – Minimizer (assuming that there is only one)

The transformation of a CE estimation method in an optimization heuristic is made by associating the optimization problem (4.1) with the estimation of a probability $\ell = P(S(\mathbf{X}) \leq \gamma)$, where γ is close to the unknown γ^* and $\mathbf{X}$ is a random variable, parameterized by a finite-dimensional real vector $\mathbf{v}$, and with some probability density function $f(\cdot; \boldsymbol{v})$ on $\mathcal{X}$. Considering that ℓ is a rare-event probability, it is possible to use a multi-level CE estimation approach to find an IS distribution that concentrates all its mass in a neighbourhood of the point $\boldsymbol{x}^*$. Sampling from such a distribution will thus produce optimal or near-optimal states. In contrast to the rare-event simulation, the final level $\gamma = \gamma^*$ is generally not known in advance. Nevertheless, the CE method for optimization produces a sequence of levels $\{\hat{\gamma}_t\}$ and reference parameters $\{\hat{\boldsymbol{v}}_t\}$ such that ideally the former tends to the optimal γ^* and the latter to the optimal reference vector $\boldsymbol{v}^*$ corresponding to the point mass at $\boldsymbol{x}^*$.

4.2 Algorithm Architecture

Fig 4.1 depicts the simplified version of the optimization algorithm used in this work. As mentioned earlier, this simplified architecture is common to both problems. It is divided in the following six steps.

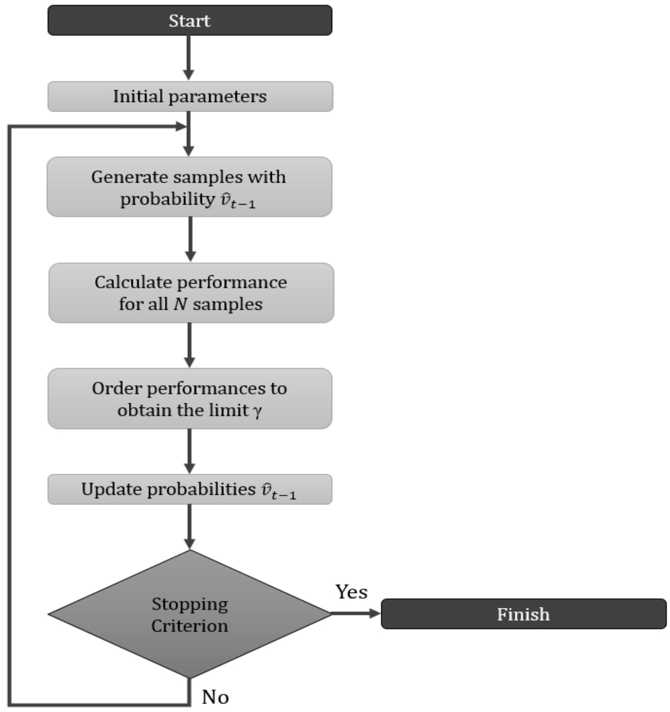


Figure 4.1: Simplified CE method for optimization

1. Initial parameters

To start the algorithm, the following parameters must be set:

- $\varrho \rightarrow$ Rarity parameter
- $N \rightarrow$ Number of independent random samples
- $N^e = [\varrho N] \rightarrow$ Number of elite samples
- $t = 1 \rightarrow$ Initiate iteration counter
- $\varepsilon \rightarrow$ Error for the stopping criterion
- $\alpha \rightarrow$ Smoothing parameter
- $\hat{\boldsymbol{v}}_{\mathbf{0}} = (1/2, \dots, 1/2) \rightarrow$ Initial vector of probabilities (start all with the same probability)

2. Generate samples with probability $\widehat{\boldsymbol{v}}_{\boldsymbol{t-1}}$

Firstly, it is necessary to choose a class of parametric sampling densities $\{f(\cdot;\boldsymbol{v}), \boldsymbol{v} \in \mathcal{V}\}$ that is capable of being flexible enough to include a reasonable parametric approximation to the optimal IS density for the estimation of the associated rare-event probability ℓ, as well as simple enough to allow fast random variable generation. Since the solution vector will be binary, a simple choice for the sampling density is the multivariate Bernoulli density:

$$f(\boldsymbol{x};\boldsymbol{v}) = \prod_{j=0}^{(n-1)} {v_j}^{x_j}(1-v_j)^{1-x_j}, \text{ for } x_j \in \{0,1\} \tag{4.2}$$

, where n is the number of binary variables in each sample defined according to the respective problem. The idea is to generate N independent random samples $(\boldsymbol{X_0}, \dots, \boldsymbol{X_{N-1}})$ from the current estimated IS density $f(\boldsymbol{x};\widehat{\boldsymbol{v}}_{\boldsymbol{t-1}})$, *i.e.*, generate N binary arrays with the same size as the probability vector $\widehat{\boldsymbol{v}}_{\boldsymbol{t-1}}$, where the value (0 or 1) for each j-th position of all samples is generated using the Bernoulli distribution (4.3) with the probability that is in the j-th equivalent position of vector $\widehat{\boldsymbol{v}}_{\boldsymbol{t-1}}$.

$$f(x_j;v_j) = \begin{cases} v_j, & x_j = 1 \\ (1-v_j), & x_j = 0 \end{cases} \tag{4.3}$$

3. Calculate performance for all N samples

The function for the performance depends on the type of problem being addressed, since it represents the objective function. The idea is the creation of a simple objective function, to be minimized or maximized, that is composed by at least two more complex functions – the value function and one or more penalty functions. By doing this separation, it is possible to add individual weights to each sub-function in the objective function and manipulate the influence (weight) of each one of them in the result. The number of performances being calculated is equal to N, *i.e.*, a single performance per sample.

4. Order performances to obtain limit γ

The ordering of the performances depends on the objective function. For minimization problems, the performances are ordered from largest to smallest: $S_{(0)} \geq \dots \geq S_{(N-1)}$. For maximization problems, the order is from smallest to largest: $S_{(0)} \leq \dots \leq S_{(N-1)}$. The limit $(\hat{\gamma}_t)$ being estimated is in both cases the (1–ϱ)-quantile of the performances: $\hat{\gamma}_t = S_{(N-N^e-1)}$. The goal in this step is to obtain the limit $\hat{\gamma}_t$ that represents the last/worst performance to be considered. Moreover, the range of performances is directly affected by N^e, which itself depends directly on ϱ.

5. Update probabilities $\widehat{\boldsymbol{v}}_{\boldsymbol{t-1}}$

The update from $\widehat{\boldsymbol{v}}_{\boldsymbol{t-1}}$ to $\widehat{\boldsymbol{v}}_{\boldsymbol{t}}$ is made with the same set of samples $(\boldsymbol{X_0}, \dots, \boldsymbol{X_{N-1}})$ used to calculate the performances in the t iteration. The solution for the stochastic problem in each iteration is given by:

$$\widehat{\boldsymbol{v}}_{t,j} = \begin{cases} \dfrac{\sum_{k=0}^{(N-1)} I_{\{\widehat{S}_k \geq \widehat{\gamma}_t\}} \cdot X_{k,j}}{\sum_{k=0}^{(N-1)} I_{\{\widehat{S}_k \geq \widehat{\gamma}_t\}}} & , maximization \\ \dfrac{\sum_{k=0}^{(N-1)} I_{\{\widehat{S}_k \leq \widehat{\gamma}_t\}} \cdot X_{k,j}}{\sum_{k=0}^{(N-1)} I_{\{\widehat{S}_k \leq \widehat{\gamma}_t\}}} & , minimization \end{cases} \quad , j = 0, \dots, (n-1) \tag{4.4}$$

, where n is the number of binary components of each sample and $X_{k,j}$ is the j-th component of the k-th random binary vector $\boldsymbol{X}$. Notice that I is an indicator that takes the value *1* if the performance of the k-th sample satisfies the condition, and the value *0* if the opposite. Since the value of $X_{k,j}$ will always be in the interval $\{0; 1\}$, the probability $\widehat{\boldsymbol{v}}_{t,j}$ is easily translated to a simple ratio between the number of times that the j-th component appears in the elite performances and the total number of elite performances being considered in the problem. This means that if the j-th component starts to take the value *1* in most of the elite samples, its probability is going to increase and the value *1* its more likely to occur. In contrast, if the j-th component takes the value *0* in most of the elite samples, its probability of being generated (4.3) decreases.

After the probability is updated, a smoothing parameter (α) can be applied if necessary to soften the change in the probability value between iterations. The equation for the smoothing is formulated as follows:

$$\widehat{\boldsymbol{v}}_{\boldsymbol{t}} = \alpha \cdot \widehat{\boldsymbol{v}}_{\boldsymbol{t}} + (1-\alpha) \cdot \widehat{\boldsymbol{v}}_{\boldsymbol{t-1}} \qquad , 0 \leq \alpha \leq 1 \tag{4.5}$$

Denote the solution for the problem by $\widehat{\boldsymbol{v}}_{\boldsymbol{t}}$, that represents the set of components (sample) with the best performance according to the objective function.

6. Stopping criterion

A possible stopping rule for combinatorial optimization problems is to stop when the overall best objective value does not change over some iterations. However, an alternative was used in this architecture that only stops when the sampling distribution has “degenerated” enough, *i.e.*, when $\{\widehat{\boldsymbol{v}}_{t,j}\}$ differ less than some small $\varepsilon > 0$ from the $\{\widehat{\boldsymbol{v}}_{t-1,j}\}$. Hence, the difference between probabilities for each iteration is obtained by:

$$d_t = \max_{0 \leq j \leq (n-1)} \{\min\{\widehat{\boldsymbol{v}}_{t,j}, (1-\widehat{\boldsymbol{v}}_{t,j})\}\} \leq \varepsilon \tag{4.6}$$

This means that the algorithm only stops if all the probabilities in the vector $\widehat{\boldsymbol{v}}_t$ are equal or bigger than $(1-\varepsilon)$, or are equal or smaller than $(0+\varepsilon)$, *i.e.*, when $\widehat{\boldsymbol{v}}_{\boldsymbol{t}}$ is a binary vector with a maximum error ε. If the criterion is not met, set $t = (t+1)$ and return to *step 2*.

If the state space was continuous, particularly if $\mathcal{X} = \mathbb{R}^n$, the CE sampling distribution would be quite arbitrary and without need of being related with the function that is being optimized. In that case, the generation of a random vector $\boldsymbol{X} = (\boldsymbol{X_0}, \dots, \boldsymbol{X_{(n-1)}})$ in the *step 2* of the algorithm would be most easily performed by drawing the n coordinates independently from some two-parameter distribution. In the most applications, a normal (Gaussian) distribution is employed for each component, resulting in a sampling distribution $f(\boldsymbol{x}; \boldsymbol{v})$ of $\boldsymbol{X}$ characterized by a vector of means $\boldsymbol{\mu}$ and a vector of variances $\boldsymbol{\sigma^2}$ – that can be write like $\boldsymbol{v} = (\boldsymbol{\mu}, \boldsymbol{\sigma^2})$. Examples of continuous optimization problems can be found in [55] and [56].

4.3 Experimental Validation

A well-known NP-complete combinatorial optimization problem that can be used to validate the CE method is the *0-1 Knapsack Packing Problem* (KPP). The KPP is simple, intuitive and makes it easy to understand how the CE method works. Moreover, it is a discrete problem like the scheduling problem.

The idea behind the KPP is to find the best set of components to pack that maximizes the total value inside the knapsack, while at same time complying with the packing restrictions – such as size, weight, shape, etc. Each set of components is represented by a binary vector (sample), that takes the value of *1* if the component is being packed, and the value of *0* if not. Each component has a given unique value or importance associated and has a different weight for each individual restriction (*e.g.*, a component may be smaller but heavier).

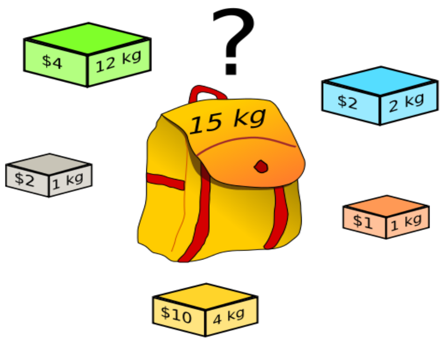


Figure 4.2: Illustration of the Knapsack Packing Problem [17]

The problem can be formulated as it follows:

$$\begin{aligned} &\max_{x} \sum_{j=0}^{(n-1)} p_j x_j \qquad , x_j \in \{0,1\} \qquad , j = 0, \dots, (n-1) \\ &\text{subject to:} \quad \sum_{j=0}^{(n-1)} w_{i,j} x_j \leq c_i \qquad , i = 0, \dots, (m-1) \end{aligned} \tag{4.7}$$

Where:

- n – Number of components in the binary vector
- m – Number of restrictions being considered
- $\{p_j\}$ – Vector with positive weights that represent the value of each j-th component
- $\{w_{i,j}\}$ – Matrix with positive weights, where each i-th row represents one restriction and contains the weight of every components in that restriction
- $\{c_i\}$ – Positive cost parameter that represents the limit for each i-th restriction

[17] From source [67]

The problem is solved using the structure presented in Fig. 4.1, where a single objective function is defined for each k-th sample with the following penalty function approach:

$$S_k = \sum_{j=0}^{(n-1)} p_j x_{k,j} - \beta \sum_{i=0}^{(m-1)} I_{\{\sum_j w_{i,j} x_{k,j} > c_i\}}, \quad \beta = \sum_{j=0}^{(n-1)} p_j \tag{4.8}$$

Notice that $S_k \leq 0$ if one of the inequality is not satisfied and $S_k = \sum_{j=1}^{n} p_j x_{k,j}$ if all the constraints are satisfied. The single objective function (4.8) is applied in the *step 3* of the structure as described below.

Algorithm 1: objective function

Input: binary vector
Output: performance of the sample
for each *i* constraint
  if sum (weights of the purchased components) > restriction limit
    indicator = indicator + 1
  end
end
β = sum (all weights $\{p_j\}$)
penalty = β * indicator
for each *j* component
  multiply p_j by the value in the j-th position of the binary vector
    and add the result to the objective function being maximized
end
subtract penalty to objective function

The algorithm for the KPP was first implemented using the *Matlab*. Since a more flexible and testable solution was sought, a *Python* version of the algorithm was also implemented. Therefore, besides the understanding of the CE method for optimization, the KPP was also an easy approach to learn a new programming language.

Two sets of standardized data were considered for the KPP, namely the *Sento1.dat* and the *Sento2.dat* given in the appendix of Senju and Toyoda [68]. Both problems have 30 constraints, 60 variables, and use the following initial parameters in the *step 1* of the structure:

- $\varrho = 0{,}02$
- $N = 1000$
- $N^e = [\varrho N] = 20$
- $t = 1$
- $\varepsilon = 0.01$
- $\alpha = 1$ (no smoothing applied in $\hat{v}_t$)
- $\hat{v}_0 = (1/2, \dots, 1/2)$

It is important to stress out that the only difference between these sets of data are the values of the positive cost parameter $\{c_i\}$. The rest remains the same.

The following subsections contain the results of both problems. A crude Monte Carlo method is applied to analyse the performance of the algorithm in terms of achieving the optimal result. The seeds for the random generation were fixed to track the different results in each simulation. The number of simulations was established by the following criterion:

$$N_{MC} = \frac{1}{\varepsilon} * 10 \tag{4.9}$$

4.3.1 KPP – *Sento1.dat*

The results obtained with the crude Monte Carlo for the *Sento1* problem are presented in Table 4.1. It is possible to notice that the algorithm converges quickly to optimal results, since the maximum number of iterations in all simulations was only 14, and the average is around 10 iterations. Moreover, the average of the performances is concentrated near the optimum solution despite the large variance obtained, as shown in Fig. 4.3.

Table 4.1: Results for *Sento1.dat*

	Performances	Iterations
Best result	7772	8
Worst result	6741	14
Average	7579,88	9,74
Variance	47732,56	1,17
Standard Deviation	218,48	1,08

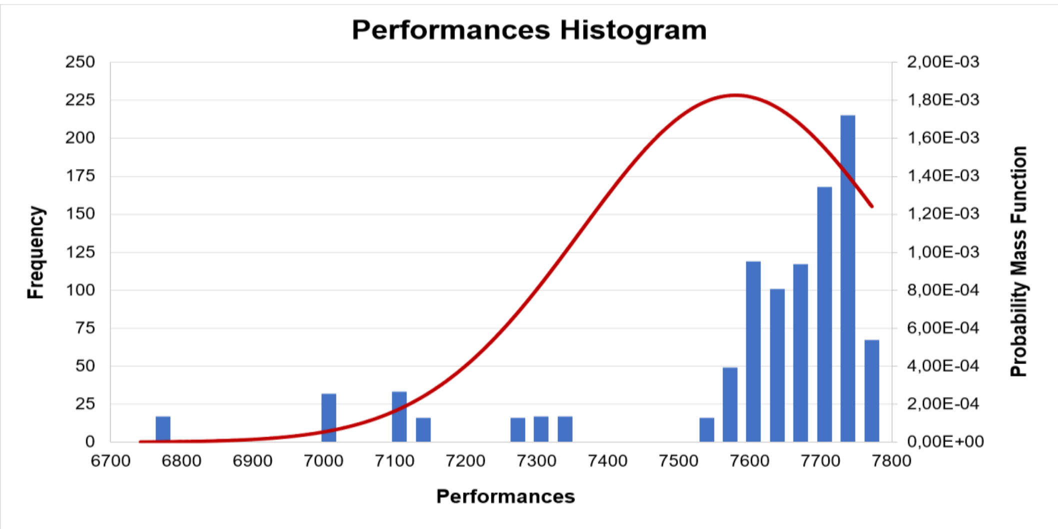


Figure 4.3: Performances histogram – *Sento1.dat*

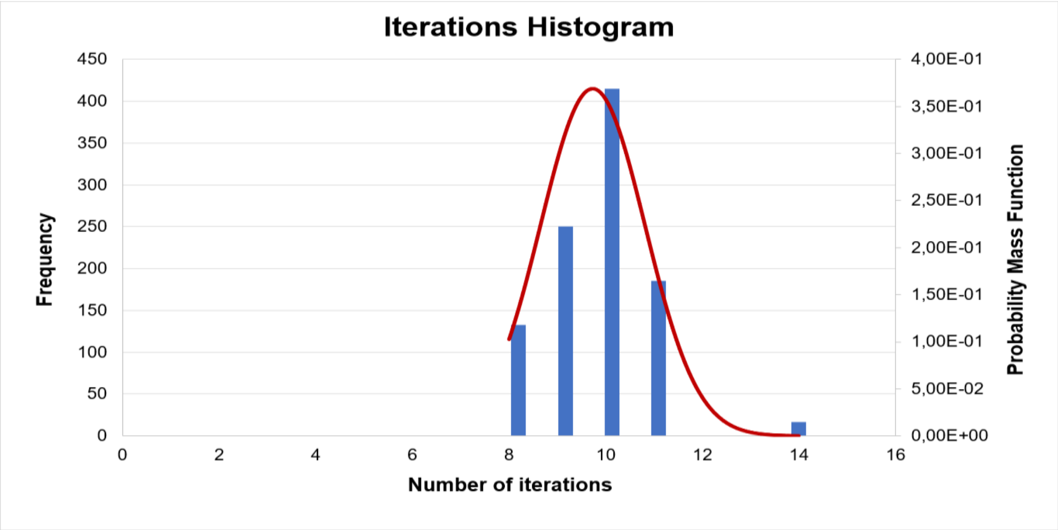


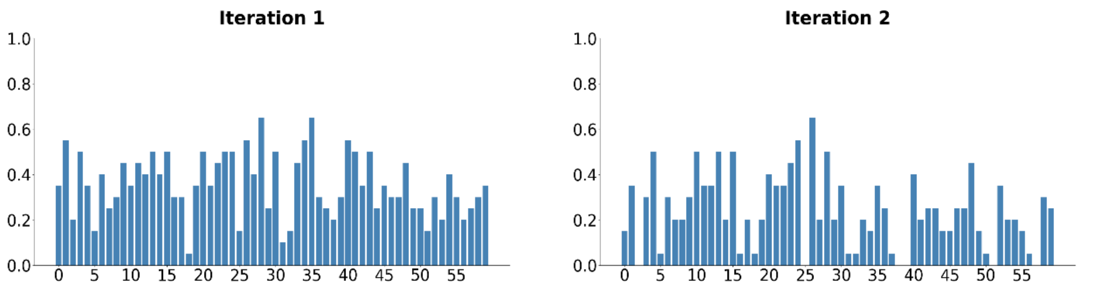
Figure 4.4: Iterations histogram – *Sento1.dat*

The evolution of the best result obtained with the combinatorial optimization algorithm on *Sento1.dat* problem is shown in Table 4.2. For each iteration t is recorded the threshold $\hat{\gamma}_t$, the largest value of $S(X_k)$ in the current population, and the stopping criterion d_t. The global maximum value is 7772.

Table 4.2: Evolution of the best performance over iterations – *Sento1.dat*

Iteration (t)	Limit ($\hat{\gamma}_t$)	Best score (S_{max})	Max. difference (d_t)
1	-118808	-53669	0,50
2	2106	4506	0,50
3	4266	5005	0,50
4	5805	6579	0,50
5	6998	7340	0,50
6	7369	7562	0,45
7	7561	7650	0,45
8	7725	7772	0,45
9	7772	7772	0,00

Fig. 4.5 shows the evolution of the probability vector v_t, which characterizes the multivariate Bernoulli distribution $f(\cdot;\hat{v}_t)$. Notice that $\hat{v}_t$ converges to a binary vector corresponding to the optimal solution, *i.e.*, a vector with the purchased components.



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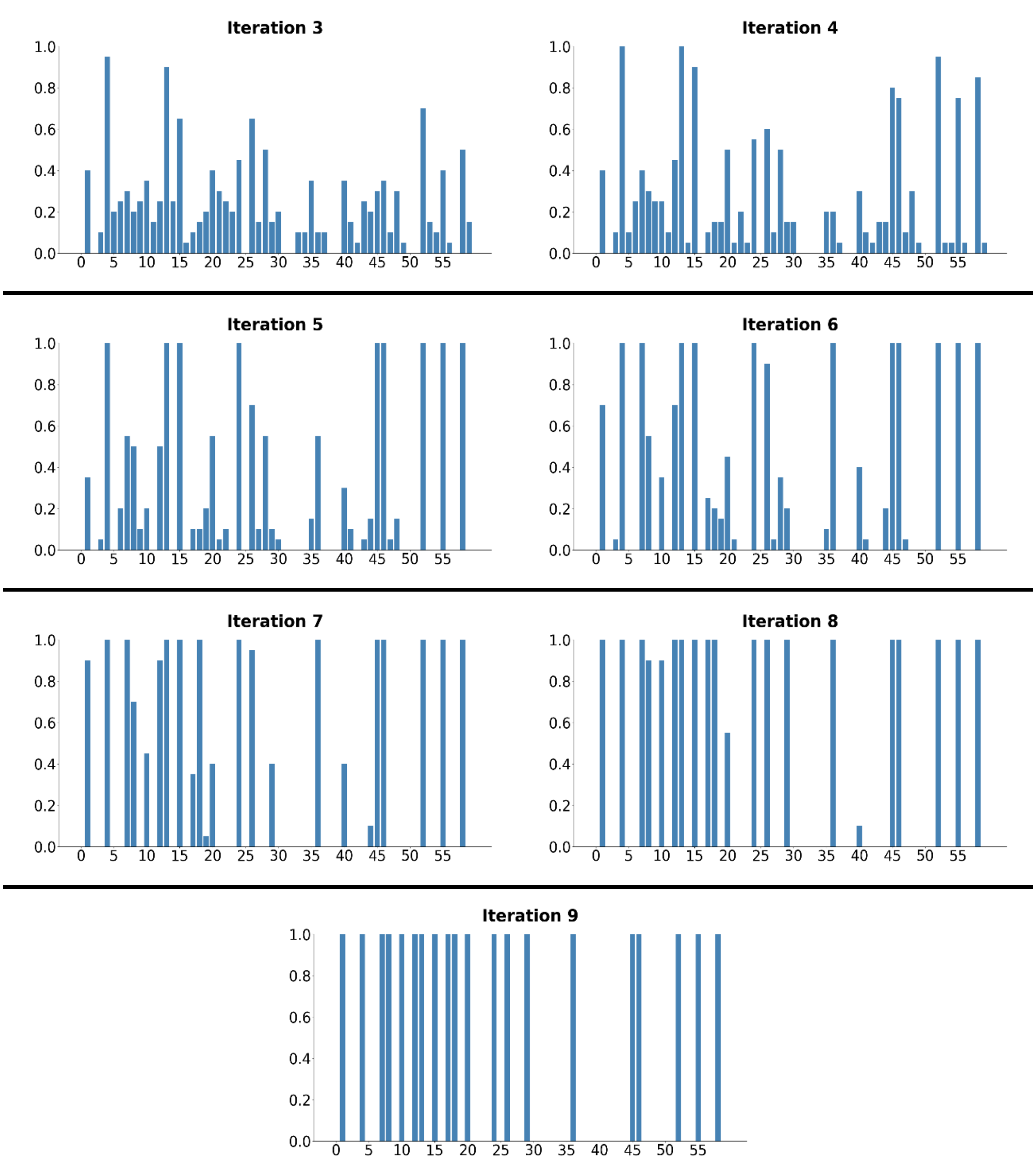

Vertical axis: probability ($\hat{v}_t$)	Horizontal axis: components (n)

Figure 4.5: Evolution of the probability vector v_t – *Sento1.dat*

4.3.2 KPP – *Sento2.dat*

The results obtained with the crude Monte Carlo for the *Sento2* problem are presented in Table 4.3. As can be seen, the algorithm shows better results in the performances when compared to the *Sento1*. The variance had a massive reduction, and the average is even more concentrated around the optimum, as shown in Fig. 4.6. Although the worst number of iterations is 49, this situation only happened one time in 1000 simulations. If was not for this value, the average of iterations would be around 12, as can be seen in Fig. 4.7.

Table 4.3: Results for *Sento2.dat*

	Performances	Iterations
Best result	8722	8
Worst result	8545	49
Average	8688,06	10,25
Variance	448,27	3,20
Standard Deviation	21,17	1,79

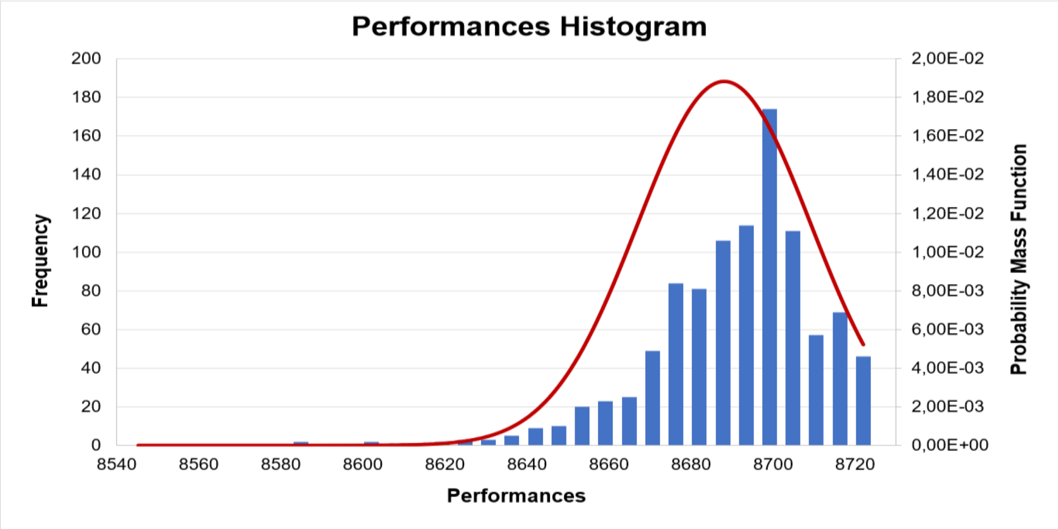

Figure 4.6: Performances histogram – *Sento2.dat*

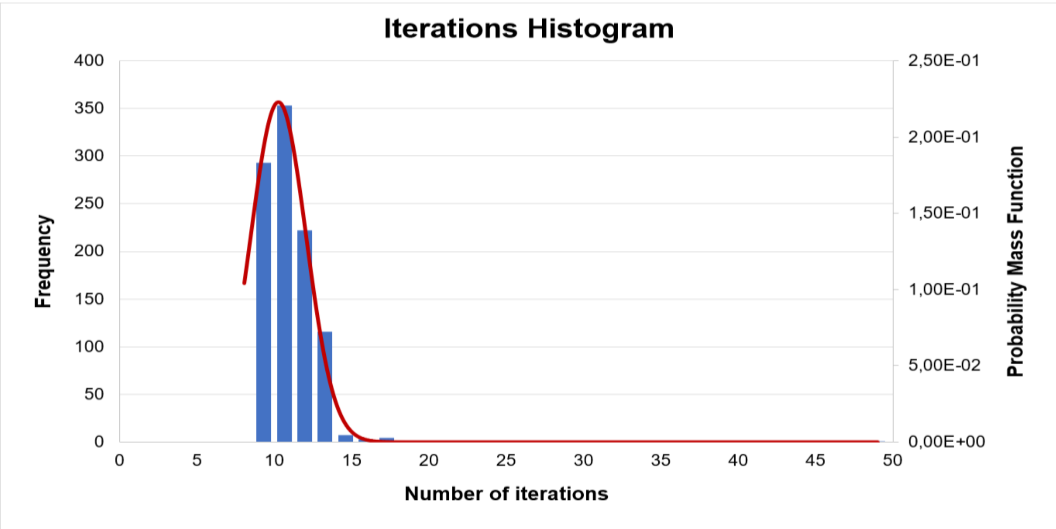

Figure 4.7: Iterations histogram – *Sento2.dat*

4.4 Electricity Consumption Scheduling

The electricity consumption scheduling is a discrete minimization problem with a state space represented by binary vectors as well. It consists in finding, for each appliance, the best activation time at the minimum cost in a finite state space (*i.e.*, for the 24 hours of the next day), while considering at the same time the physical and operational constraints of each appliance. Here, instead of a final binary vector with purchased components, the result is a binary vector that indicates the time(s) that the device is going to be activated during the next day. Moreover, this binary vector will be expressed in periods and not in hours, and therefore, every appearance of the $[per]$ unit means that the variable was converted from hours to periods.

$$[per] = \frac{[h]*60}{gap} \tag{4.10}$$

The problem is solved using the structure presented in Fig. 4.1. However, since the obtainment of the objective function is a lot more complex than the one presented for the KPP, the *steps 1* and *2* will be detailed with the support of flow diagrams and some algorithms, following a vertical structure from the initial parameters until the objective function. Hence, in order to run the algorithm, the following initial parameters must be provided for *step 1*:

CE method parameters:

- $\varrho \rightarrow$ Rarity parameter $[-]$
- $N \rightarrow$ Number of independent random samples $[\#]$
- $N^e = [\varrho N] \rightarrow$ Number of elite samples $[\#]$
- $\varepsilon \rightarrow$ Error for the stopping criterion $[-]$
- $\alpha \rightarrow$ Smoothing parameter $[-]$
- $t = 1 \rightarrow$ Initiate iteration counter $[\#]$
- $t_{max} \rightarrow$ Maximum number of iterations $[\#]$
- $\hat{v}_0 = (1/2, \dots, 1/2) \rightarrow$ Initial vector of probabilities (start all with the same probability)

Scheduling parameters:

- $gap \rightarrow$ Time interval between activation periods along the day $[min]$
- $n = (24 * 60)/gap \rightarrow$ Number intervals (periods) being considered $[\#]$
- $\Delta t = gap/60 \rightarrow$ Time step for thermal equations $[h]$

External data:

- $Price_j \rightarrow$ Dynamic price tariff in the j-th period $[€/kW]$
- $T_j^{house} \rightarrow$ House temperature in the j-th period $[℃]$
- $T_j^{amb} \rightarrow$ Ambient temperature in the j-th period $[℃]$
- $P_j^{PV} \rightarrow$ PV generation in the j-th period $[kW]$
- $RM_j \rightarrow$ PV remuneration in the j-th period $[€/kW]$

Shiftable appliances data:

- $n^{SH} \rightarrow$ Number of shiftable appliances $[\#]$
- $P_s^{SH} \rightarrow$ Power of the s-th shiftable appliance $[kW]$
- $D_s^{SH} \rightarrow$ Duration of the operation of the s-th shiftable appliance $[per]$

- Rep_s^{SH} → Number of times that the s-th shiftable appliance is activated [#]
- $Start_{s,f}^{SH}$ → Starting time for the f-th timeframe of the s-th shiftable appliance [per]
- $End_{s,f}^{SH}$ → Deadline for the f-th timeframe of the s-th shiftable appliance [per]

Thermal appliances data:

- n^{TH} → Number of thermal appliances [#]
- C_h^{TH} → Thermal capacity of the h-th thermal appliance [$kWh/℃$]
- R_h^{TH} → Thermal resistance of the h-th thermal appliance [$℃/kW$]
- η_h^{TH} → Coefficient of performance of the h-th thermal appliance [$-$]
- P_h^{TH} → Power of the h-th thermal appliance [kW]
- θ_{SP_h} → Set point temperature of the h-th thermal appliance [℃]
- θ_{max_h} → Maximum temperature of the h-th thermal appliance [℃]
- θ_{min_h} → Minimum temperature of the h-th thermal appliance [℃]
- θ_{e_h} → External temperature of the h-th thermal appliance [℃]
- θ_d → Desired shower temperature for the EWH [℃]
- θ_{in} → Water inlet temperature in the cylinder for the EWH [℃]
- $Start_h^{TH}$ → Starting time for the h-th thermal appliance [per]
- End_h^{TH} → Deadline for the h-th thermal appliance [per]
- w_j^{shower} → Water consumption in the j-th period for the EWH [$Ltr./per$]
- $c_p = 1{,}16 \cdot 10^{-3}$ → Water specific heat [$kWh/\ (Ltr.°C)$]
- $\alpha = 9{,}42 \cdot 10^{-4}$ → Thermal losses constant [$kW/°C$]

Since the external data is usually provided for 24 hours, it must be converted to periods. The same happens if the external data has more information than the number of periods considered. Therefore, the following algorithm is applied:

Algorithm 2: convert hours to periods

```
Input: data array, n, gap
Output: converted array
if size data array = n
    return same data array
else
    create new array with size n
    if size data array > n
        use the average of the values in data array
            according to the number of positions
    else
        fill new array from position a until (a + 60/gap) with
            same value according to the number of positions
    end
    return converted array
end
```

Once all the initial data and parameters are defined, it is possible to start the iterative process. In the scheduling problem, the generation of samples with probability $\hat{v}_{t-1}$ in the *step 2* of the algorithm is made individually for each appliance, *i.e.*, each appliance has its own N independent random samples $(\boldsymbol{X_0}, \dots, \boldsymbol{X_{N-1}})$. Therefore, these samples are separated as follows:

- $X^{SH}_{s_{k,j}} \rightarrow j$-th binary variable of the k-th sample of the s-th shiftable appliance, $\in \{0,1\}$
- $X^{TH}_{h_{k,j}} \rightarrow j$-th binary variable of the k-th sample of the h-th thermal appliance, $\in \{0,1\}$

, where the j-th binary variables for all N samples are generated according to the multivariate Bernoulli distribution presented in (4.3) with the probability vector $\hat{v}_{t-1}$.

In order to achieve a single objective function to calculate the performances in *step 3*, the structure presented in Fig. 4.8 is considered for each t-th iteration.

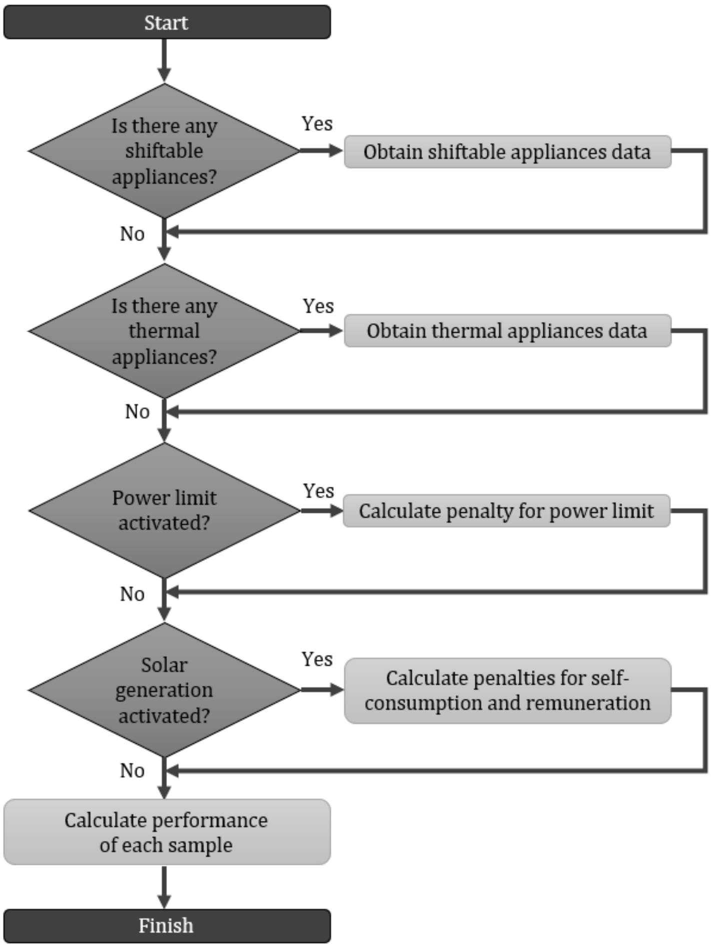

Figure 4.8: Simplified structure for the obtainment of performances

The idea is to determine, in each stage, the value functions to minimize and the respective penalty functions, in order to have a single objective function composed by the sum of all these sub-functions. In this way, as mentioned earlier, it is possible to add individual weights to each sub-function and manipulate their influence (weight) in the final result. Nonetheless, for this approach to be successful, it is necessary to normalize all the values that will be included in the objective function, as it will be explained after.

The first stage concerns all the information related to the shiftable appliances. If there is at least one shiftable in the problem, the following structure is performed:

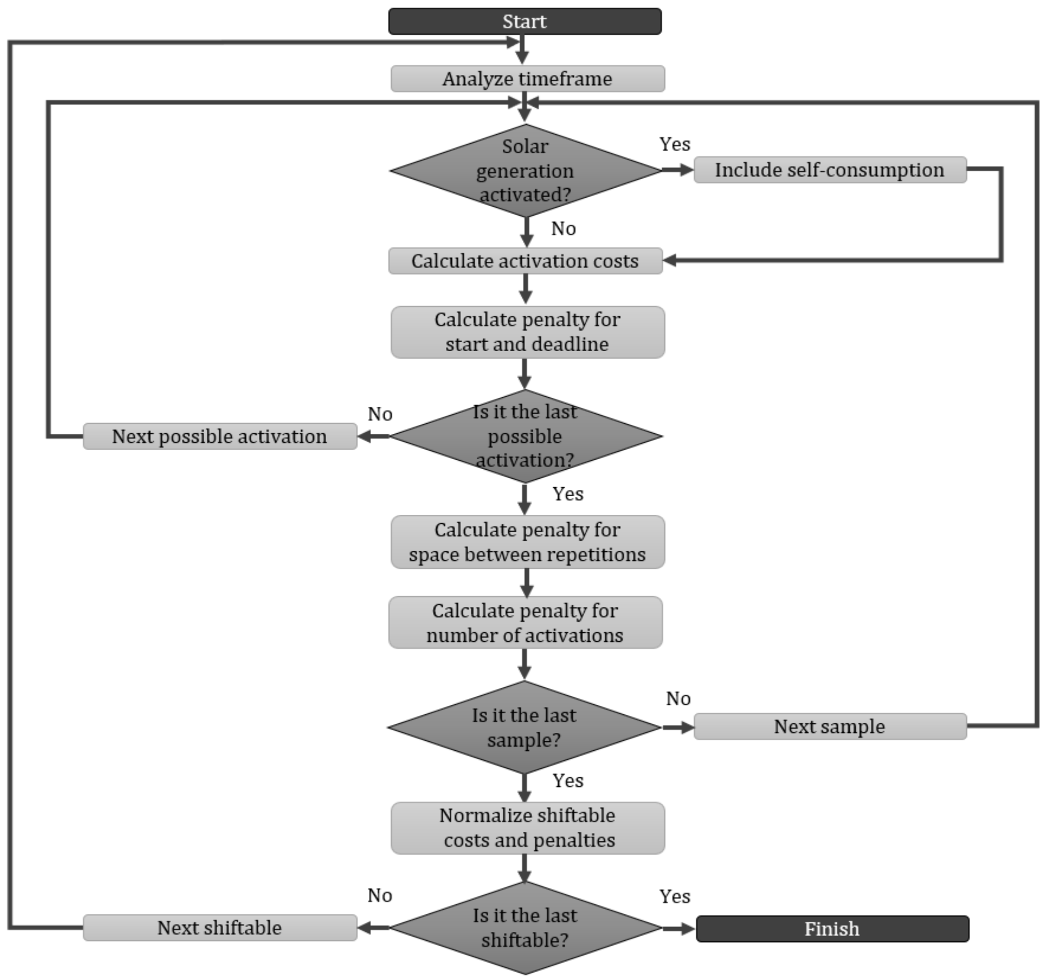

Figure 4.9: Simplified structure for the obtainment of shiftable appliances data

Analyse Timeframe

This step consists in the creation of two vectors according to all timeframes of the appliance. One is a binary vector that indicates if it is possible (1) or not (0) to activate the shiftable in the j-th period; the second is a vector with all the positions of the first that are equal to *1*, *i.e.*, all the possible periods for activation within all the timeframes. The vectors and the process to obtain their values can be represented as follows:

- $B_{s,j} \rightarrow j$-th binary variable of the s-th shiftable appliance, $\in \{0,1\}$
- $b_s \rightarrow$ number of possible activations of the s-th shiftable appliance, $\in \{0,(n-1)\}$
- $G_{s,l} \rightarrow l$-th possible period for activation of the s-th shiftable appliance, $l \in \{0, b_s\}$

Algorithm 3: indicator for possible activation

Input: $Start_s^{TH}$, End_s^{TH} → receive timeframes of the s-th shiftable
Output: B_s → array with possible activations of the s-th shiftable
for each timeframe f
  if $Start_{s,f}^{TH} < End_{s,f}^{TH}$ → normal timeframe
    $B_{s,j} = 1, \quad \forall\, j \in [\, Start_{s,f}^{TH},\ (End_{s,f}^{TH} - D_s^{SH})[$
  else → inverted timeframe
    $B_{s,j} = 1, \quad \forall\, j \in [0,\ (End_{s,f}^{TH} - D_s^{SH})[\ \cup\ [\, Start_{s,f}^{TH},\ (n-1)[$
  end
end

Notice that the case of inverted timeframe (*e.g.*, [6 pm – 8 am] ⟹ [0 am – 8 am] ∪ [6 pm – 12 pm]) only occurs when the total number of timeframes is one, *i.e.*, cases where the appliance only operates once during the day, or in case the appliance that is being analysed is the EV. Furthermore, these two vectors are only created once for each shiftable and are used in all N samples. Both will be useful in determining the start and deadline penalty values.

It is important to stress out that the range for activation begins in the period $j = 0$ and ends in $j = (n-1)$. For instance, if the appliance operates for two periods and starts in $j = 0$, it operates in the periods $j = 0 \wedge j = 1$, and ends in $j = 2$, not included.

Before going for the next stage, another vector needs to be obtained, namely one that contains all the j-th periods of the k-th random sample $X_{s_k}^{SH}$ that are equal to *1*. This vector is created once for each k-th sample and represents all the possible activation times that were generated in that same random sample.

- m_k → number of possible activations of the k-th sample, $\in \{0, (n-1)\}$
- $Y_{k,i}$ → i-th possible period for activation of the s-th shiftable, $i \in \{0, (m_k - 1)\,\}$

For example, if $X_{s_k}^{SH}$ contains $\{1, 0, 1, 0, \dots, 0, 1, 1, 0\}$, $Y_{k,i}$ would be $\{0, 2, \dots, n-3, n-2\}$. The same logic is applied to the previous B_s and G_s.

Calculate activation costs

The activation costs and limit penalties are both determined within the same cycle. The idea is to cover all the activation periods saved in Y_k and evaluate each one of them individually. The goal is to know how much it is going to cost the operation if the appliance is activated in the j-th period. Moreover, it is also intended to calculate the penalty for start and deadline if the limits are not met and save the power being consumed as well (only used if the contracted power is being considered).

The total cost of the s-th appliance in the k-th sample will depend on the price and on the appliance power. In turn, the appliance power will rely on whether the solar generation is activated or not. Since the price tariff is usually given in cents and the result for the cost in the objective function will be normalized, the price is multiplied by 10^3 to obtain values larger than *0*. Thus, the function for the total cost of the s-th shiftable in the k-th sample can be formulated as follows:

$$Cost_{k,s}^{SH} = \sum_{i=0}^{(m_k-1)} \sum_{j=Y_{k,i}}^{(Y_{k,i}+D_s^{SH}-1)} Price_j \cdot P_{s,j}^{SH'} \cdot 10^3 \tag{4.11}$$

$$P_{s,j}^{SH'} = \begin{cases} \begin{cases} P_s^{SH} - P_{k,j}^{PV'} & , P_{k,j}^{PV'} < P_s^{SH} \\ P_s^{SH} & , P_{k,j}^{PV'} = 0 \\ 0 & , P_{k,j}^{PV'} \geq P_s^{SH} \end{cases} & , if\ PV\ activated \\ P_s^{SH} & , if\ PV\ not\ activated \end{cases} \tag{4.12}$$

Where*:*

- $P_{s,j}^{SH'}$ → power of the s-th shiftable appliance in the j-th period $[kW]$
- $P_{k,j}^{PV'}$ → PV power available in the j-th period of the k-th sample $[kW]$

The vector $P_k^{PV'}$ is always the same for all the appliances in each t-th iteration. It starts with the same values as the vector P^{PV} (total PV generation) in the beginning of the iteration and starts to decrease according to the power being consumed by the appliances. If the solar generation is activated, this vector will change every time that is used and take one of the following values:

$$P_{k,j}^{PV'} = \begin{cases} 0 & , P_{k,j}^{PV'} < P_s^{SH} \\ P_{k,j}^{PV'} & , P_s^{SH} = 0 \\ P_{k,j}^{PV'} - P_s^{SH} & , P_{k,j}^{PV'} \geq P_s^{SH} \end{cases} \tag{4.13}$$

While the cost is being calculated, the consumed power in the j-th period of the k-th sample can be saved in an auxiliary vector to be later used to determine the contracted power penalty. As in the case of $P_{k,j}^{PV'}$, the auxiliary vector for power is always the same for all the appliances in each t-th iteration.

$$P_{k,j}^{Total} = P_{k,j}^{Total} + P_{s,j}^{SH'} \tag{4.14}$$

Calculate penalty for start and deadline

This penalty is calculated with the vectors B_s and G_s. Each period of activation in the i-th position of Y_k is tested to find out if the operation of the appliance complies with the timeframe when activated in that period. If the operation begins before the start of the timeframe or finishes after the end, the excess will be added to penalize in the objective function. The vector B_s is used to check if the operation from the $Y_{k,i}$ period until $(Y_{k,i} + D_s^{SH} - 1)$ can be performed inside the limits or not. The vector G_s is used to determine the excess and the value for the penalization will depend on the activation period being tested.

The formulation for this penalty can be expressed as presented below and the process to obtain the excess to add in the penalty is explained in Algorithm 4.

$$Limit_{k,s}^{SH} = \sum_{i=0}^{(m_k-1)} \begin{cases} |ini - M_1| \cdot I_{\{ini > G_{s,(b_s-1)}\}} + |M_2 - ini| \cdot I_{\{ini \le G_{s,(b_s-1)}\}} & , B_{s,ini} = 0 \\ 1 + |end - G_{s,(b_s-1)}| \cdot I_{\{end \ge n\}} + |ini - M_3| \cdot I_{\{B_{s,end} = 0\}} & , B_{s,ini} = 1 \end{cases}$$

$$ini = Y_{k,i} \quad , end = Y_{k,i} + D_s^{SH} \quad , M_1 = \max_{m_1}(m_1 \subset [0, ini\,[\,) \subset G_s \tag{4.15}$$

$$M_2 = \min_{m_2}(m_2 \subset]ini, n\,[\,) \subset G_s \quad , M_3 = \max_{m_3}(m_3 \subset [0, end\,[\,) \subset G_s$$

Algorithm 4: calculate excess for start and deadline penalty

Input: Y_k, D_s^{SH}, B_s, G_s
Output: excess to add in the limit penalty
for each i-th activation period in Y_k being tested
  if operation starts outside the possible timeframe $\rightarrow B_{s,ini} = 0$
    if activation period being tested is after the last possible one $\rightarrow ini > G_{s,(b_s-1)}$
      excess is the difference between both $\rightarrow |ini - M_1|$
    else $\rightarrow ini \le G_{s,(b_s-1)}$
      excess is the difference between the closest possible activation period inside the timeframe and the period being tested $\rightarrow |M_2 - ini|$
    end
  else if operation starts inside possible timeframe, test deadline $\rightarrow B_{s,ini} = 1$
    if it ends after or in the end of the day $\rightarrow end \ge n$
      excess is the difference between the end period of the operation and the last possible activation period $\rightarrow 1 + |end - G_{s,(b_s-1)}|$
    else if it ends outside the possible timeframe $\rightarrow B_{s,end} = 0$
      excess is the difference between the period being tested and the closest period to the end inside the timeframe $\rightarrow 1 + |ini - M_3|$
    end
  end
end

The value *1* is added to the excess of the deadlines to consider the cases when the appliance is operating in the deadline period. As mentioned before, the appliance cannot operate in the j-th period equal to the deadline. The coefficients M represent the closest periods for activation inside the possible options in G_s.

Calculate penalty for space between repetitions

This penalty is obtained outside the previous cycle and it is only necessary when the shiftable appliance operates more than once. Basically, it consists in going over all the m_k possible periods for activation in Y_k and confirm if the time space between operations of the s-th appliance is being satisfied, *i.e.*, if it only starts when the previous operation is over. This penalty takes high values in the first iterations due to the large number of possibilities but starts to decrease when the penalty for the total number of activations starts working.

$$Space_{k,s}^{SH} = \sum_{i=0}^{(m_k-1)} |end - V^{sup}| \cdot I_{\{end > V^{sup}\}} \quad , if \;\; Rep_s^{SH} > 1 \tag{4.16}$$

$$ini = Y_{k,i} \quad , end = Y_{k,i} + D_s^{SH} \quad , V^{sup} = \begin{cases} \min_{m_4}(m_4 \subset]Y_{k,i}, n\,[\,) \subset Y_k & , i < (m_k - 1) \\ n & , i = (m_k - 1) \end{cases}$$

The variable V^{sup} represents the next activation period concerning the one being tested. Thus, for each end, this variable will take the value of the next ini. If there is no other possible period in Y_k, the superior value V^{sup} will be equal to n (end of the day).

Calculate penalty for number of activations

This penalty is divided in two stages: one to ensure the total number of activations and another to guarantee that the activations are inside each timeframe. The first is determined by the difference between the total number of activations generated in the k-th sample and the intended one (Rep_s^{SH}); the latter is given by β and depends on whether the s-th appliance is the EV and on the type of timeframe being considered (normal or inverted). The total number of timeframes for the s-th appliance is given by n_s.

If the appliance is an EV, it is only necessary to ensure that it is being activated the required amount of times to comply with the required charging, being the penalty for the start and deadline enough to push the activation periods into the timeframe. Hence, β will take the same value as the left-hand side of the penalty. If the appliance is not the EV, it is necessary to determine the variable U_f, that represents a counter for the number of activation periods that were generated inside the f-th timeframe. If there are no activations, the penalization will be the total number of timeframes squared (${n_f}^2$); if there is only one activation, the penalization will be the excess. Remember that the inverted timeframe is just for cases where the appliance only operates once during the day.

$$Activation_{k,s}^{SH} = |m_k - Rep_s^{SH}| + \beta \tag{4.17}$$

$$\beta = \begin{cases} |m_k - Rep_s^{SH}| & ,if\ is\ the\ EV \\ \sum_{f=1}^{n_s} {n_s}^2 \cdot I_{\{U_f<1\}} + \left|U_f - 1\right| \cdot I_{\{U_f>1\}} & ,if\ is\ not\ the\ EV \end{cases}$$

$$U_f = \begin{cases} \sum_{j=ini}^{(end-1)} X_{s_{k,j}}^{SH} & ,Start_{s,f}^{SH} < End_{s,f}^{SH} \\ \sum_{j=0}^{(end-1)} X_{s_{k,j}}^{SH} + \sum_{j=ini}^{(n-1)} X_{s_{k,j}}^{SH} & ,Start_{s,f}^{SH} > End_{s,f}^{SH} \end{cases} \quad ,ini = Y_{k,i} \quad ,end = Y_{k,i} + D_s^{SH}$$

Notice that if $m_k = Rep_s^{SH}$, the activations penalty continues to be applied if the activations are not inside the intended timeframes.

Normalize shiftable costs and penalties

After gathering the data for all the N samples, the total cost and the penalties for each k-th sample of the s-th shiftable are normalized. This procedure is applied because the values determined in each sub-function for the final objective function are calculated separately and differently. Therefore, if the normalization is not considered, it is a lot more difficult to adjust the weights to obtain the final performances of the samples. Moreover, it was necessary to find a method that considers all the sub-functions equally, regardless of the total number of appliances.

Two different approaches were considered in terms of normalization. One regards the values that will always be greater than zero in the objective function; the other is to be applied in the values of the penalty functions. This division is made because there will always be costs for the appliances and this value will never be zero. Even with PV-self consumption, the uncontrollable loads in the house always contribute somehow for the energy costs. Besides that, if the zero value was considered, the algorithm would prefer the sample that gives free costs rather than the ones with small costs, which would result in a final vector without any activation (because the goal is costs minimization). In contrast, it is expected that the values resulting from penalties converge to zero when the constraints are satisfied.

The method used for the normalization is the *min-max* method. The idea is to obtain an equal range of values between [0-100] for all sub-functions, where the worst value of each one always equals *100* and the best equals *0*. For example, if there are only two different values in a penalty for all the N samples, the minor takes the value *0* and the other the value *100*. Therefore, it is easier for the algorithm to choose between samples. Moreover, the impact of the normalization starts to increase as the values begin to get closer. Hence, the following equations are applied:

$$NormC_{k,s}^{SH} = \frac{M}{n^{SH}} \cdot \frac{Cost_{k,s}^{SH} - \min_a(a \subset Cost_s^{SH} \wedge a>0)}{\max_a(a \subset Cost_s^{SH} \wedge a>0) - \min_a(a \subset Cost_s^{SH} \wedge a>0)} \tag{4.18}$$

$$NormL_{k,s}^{SH} = \frac{M}{n^{SH}} \cdot \frac{Limit_{k,s}^{SH} - \min_a(a \subset Limit_s^{SH})}{\max_a(a \subset Limit_s^{SH}) - \min_a(a \subset Limit_s^{SH})} \tag{4.19}$$

$$NormS_{k,s}^{SH} = \frac{M}{n^{SH}} \cdot \frac{Space_{k,s}^{SH} - \min_a(a \subset Space_s^{SH})}{\max_a(a \subset Space_s^{SH}) - \min_a(a \subset Space_s^{SH})} \tag{4.20}$$

$$NormA_{k,s}^{SH} = \frac{M}{n^{SH}} \cdot \frac{Activation_{k,s}^{SH} - \min_a(a \subset Activation_s^{SH})}{\max_a(a \subset Activation_s^{SH}) - \min_a(a \subset Activation_s^{SH})} \tag{4.21}$$

, where M is the intended range. Despite all the values that were tried for this variable, $M = 100$ is the value that worked the best in this problem. If the range is to large – such as $M = 1000$ –, the algorithm takes too long to converge (if it converges). Conversely, if the range is too small – such as $M = 10$ –, the difference between values is not enough to distinguish the optimum. The division by the total number of shiftable (n^{SH}) intends to maintain the normalization range (M) in the objective function always the same, regardless the number of appliances. Otherwise, the final weights would need to be adjusted according to this number.

This step marks the end of the structure presented in Fig. 4.9. After this phase, the algorithm either repeats the same cycle again for the other shiftable appliances or, if there is none left, it moves on to the second stage of the Fig. 4.8.

The second stage concerns all the information related to the thermal appliances. If there is at least one thermal in the problem, the structure presented in Fig. 4.10 is performed. As can be seen, the collection of the thermal appliances data follows a similar structure to the previous. The main difference is how the penalties are determined and in which order. Furthermore, the penalties will rely mainly on the thermal equations of the PBLMs presented in *Chapter 3*.

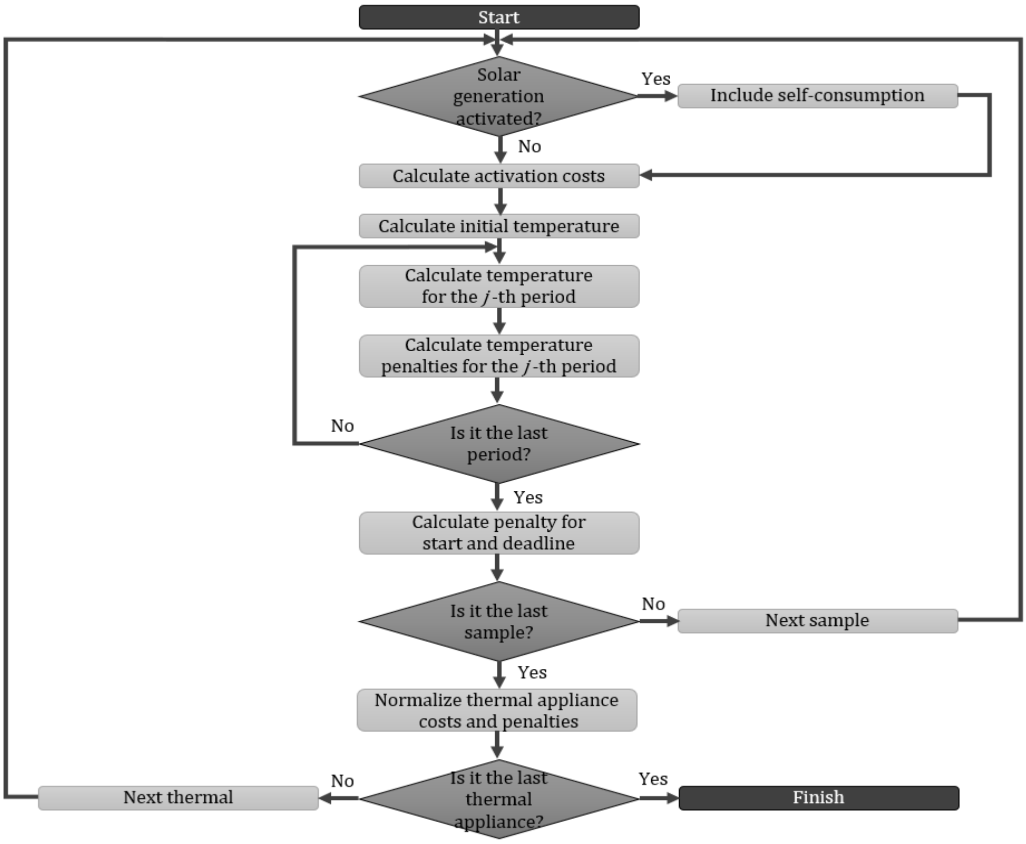

Figure 4.10: Simplified structure for the obtainment of thermal appliances data

Calculate activation costs

As it happens in the shiftable, the total cost of the h-th thermal appliance in the k-th sample will also depend on the price and on the power being consumed. However, instead of considering only the possible activation periods, the entire vector $X_{h_k}^{TH}$ is used. The idea is to determine if the set of periods for activation generated in the k-th random sample is the one that minimizes the costs, while complying with the temperature constraints and the timeframe defined by the user. Hence, the total cost of the sample for thermal appliances is given by:

$$Cost_{k,h}^{TH} = \sum_{j=0}^{(n-1)} Price_j \cdot P_{h,j}^{TH'} \cdot X_{h_{k,j}}^{TH} \cdot 10^3 \tag{4.22}$$

$$P_{h,j}^{TH'} = \begin{cases} \begin{cases} P_h^{TH} - P_{k,j}^{PV'} & , P_{k,j}^{PV'} < P_h^{TH} \\ P_h^{TH} & , P_{k,j}^{PV'} = 0 \\ 0 & , P_{k,j}^{PV'} \geq P_h^{TH} \end{cases} & , \text{if PV activated} \\ P_h^{TH} & , \text{if PV not activated} \end{cases} \tag{4.23}$$

Where*:*

- $P_{h,j}^{TH'}$ → power of the h-th thermal appliance in the j-th period $[kW]$

As mentioned earlier, the vectors $P_k^{PV'}$ and P_k^{Total} are always the same for all the appliances in each t-th iteration. Thus, the same logic is applied:

$$P_{k,j}^{PV'} = \begin{cases} 0 & , P_{k,j}^{PV'} < P_h^{TH} \\ P_{k,j}^{PV'} & , P_h^{TH} = 0 \\ P_{k,j}^{PV'} - P_h^{TH} & , P_{k,j}^{PV'} \geq P_h^{TH} \end{cases} \tag{4.24}$$

$$P_{k,j}^{Total} = P_{k,j}^{Total} + P_{h,j}^{TH'} \tag{4.25}$$

Before starting the cycle to obtain the temperatures in each period and applying the penalties related to its limits, it is important to define the type of thermal appliance that is being analysed, *i.e.*, determine which equation to use. Therefore, the PBLMs for thermal appliances presented in *Chapter 3* can be expressed in the scheduling problem as follows:

$$AC \Rightarrow \begin{cases} \theta_j = \theta_{j-1} + \frac{\Delta t}{R_h^{TH} \cdot C_h^{TH}} \left[\theta_{j-1} - T_j^{amb} + \eta_h^{TH} \cdot R_h^{TH} \cdot P_h^{TH}\right] & , cooling\ mode \\ \theta_j = \theta_{j-1} + \frac{\Delta t}{R_h^{TH} \cdot C_h^{TH}} \left[\theta_{j-1} - T_j^{amb} - \eta_h^{TH} \cdot R_h^{TH} \cdot P_h^{TH}\right] & , heating\ mode \end{cases} \tag{4.26}$$

$$EWH \Rightarrow \{\, \theta_j = \theta_{j-1} + \frac{\Delta t}{C_h^{TH}} \left[-\alpha\left(\theta_{j-1} - T_j^{house}\right)\right] - c_p \cdot w_j^{shower}(\theta_d - \theta_{in}) + P_h^{TH} \tag{4.27}$$

The AC operation mode will depend on the external temperature. If the ambient temperature is equal or higher than the set point, the AC works in cooling mode; if the temperature is lower than the set point, the AC works in heating mode. The thermal losses constant (α) and the water specific heat capacity (c_p) for the EWH (4.27) are given in the thermal appliances initial data.

Calculate initial temperature

Since it is necessary the temperature of the previous j-th period (θ_{j-1}) to obtain the temperature in the current j-th period (θ_j), the initial temperature ($\theta_{j=0}$) must be calculated before the others. This value is determined using the set point temperature: $\theta_{0-1} = \theta_{SP_h}$.

The cycle that starts after this step will serve to calculate the temperatures in each period according to the activations generated in the *k*-th sample and type of equation. During this cycle, the temperature in each period will be tested to find out if the maximum and minimum limits are satisfied. This test will determine the penalties to be applied, if necessary, and is divided in two types of penalization: one that penalizes the sample for not being activated when needed; another that penalizes for being activated when not needed. The goal is to maintain the values inside the temperature range while reducing the total number of activations to minimize the energy costs. In order to avoid values on top of the limits, a superior and inferior limit are defined to slightly move away the temperature from the borders. These two limits are only used during this cycle.

$$l_h^{sup} = \theta_{max_h} - 0.1 \cdot \left|\theta_{max_h} - \theta_{SP_h}\right| \qquad , l_h^{inf} = \theta_{min_h} + 0.1 \cdot \left|\theta_{SP_h} - \theta_{min_h}\right| \tag{4.28}$$

Calculate temperature and penalties for the j-th period

Besides the division in two types of penalization, the penalties applied in each j-th period will also differ according to the type of equation being used, *i.e.*, if the appliance is lowering or raising the temperature. The two penalties that result in the end of the cycle for the h-th thermal appliance can be obtained with the following formulation:

$$\begin{cases} case\ 1 \Longrightarrow & AC\ in\ cooling\ mode \\ case\ 2 \Longrightarrow & AC\ in\ heating\ mode\ or\ EWH \end{cases}$$

$$NoNeedt_{k,h}^{TH} = \begin{cases} I_{\left\{X_{h_{k,j}}^{TH}=1\right\}} \cdot \sum_{j=0}^{(n-1)} \left|\theta_{SP_h} - \theta_{j-1}\right| \cdot I_{\left\{\theta_{j-1} \leq l_h^{inf}\right\}} + \left|\theta_{SP_h} - \theta_j\right| \cdot I_{\left\{\theta_j \leq \theta_{min_h}\right\}} & ,case\ 1 \\ I_{\left\{X_{h_{k,j}}^{TH}=1\right\}} \cdot \sum_{j=0}^{(n-1)} \left|\theta_{j-1} - \theta_{SP_h}\right| \cdot I_{\left\{\theta_{j-1} \geq l_h^{sup}\right\}} + \left|\theta_j - \theta_{SP_h}\right| \cdot I_{\left\{\theta_j \geq \theta_{max_h}\right\}} & ,case\ 2 \end{cases} \tag{4.29}$$

$$NoAct_{k,h}^{TH} = \begin{cases} I_{\left\{X_{h_{k,j}}^{TH}=0\right\}} \cdot \sum_{j=0}^{(n-1)} \left|\theta_{j-1} - \theta_{SP_h}\right| \cdot I_{\left\{\theta_{j-1} \geq l_h^{sup}\right\}} + \left|\theta_j - \theta_{SP_h}\right| \cdot I_{\left\{\theta_j \geq \theta_{max_h}\right\}} & ,case\ 1 \\ I_{\left\{X_{h_{k,j}}^{TH}=0\right\}} \cdot \sum_{j=0}^{(n-1)} \left|\theta_{SP_h} - \theta_{j-1}\right| \cdot I_{\left\{\theta_{j-1} \leq l_h^{inf}\right\}} + \left|\theta_{SP_h} - \theta_j\right| \cdot I_{\left\{\theta_j \leq \theta_{min_h}\right\}} & ,case\ 2 \end{cases} \tag{4.30}$$

Notice that the penalty for being activated when not needed ($NoNeedt_{k,h}^{TH}$) is only applied if the appliance is activated in j-th period of the k-th sample ($X_{h_{k,j}}^{TH} = 1$) and the values are lower/higher than the desired. In contrast, the penalty for not being activated when needed ($NoAct_{k,h}^{TH}$) is only applied if the appliance is inactive ($X_{h_{k,j}}^{TH} = 0$) and the values are higher/lower than the desired. Furthermore, the superior and inferior limits previously established are only applied for the temperature in the previous period, being the temperature in the current gap tested with the maximum and minimum preferences. When the cycle is over, all the values related to the temperature are determined.

Calculate penalty for start and deadline

The next step is where the penalty concerning the timeframe is calculated. This penalty is only applied to the AC, and only if a timeframe is defined by the user. Although the algorithm can consider a start and deadline for the EWH as well, it is always assumed that this appliance can be activated any time during the day.

Conversely to what happens in the shiftable, this penalty is determined in a simpler way. The idea is to analyse each j-th position of the vector $X_{h_k}^{TH}$ and penalize the cases where the appliance is activated outside the possible timeframe. It is important to stress out that this penalty will go against the penalty for the temperature range. However, the algorithm will guarantee that the temperature preferences are satisfied inside the desired timeframe and that the amount of times that it is activated outside the timeframe is minimized. Hence, the goal for the start and deadline penalty of thermal appliances is not to control the activation periods of the device, but rather to ensure that the temperature preferences are inside the limits during the timeframe.

As explained before, two types of timeframes can be set for the AC, namely normal and inverted. The penalty associated with each type for the k-th sample is given by:

$$Limit_{k,h}^{TH} = \begin{cases} I_{\left\{X_{h_{k,j}}^{TH}=1\right\}} \cdot \sum_{j=0}^{(n-1)} |Start_h^{TH} - j| \cdot I_{\{j < Start_h^{TH}\}} + |1 + j - End_h^{TH}| \cdot I_{\{j \geq End_h^{TH}\}} & ,normal \\ I_{\left\{X_{h_{k,j}}^{TH}=1\right\}} \cdot \sum_{j=0}^{(n-1)} |1 + j - End_h^{TH}| \cdot I_{\{j < Start_h^{TH} \wedge j \geq End_h^{TH}\}} & ,inverted \end{cases} \tag{4.31}$$

Notice that the addition of the value *1* in the penalties related to the deadline is to consider the cases when the j-th period is equal to the deadline.

Normalize thermal appliance costs and penalties

The normalization of the thermal appliances is performed with the same methodology applied to the shiftable. The costs and penalties normalized for each k-th sample are expressed by the following equations:

$$NormC_{k,h}^{TH} = \frac{M}{n^{TH}} \cdot \frac{Cost_{k,h}^{TH} - \min_a(a \subset Cost_{k,h}^{TH} \wedge a>0)}{\max_a(a \subset Cost_{k,h}^{TH} \wedge a>0) - \min_a(a \subset Cost_{k,h}^{TH} \wedge a>0)} \tag{4.32}$$

$$NormN_{k,h}^{TH} = \frac{M}{n^{TH}} \cdot \frac{NoNeed_{k,h}^{TH} - \min_a(a \subset NoNeed_{k,h}^{TH})}{\max_a(a \subset NoNeed_{k,h}^{TH}) - \min_a(a \subset NoNeed_{k,h}^{TH})} \tag{4.33}$$

$$NormA_{k,h}^{TH} = \frac{M}{n^{TH}} \cdot \frac{NoAct_{k,h}^{TH} - \min_a(a \subset NoAct_{k,h}^{TH})}{\max_a(a \subset NoAct_{k,h}^{TH}) - \min_a(a \subset NoAct_{k,h}^{TH})} \tag{4.34}$$

$$NormL_{k,h}^{TH} = \frac{M}{n^{TH}} \cdot \frac{Limit_{k,h}^{TH} - \min_a(a \subset Limit_{k,h}^{TH})}{\max_a(a \subset Limit_{k,h}^{TH}) - \min_a(a \subset Limit_{k,h}^{TH})} \tag{4.35}$$

This step marks the end of the structure presented in Fig. 4.10. After this phase, the algorithm either repeats the same cycle again for the other thermal appliances or, if there is none left, it moves on to the next stage of the Fig. 4.8.

Calculate penalty for power limit

The third and fourth stages presented in Fig. 4.8 are only performed if a power limit (contracted power) is being considered or if the solar generation is activated, respectively. The third stage consists in a comparison between the power being consumed in each j-th period of the vector P_k^{Total} with a previously defined power limit. If the power in each period is equal or higher than the limit, the sample will be penalized with the excess. The expression for this penalty and the respective normalization are formulated as follows:

$$Power_k = \sum_{j=0}^{(n-1)} \left|1 + P_{k,j}^{Total} - P^{Limit}\right| \cdot I_{\left\{P_{k,j}^{Total} \geq P^{Limit}\right\}} \tag{4.36}$$

$$NormP_k = M \cdot \frac{Power_k - \min_a(a \subset Power_k)}{\max_a(a \subset Power_k) - \min_a(a \subset Power_k)} \tag{4.37}$$

Where:

- $P^{Limit} \rightarrow$ value of the power limit considered in the problem $[kW]$

The addition of the value *1* to the penalty is to consider the cases in which the power in the j-th period is equal to the limit. Since the power penalty concerns all appliances, the range M for the normalization is not divided by any number.

Calculate penalties for self-consumption and remuneration

The penalties in the fourth stage of the Fig. 4.8 are divided in two approaches: one that maximizes the PV self-consumption and another that maximizes the total remuneration for injecting energy into the grid. It seems a little contradictory having goals that go in opposite directions. However, since the energy scheduling problem aims to minimize the energy costs and not maximize the PV self-consumption, the algorithm will find the best combination for these targets that produce the optimal solution. Moreover, the remuneration from the PV energy fed into the grid is usually much lower than the electricity rate - making self-consumption almost always more profitable than injecting energy into the grid.

Both approaches are determined using the same vector, namely the one with the PV power available after withdrawing the consumption of all the appliances ($P_k^{PV'}$). The penalty for the maximization of PV self-consumption is achieved by minimizing the total amount of solar energy not used:

$$Solar_k = \sum_{j=0}^{(n-1)} P_{k,j}^{PV'} \tag{4.38}$$

The obtainment of the PV remuneration is analogous to the calculation of the appliance's cost. The available PV power is the equivalent to the power of the appliance and the price tariff is replaced with the remuneration. Since the problem aims to minimize the objective function, a negative signal is also added to the formulation. The multiplication by the value 10^3 is also considered in order to have penalty values larger than *0* and to be coherent with the calculation of the appliance's cost.

$$Remun_k = -\sum_{j=0}^{(n-1)} P_{k,j}^{PV'} \cdot RM_j \cdot 10^3 \tag{4.39}$$

These two penalties are normalized following the same reasoning applied to the power limit. Hence, the normalized solar and remuneration values for each k-th sample are given by:

$$NormS_k = M \cdot \frac{Solar_k - \min_a(a \subset Solar_k)}{\max_a(a \subset Solar_k) - \min_a(a \subset Solar_k)} \tag{4.40}$$

$$NormR_k = M \cdot \frac{Remun_k - \min_a(a \subset Remun_k)}{\max_a(a \subset Remun_k) - \min_a(a \subset Remun_k)} \tag{4.41}$$

Calculate performance of each sample

Finally, it is possible to formulate a single objective function that includes all the normalized sub-functions determined since the first stage:

$$S_k = S_k^{SH} + S_k^{TH} + S_k^{PL} + S_k^{PV} \tag{4.42}$$

$$S_k^{SH} = \sum_{s=1}^{n^{SH}} \frac{2}{W} \cdot NormC_{k,s}^{SH} + \left(NormL_{k,s}^{SH}\right)^2 + \left(NormS_{k,s}^{SH}\right)^2 + \left(NormA_{k,s}^{SH}\right)^2$$

$$S_k^{TH} = \sum_{h=1}^{n^{TH}} \frac{1}{W} \cdot NormC_{k,h}^{TH} + \frac{1}{2} \cdot \left(1 + NormN_{k,h}^{TH}\right)^2 + \left(1 + NormA_{k,h}^{TH}\right)^2 + \left(NormL_{k,h}^{TH}\right)^2$$

$$S_k^{PL} = 2 \cdot NormP_k \qquad , S_k^{PV} = NormS_k + NormR_k \qquad , W = \begin{cases} 1 & , if\ PV\ not\ activated \\ 2 & , if\ PV\ activated \end{cases}$$

Where each sub-function concerns*:*

- S^{SH} → Shiftable appliances
- S^{TH} → Thermal appliances
- S^{PL} → Power limit
- S^{PV} → PV generation

Each normalized value has a different weight in the objective function. The general idea for this formulation is to square all the values that will converge to zero – namely the penalties, when the constraints are satisfied –, while the other values follow a linear behaviour. Since the costs of the appliances will never be zero, when all restrictions are verified only the cost will count for the performance. The same linear logic is applied when considering the function S^{PV}. Notice that the functions S^{PV} and S^{PL} are only applied when the PV generation and the power limit are considered, respectively. Furthermore, although S^{PL} is a penalty that will converge to zero, a linear function (multiplication by *2*) works better than a squared function.

As can be seen, the weight of shiftable's costs is the double of the weight applied in the thermal's costs. This happens because thermal appliances, namely the AC, are considerably more expensive than the shiftable ones. If both had the same weight, the costs of the shiftable would be neglected most of the time. Moreover, a division by the variable W is made to increase the importance of the PV generation when it is activated. Otherwise, the influence of the term S^{PV} would not be enough to maximize self-consumption.

The value 1 is added to the thermal penalties of activation when not needed and lack of activation when needed. This step is used to improve the influence of the temperature range in the objective function. Besides, the penalty of activation when the temperature is inside the limits is divided by a factor of *2*. The idea is to provide some flexibility to the algorithm by reducing the number of unnecessary activations, while at same time allowing the appliance to be activated in periods when the electricity price is cheaper.

Notice that if the goal was to maximize PV self-consumption, it would be enough not to consider the term $NormR$ in the function S^{PV}. In this way, only the amount of PV power not used is applied for the minimization and the remuneration is excluded.

After all the performances are determined, the algorithm moves on to *step 4* of the structure presented in Fig. 4.1, updates the probabilities (4.4), and repeats the cycle until the stopping criterion is met (4.6) or the maximum number of iterations has been reached. The evolution of the results can be divided in three main phases:

1. In the first iterations, the samples are severely penalized, and the costs have little significance when compared with the penalties. This stage is when the algorithm slowly starts to generate samples towards the optimum region by excluding the ones that penalize the most;

2. When the quadratic functions begin to have the same order of magnitude as the linear functions, the algorithm starts to search the samples that minimize the costs in the objective function. In this stage, the impacts of the normalization in the selection of samples is still normal;

3. The algorithm produces samples around the optimal solution and the normalization starts to have greater impact in the selection of the samples. At this stage, the performances start to increase instead of decreasing because the normalization enlarges the difference between closer solutions. Therefore, the best result in different races of the algorithm is not measured by the value of the performances but rather by the total cost that results from the set of activations of the sample with the best performance in each race.

4.5 Parameters Calibration

Since the parameters calibration has a great influence in the results of the CE method, the main findings about their adjustment are discussed in a separated subsection. Different sets of parameters were tested in the algorithm for the scheduling problem. The main conclusions about each one of them are the following:

N → *Number of independent random samples*

The number of samples is probably the most important baseline for the problem. Besides its impact on the algorithm speed, it also determines the search range for optimal solutions. If the number of samples is too small, the algorithm becomes limited and will always converge to sub-optimal solutions. Conversely, if N is too large, the algorithm is capable of converging to the optimal solution, but the running time increases considerably due to the number of cycles that are required to perform for each sample. Moreover, if the number of samples is not adequate for the number of appliances being analysed, the constraints will not be satisfied, and the minimum cost will not be found. Thus, a middle term is necessary to have optimal results while at same time the algorithm does not take too long to perform.

While running some tests for the energy scheduling problem, it was noticed that this parameter is linked to the number of appliances being considered. Furthermore, it was also linked to the type of appliance – shiftable or thermal. At first, the possibility of having the power of the appliance related to the number of samples was also considered, but the idea was quickly discarded because it was not the best approach. Thus, the first step for the calibration was to run the algorithm for each appliance individually and find out the minimum number of samples required to achieve the optimal solution. Shiftable appliances showed good results with at least *1600* samples. Thermal appliances need at least *2000* to achieve always the optimum. Then, the algorithm was tested with different sets of appliances and numbers of samples (until $N = 10000$), resulting in the following rule to determine N according to the number of appliances:

Algorithm 5: number of samples N

Input: n^{SH}, n^{TH}
Output: number of samples for the algorithm
if only one appliance
  N = 2000
else
  N = 1000 * (1 + n^{SH}+ n^{TH})
end
if N > 5000
  N = 5000
end

ϱ → *Rarity parameter*

The rarity parameter is responsible for determining the number of elite samples ($N^e = [\varrho N]$) and is linked to the update of the probability $\hat{v}_{t-1}$. If the number of elite samples is too large (*e.g.*, $\varrho \geq 0.05$), the algorithm will produce near-optimal solutions almost every time and the speed of convergence will increase because the selection of samples is not accurate enough; if it is too small (*e.g.*, $\varrho \leq 0.005$), the range of samples becomes too strict and excludes possibilities that could lead to the optimal solution. This parameter showed good results when inside the range $0.01 \leq \varrho \leq 0.02$. The value for the rarity parameter used for the scheduling problem is $\varrho = 0.01$.

α → *Smoothing parameter*

The smoothing parameter is applied in the update of the probability $\hat{v}_{t-1}$ (4.5). As its name suggests, it is used to smoothen the probability over iterations. At first, the smoothing was not considered because it did not seem to have a great impact on the results. However, when the number of samples (N) is adjusted, the solutions can be improved by changing the smoothing of probabilities. This parameter must be adjusted with caution because it affects directly the generation of random samples and consequently the speed of convergence.

Since the algorithm already produces optimal solutions without smoothing, this parameter cannot take small values. Hence, it was concluded that the range $0.7 \leq \alpha \leq 1$ is the most indicated for the problem being addressed. It was also noticed that its influence is greater when the thermal appliances are considered, because the probabilities for the samples of these type of appliances have slower variations when compared to the shiftable ones. The value for the smoothing parameter used for the scheduling problem is $\alpha = 0.8$.

ε → *Error for the stopping criterion*

Since the vector of probabilities $\hat{v}_t$ converges without problems to a binary vector, the error for the stopping criterion does not affect the results too much as long as it is not extremely small (*e.g.*, $\varepsilon \leq 0.001$). Thus, the value used in (4.6) for the scheduling problem is $\varepsilon = 0.01$.

t_{max} → *Maximum number of iterations*

This parameter was defined for precaution. The algorithm usually takes less than 50 iterations to converge. Being so, a maximum number for iterations $t_{max} = 100$ was deemed enough.

4.6 Summary and Main Conclusions

A methodology for using the CE method for electricity consumption optimization is provided in this chapter. A general structure for the CE method is presented that can be flexible enough to be applied in a considerable range of combinatorial optimization problems.

The CE method is tested in a well-known NP-complete combinatorial optimization problem, namely the *0-1 Knapsack Packing Problem*, in which a crude Monte Carlo method is applied to evaluate the performance of the algorithm in terms of achieving the optimal result. The experimental validation shows that the algorithm can provide optimal solutions under the structure that was implemented.

The formulation for the scheduling of the electricity consumption in a building is also detailed in this chapter, where a single objective function is developed to be used in the general structure. Although the mathematical formulation has some complexity associated to it, the convergence of the algorithm to optimal or sub-optimal results is assured. However, this is only possible when the algorithm receives information about dynamic electricity prices, otherwise it will not converge.

The formulation of the shiftable appliances poses some challenges, namely to guarantee that the appliance is activated inside pre-defined timeframes. Conversely, the formulation for the thermal appliances is simplified with the use of the PLBMs. The results for the algorithm of the electricity consumption scheduling problem are presented in the next chapter.

Chapter 5

Operation Scenarios and Simulations

5.1 Introduction

The energy management methodology presented in the previous chapter was tested in a different set of scenarios that are likely to be found in typic daily-life applications. The formulation to solve the electricity consumption scheduling was implemented in Python language, in which a simple interface that allows the user to input his comfort requirements and add new appliances was developed to make the tests. These settings were tested using real-data sets concerning two distinct countries, namely Portugal and Spain, in order to evaluate the algorithm with two different types of external data. This chapter intends to address one of these scenarios with more detail using the data of both countries, being the remaining settings presented in Appendix A-D (case scenario with winter temperatures, PV self-consumption, EV and appliances with deadlines for operation, and all appliances plus EV with PV self-consumption, respectively). Hence, this chapter includes the assumptions made for the results of all the scenarios, the internal and external data considered and the algorithm evaluation for two cases (Portugal and Spain).

5.2 Assumptions

The results presented in this work for each scenario were obtained with a crude Monte Carlo method. The number of simulations performed for each case was determined by (4.9), meaning a total of one thousand simulations per case ($N_{MC} = 1000$). Since the algorithm takes some time to perform a single simulation, it was necessary to use different processing cores simultaneously in order to have all the results in time. The number of fixed seeds for the random generation was divided according to the number of simulations running in each core. With this in mind, some considerations must be taken into account:

- The running time for each simulation depends on the availability and load of the processing core being used and on the respective Operative System (OS). Therefore, the running times presented in the results are merely indicative;

- Although the seeds were fixed and distributed equally between all processing cores, it is not guaranteed that the random generator of one OS will produce the same result of a different one, *i.e.*, the same seed can generate two different values in different OSs.

5.3 Internal Data

All scenarios consider at least *5* appliances that are likely to be found in a typical home, namely *3* shiftable ones – Clothes Dryer (CD), Dishwasher (DW) and Washing Machine (WM) – and *2* thermal ones – AC and EWH. The differences between scenarios will consist in the consumption patterns for the shiftable loads (number of times that the appliance operates and respective deadlines), and in the change of the external temperature according to the external data – for the thermal ones. The common data used in all the cases for the shiftable and thermal appliances is presented in Table 5.1 and 5.2, respectively.

Table 5.1: Common data for the shiftable appliances

	Clothes Dryer	Dishwasher	Washing Machine
Characteristics			
Maximum power $[kW]$	0.7	2	1
Average duration cycle $[h]$	1	1,5	1

Table 5.2: Common data for the thermal appliances

	Air Conditioner		Electric Water Heater
	Cooling mode	Heating mode	
Characteristics			
Maximum power $[kW]$	3		2
Thermal capacity $[kWh/°C]$	2,72		0,117
Thermal resistance $[°C/kWh]$	4		1 / (9,42 E-4)
Coefficient of performance $[-]$	3,6		3,6
Consumption Patterns			
Set point temperature $[°C]$	21		64,3
Number of baths $[\#]$	–		2
Bath hours $[h]$	–		7 & 17
Comfort Requirements			
Minimum temperature $[°C]$	17,5		45
Maximum temperature $[°C]$	24,2		80
Desired temperature for bath $[°C]$	–		38

In order to include the influence of the uncontrollable loads in the optimal scheduling, the values presented in Table 5.3 are considered as well for each scenario.

Table 5.3: Typical values of uncontrollable loads for timeframe of *24* hours

Uncontrollable Loads $[kWh]$											
00 h	**01 h**	**02 h**	**03 h**	**04 h**	**05 h**	**06 h**	**07 h**	**08 h**	**09 h**	**10 h**	**11 h**
0,109	0,104	0,105	0,104	0,109	0,120	0,207	0,255	0,227	0,213	0,188	0,196
12 h	**13 h**	**14 h**	**15 h**	**16 h**	**17 h**	**18 h**	**19 h**	**20 h**	**21 h**	**22 h**	**23 h**
0,257	0,234	0,323	0,192	0,165	0,231	0,244	0,252	0,173	0,187	0,192	0,141

Table 5.4 shows the values assumed constant in all cases according to the country. The time step for the control sample is established at *15* minutes. The house temperature is considered constant and equal to the temperature set point of the AC. The power limitation represents the contracted power and is only applied in the Portuguese case.

Table 5.4: Case study data

	Portugal	Spain
Timeframe $[h]$	24	
Time step $[min]$	15	
House temperature $[°C]$	21	
Water inlet temperature for the EWH $[°C]$	17	12
Power limitation $[kVA]$	6,9	–

5.4 External Data

As mentioned before, this work considers the external data concerning two different countries. This data consists in dynamic electricity prices and external temperatures. The price values and temperatures for a 24 hours timeframe used in the Portuguese cases are presented in Table 5.5. A bi-hourly TOU tariff [69] is used, and the temperatures correspond to a typical day of summer/winter in a warm Mediterranean climate (Alentejo – Portugal). The values for the Spanish cases are presented in Table 5.6. The dynamic price tariff used is the PVPC [70] – *Precio Voluntario para el Pequeño Consumidor* – and temperatures concern a typical day of summer/winter in a cold Semi-Arid climate (Corunha – Spain).

Table 5.5: External data for the Portuguese cases

Timeframe $[h]$	Warm Mediterranean Climate (Alentejo – Portugal)		Electricity Prices (TOU) $[€/kWh]$
	Summer $[°C]$	Winter $[°C]$	
00:00:00	28,00	6,00	0,1009
01:00:00	25,00	6,00	0,1009
02:00:00	26,00	5,00	0,1009
03:00:00	24,00	4,00	0,1009

(Continuation of the table in the next page)

04:00:00	24,00	4,00	0,1009
05:00:00	22,00	4,00	0,1009
06:00:00	24,00	3,00	0,1009
07:00:00	22,00	4,00	0,1009
08:00:00	27,00	4,00	0,1948
09:00:00	32,00	6,00	0,1948
10:00:00	33,00	7,00	0,1948
11:00:00	37,00	11,00	0,1948
12:00:00	39,00	11,00	0,1948
13:00:00	41,00	12,00	0,1948
14:00:00	42,00	12,00	0,1948
15:00:00	43,00	12,00	0,1948
16:00:00	43,00	12,00	0,1948
17:00:00	42,00	10,00	0,1948
18:00:00	40,00	8,00	0,1948
19:00:00	37,00	7,00	0,1948
20:00:00	33,00	7,00	0,1948
21:00:00	31,00	7,00	0,1948
22:00:00	31,00	6,00	0,1009
23:00:00	28,00	6,00	0,1009

Table 5.6: External data for the Spanish cases

Timeframe $[h]$	**Cold Semi-Arid Climate (Corunha – Spain)**		**Electricity Prices (PVPC)** $[€/kWh]$
	Summer $[°C]$	**Winter** $[°C]$	
00:00:00	18,00	4,00	0,0664
01:00:00	18,00	4,00	0,0599
02:00:00	17,00	5,00	0,0582
03:00:00	17,00	3,00	0,0577
04:00:00	16,00	3,00	0,0580
05:00:00	16,00	3,00	0,0600
06:00:00	16,00	2,00	0,0662
07:00:00	16,00	2,00	0,0735
08:00:00	15,00	2,00	0,0726
09:00:00	17,00	2,00	0,0714
10:00:00	18,00	2,00	0,0696
11:00:00	18,00	6,00	0,0704
12:00:00	20,00	8,00	0,0712
13:00:00	21,00	11,00	0,1378
14:00:00	20,00	12,00	0,1374
15:00:00	21,00	14,00	0,1380
16:00:00	21,00	14,00	0,1376
17:00:00	21,00	13,00	0,1374
18:00:00	21,00	11,00	0,1362
19:00:00	20,00	10,00	0,1358
20:00:00	19,00	9,00	0,1389
21:00:00	18,00	8,00	0,1404
22:00:00	17,00	7,00	0,1390
23:00:00	17,00	6,00	0,0660

5.5 Results

The scenario discussed in this sector uses the data presented in the previous sectors. The climatological conditions for both Portuguese and Spanish cases concern the temperatures of a summer day, and the criteria inputs for the optimization are the respective price tariffs. The consumption patterns used for the shiftable appliances are presented in Table 5.7. As can be seen, all *3* shiftable appliances have a deadline established for the operation. In the case of the DW, two deadlines are defined, since the appliance operates *2* times. The PV generation and EV are not included in this analysis.

Table 5.7: Consumption patterns for the shiftable appliances

	Clothes Dryer	Dishwasher	Washing Machine
Consumption Patterns			
Number of activations [#]	1	2	1
Deadlines [h]	22	9 & 18	19

The following subsections begin by presenting the graphical information provided by the code implemented in *Python* language, and then an analysis of the algorithm performance is made. This information includes the day ahead consumption profile with the optimal scheduling, the temperature profile for the thermal loads, the electricity costs of each appliance and the respective contribution for the total cost.

5.5.1 Portugal

The optimized scenario for the Portuguese case is presented in Fig. 5.1. As shown in the figure, all the consumption is shifted to the hours when the energy prices are lower, all the shiftable appliances comply with the deadline constraints, and the power limit is meet.

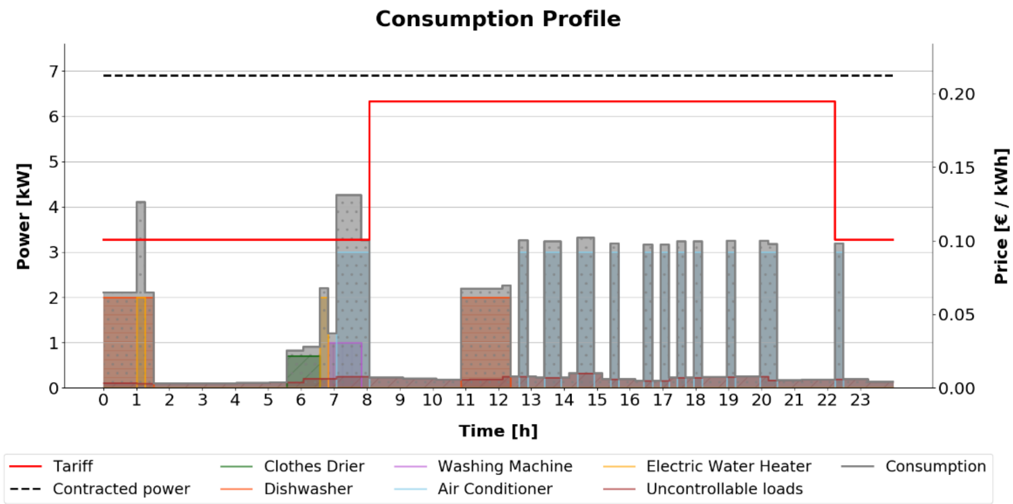

Figure 5.1: Consumption profile for the day ahead – Portugal

In terms of thermal appliances, it is possible to notice that the AC takes advantage of the lower price periods to be activated during more time. After that, it is only activated enough time to satisfy the comfort requirements of the user, as shown in Fig. 5.2. The EWH only needs to be activated two times to comply with the requirements, and its behaviour is shown is Fig. 5.3.

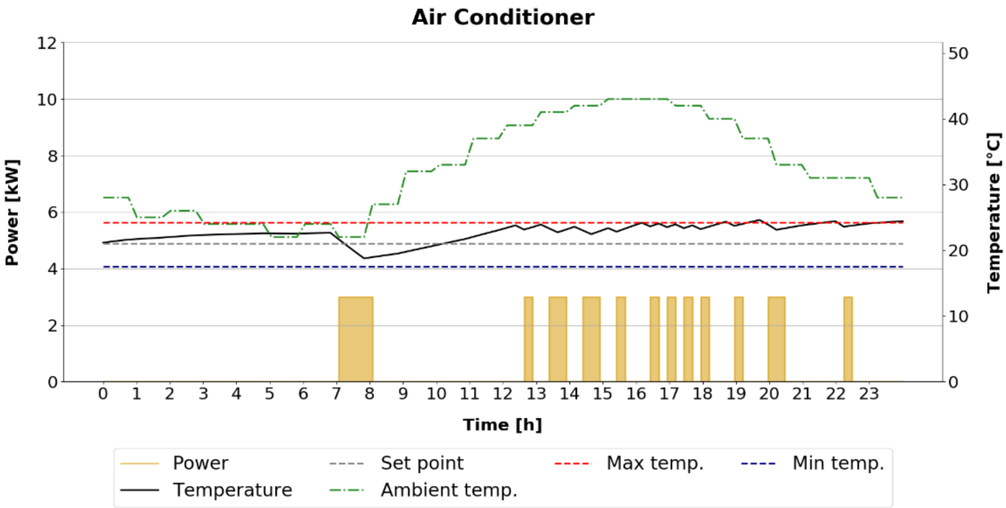

Figure 5.2: Temperature profile for the AC – Portugal

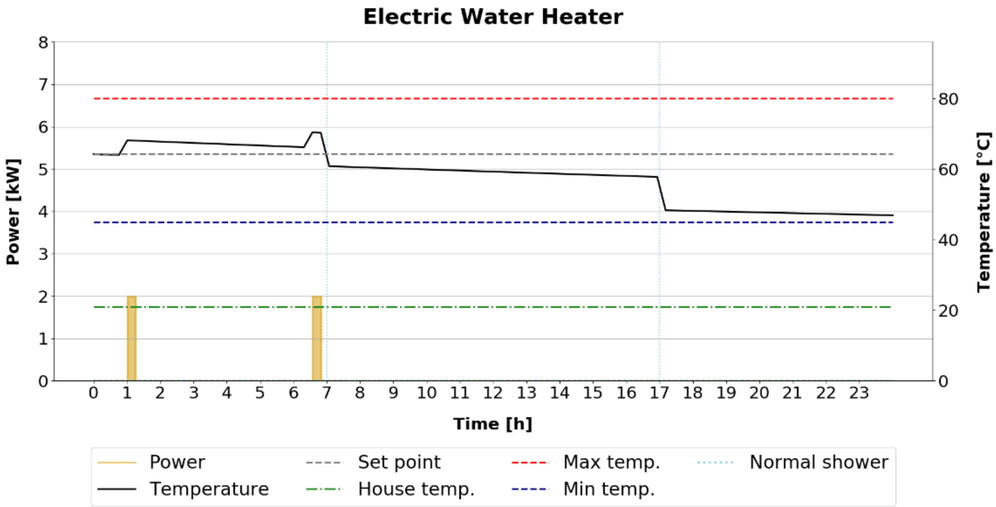

Figure 5.3: Temperature profile for the EWH – Portugal

The individual electricity costs of the appliances and respective share of contribution for the total cost are presented in Fig 5.4 and Fig 5.5, respectively. It is possible to perceive without any doubt that the AC is the main contributor for the total cost – more than 50%. This is justified by three main reasons: (i) it is the appliance with the highest electricity consumption; (ii) the summer temperatures used in this scenario require the AC activation considerable amounts of times; (iii) the inflexible electricity tariff does not allow the algorithm to choose other activation periods within the defined comfort parameters.

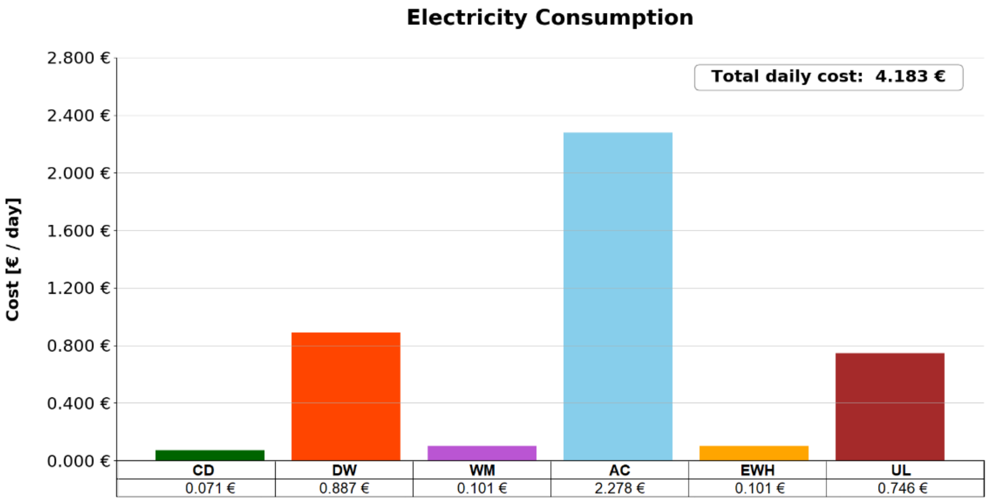

Figure 5.4: Individual electricity costs – Portugal

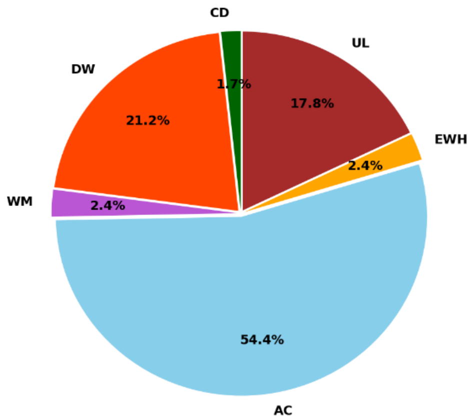

Figure 5.5: Share of total daily cost – Portugal

The results obtained with the crude Monte Carlo method for the Portuguese case are presented in Table 5.8 and illustrated with more detail in Fig. 5.6. The fact of having the worst number of iterations equal to the maximum possible number (t_{max}) indicates that the algorithm does not converge in all the simulations – more specifically, *9* times out of *1000*. In terms of performances, it is noticeable that the objective function was severely penalized in some cases – but only *2* times out of *1000* –, and despite the large variance and the difference between the average and the best result, the algorithm finish *997* times with the same performance.

Table 5.8: Results for the Crude Monte Carlo method – Portugal

	Iterations	Performances	Running Time [min]	Total Cost [€]
Best result	35	201,5	13	4,183
Worst result	100	2876,503	53,583	4,622
Average	47,07	278,10	22,15	4,40
Variance	53,44	13732,31	17,60	0,00
Standard Deviation	7,31	117,18	4,20	0,05

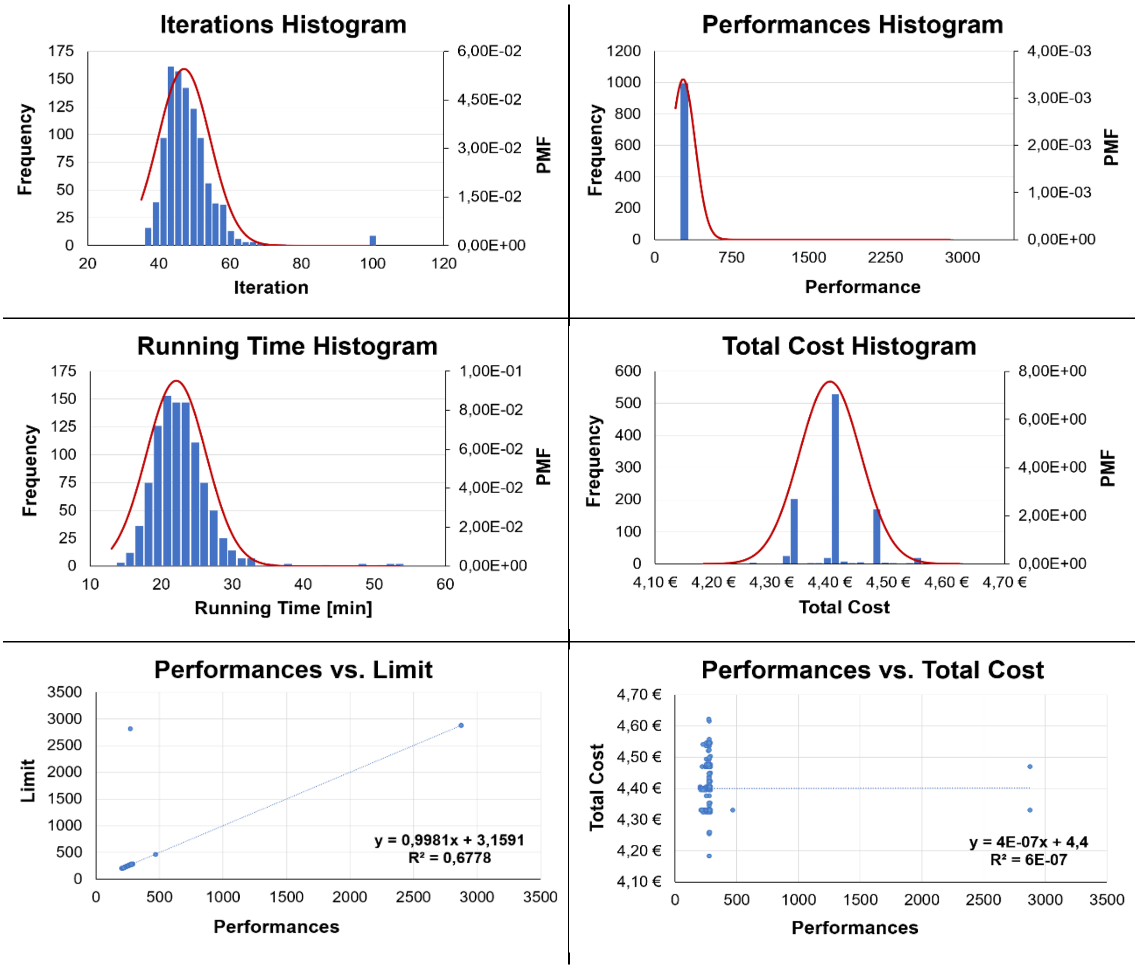

Figure 5.6: Algorithm analysis – Portugal

The correlation between performances and limit, as well as between performances and total cost are also presented in Fig. 5.6. The first correlation allows to verify that the last performance considered in the elite samples is almost always equal to the best performance, as it should be. The Pearson coefficient (R^2) only takes a value inferior to *1* due to a single simulation. The second correlation serves to validate the previous statement about the best result in different races of the algorithm not being measured by the value of the performances, but rather by the total cost that results from the set of activations of the sample with the best performance in each simulation – derived from the normalization applied to determine the objective function.

5.5.2 Spain

The optimized scenario for the Spanish case is presented in Fig. 5.7. As it happens in the previous case, all the consumption is shifted to the hours when the energy prices are lower and all the shiftable appliances comply with the deadline constraints. Nevertheless, even without the power limitation, the algorithm is not always activating the appliances exactly in the periods with the lowest prices. Sometimes the appliance is activated one or two periods after, sometimes it is activated before. Although these situations represent only a difference of a few cents in the total cost (in the worst cases not more than 50 cents), the algorithm is not being accurate enough in the loads allocation all the times when using a dynamic tariff with so many variations over time such as the one being used. However, this behaviour can be justified by the presence of the uncontrollable loads, since they are also being considered in the optimization criterion.

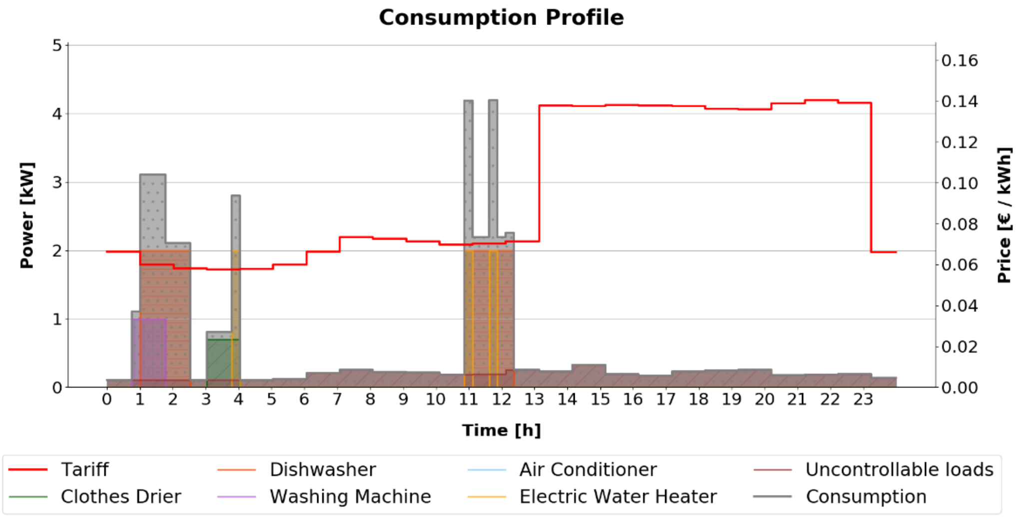

Figure 5.7: Consumption profile for the day ahead – Spain

In what concerns the thermal appliances, the AC is not activated any time, since the external temperature corresponds to the comfort requirements established by the user. This can be verified in Fig. 5.8. In relation to the EWH, although the activation periods correspond to periods with lower prices and the comfort requirements are met, the same lack of accuracy that occurs in the shiftable case happens with this appliance. The EWH should be activated during more time in the first activation, since the temperature is still sufficiently far from the upper limit and inside the defined range. The behaviour of this appliance is shown in Fig. 5.9.

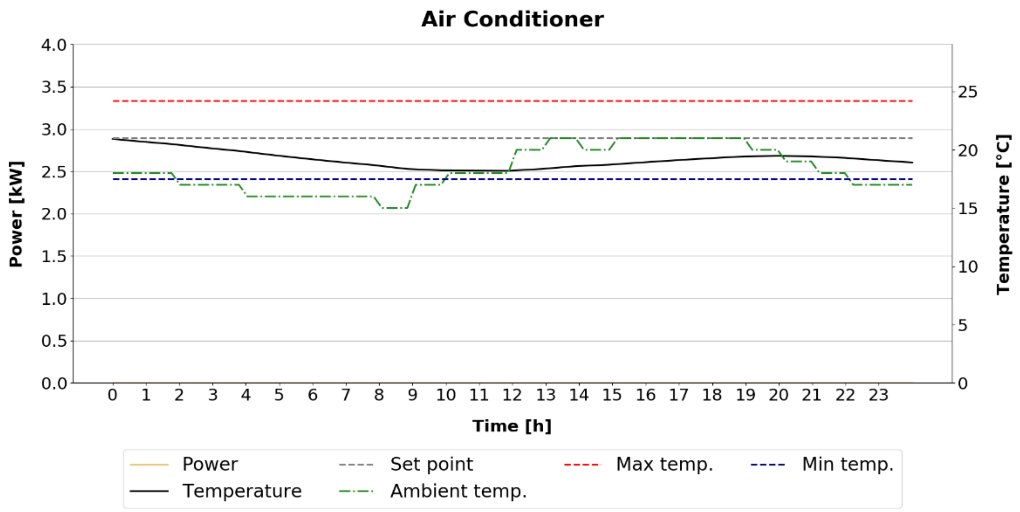

Figure 5.8: Temperature profile for the AC – Spain

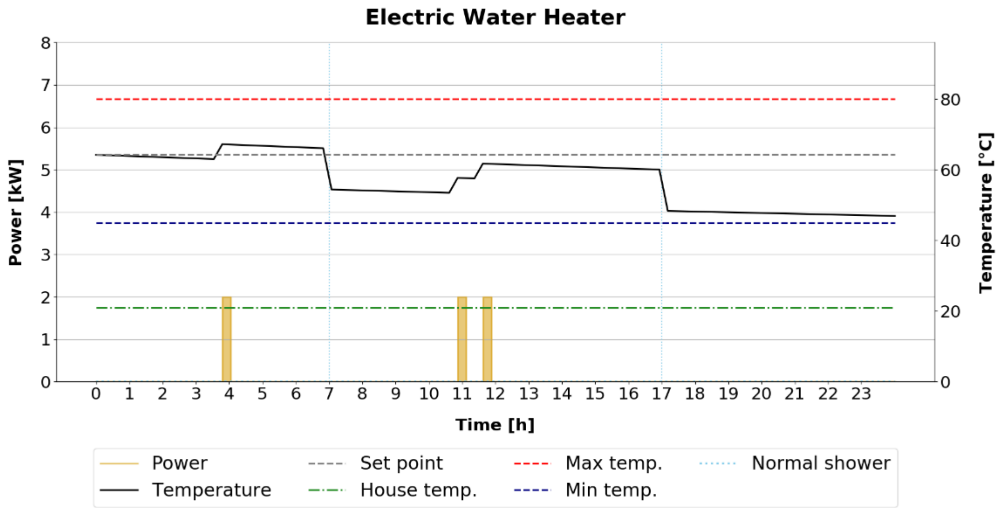

Figure 5.9: Temperature profile for the EWH – Spain

The individual electricity costs of the appliances and respective share of contribution for the total cost of the Spanish case are presented in Fig 5.10 and Fig 5.11, respectively. As can be seen, the total daily cost is almost *4* times smaller than the one obtained for the Portuguese case. This is mainly caused by the absence of activations of the AC – that contributed with almost half of the total spending in the previous case –, as well as by the dynamic price tariff being used – that allows the reduction of almost half of the cost of each appliance and uncontrollable loads. In this case, the main contributors for the total cost are the DW and the uncontrollable loads.

Even without the AC contribution, it is possible to perceive that the use of more volatile price tariffs enlarges the range of options for the algorithm searching. Moreover, conversely to what happens with the bi-hourly TOU tariff, it improves the integration of the uncontrollable loads in the optimized scheduling of the appliances.

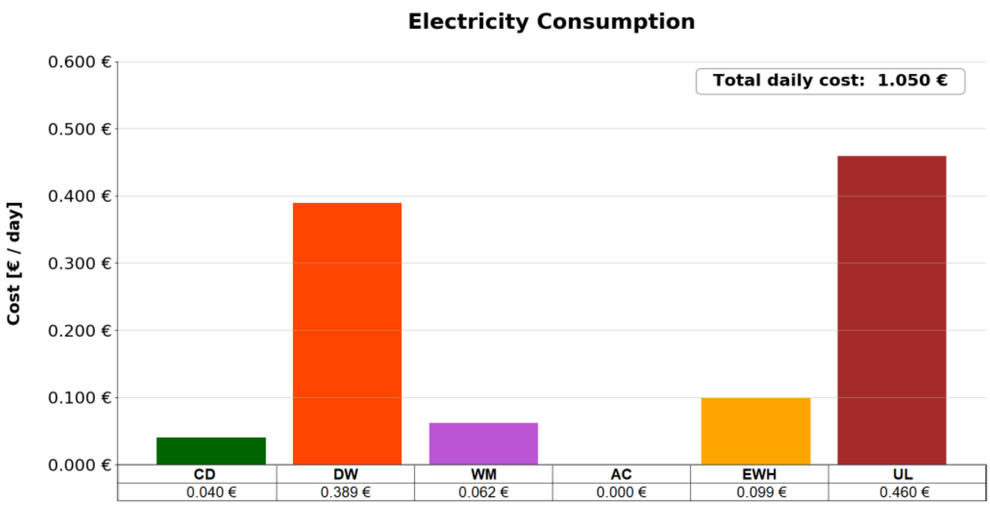

Figure 5.10: Individual electricity costs – Spain

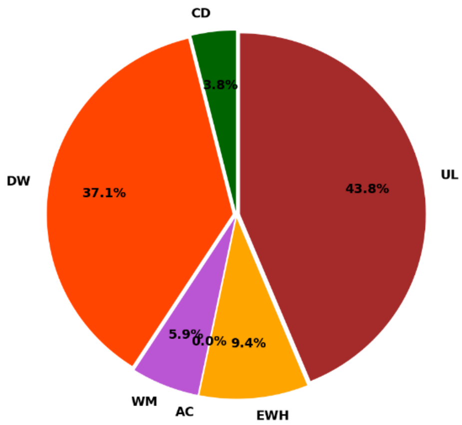

Figure 5.11: Share of total daily cost – Spain

The results obtained with the crude Monte Carlo method for the Spanish case are presented in Table 5.9 and illustrated with more detail in Fig. 5.12. In comparison with the Portuguese case, the first conclusion that can be taken is that the use of a more volatile tariff enables a faster convergence of the algorithm. This can be verified by comparing the average number of iterations and the average running time of the simulations – that decreases significantly. Moreover, the results for these two parameters are a lot more concentrated around the average than in the previous case. Nonetheless, although the maximum possible number of iterations (t_{max}) has been reached as well, this only happened *3* times out of *1000*.

In terms of performances, all the simulations complied with the constraints without being penalized once, but in return the results are much more distributed around the average. This causes an increase in the variance of the total cost, as can be seen in the figure. Yet, the difference between maximum and minimum total costs is still inferior than in the previous case with the bi-hourly TOU tariff.

The correlation between performances and limit, as well as between performances and total cost are also presented in Fig. 5.12. Since not a single performance was severely penalized in this case, the last elite performance is practically always equal to the best performance of each simulation ($R^2 = 0{,}9999$). The second correlation (right side) presents a small value as expected.

Despite the larger variance of the results for the performances, the variance of the total cost is still low. Therefore, it is possible to conclude for both Portuguese and Spanish cases that the number of simulations was enough to overcome the difference between distinct OSs.

Table 5.9: Results for the crude Monte Carlo method – Spain

	Iterations	Performances	Running Time [min]	Total Cost [€]
Best result	30	25,649	11,567	1,05
Worst result	100	284,961	53,844	1,476
Average	35,20	214,65	16,19	1,14
Variance	18,73	2627,28	7,66	0,00
Standard Deviation	4,33	51,26	2,77	0,07

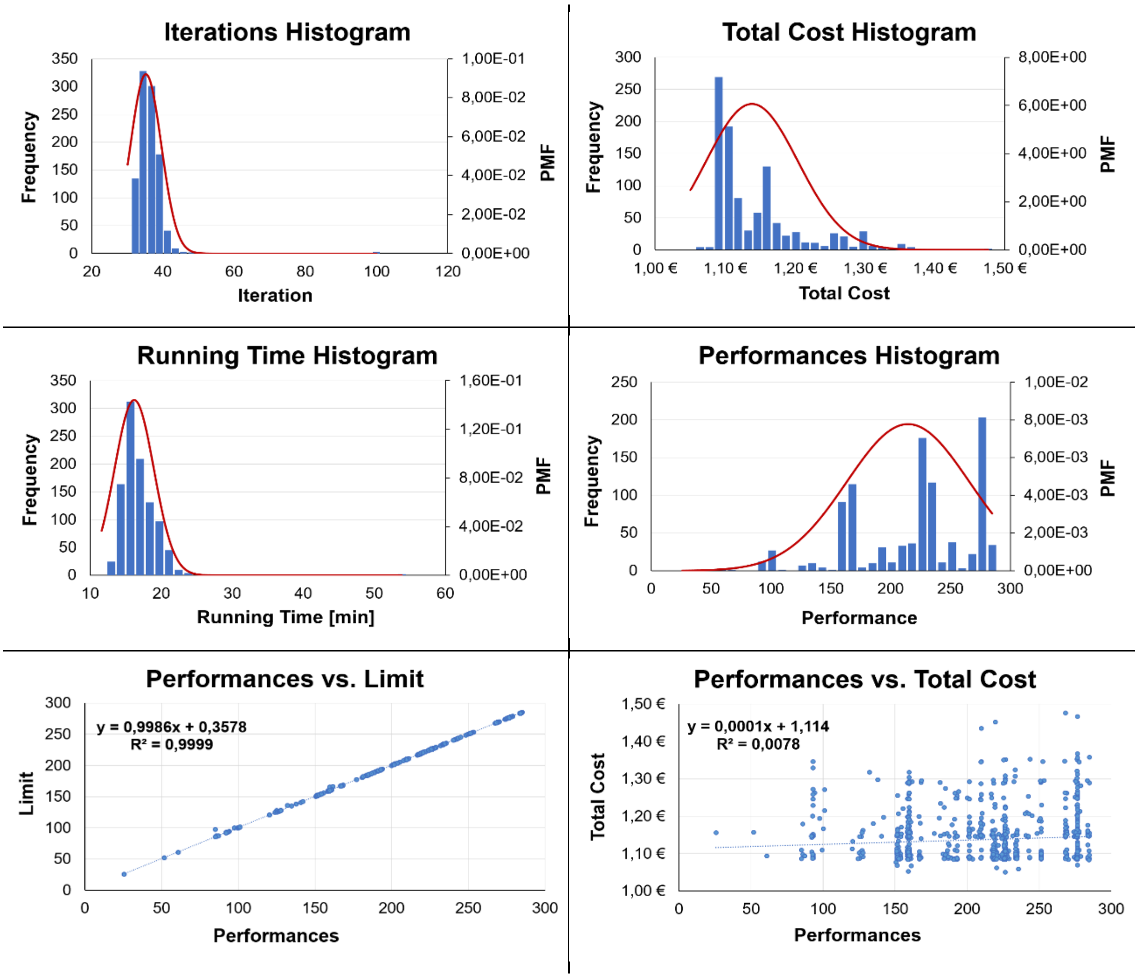

Figure 5.12: Algorithm analysis – Spain

5.6 Summary and Main Conclusions

This chapter presented the main results for one of the scenarios in which the algorithm was tested. The scenario was evaluated considering 5 appliances that are likely to be found in a typical home – 3 shiftable and 2 thermal appliances – and external data concerning two distinct countries, in order to compare the results of the algorithm when different external temperatures and dynamic prices tariffs are applied. The performance of the algorithm was evaluated with a crude Monte Carlo method, similar to the one applied for the experimental validation.

The results showed that the algorithm converges faster and with better results with tariffs more dynamics such as the PVPC. Since the bi-hourly tariff only has two price values, the performances have more tendency to be penalized. This happens because when all the constraints are satisfied, only the linear functions will count for the performance, and the algorithm allocates the activation of the loads in the periods with lower price. However, when the discrepancies between prices are too high, this lower price periods could mean the violation of a constraint. If the probabilities vector is almost changed to a binary vector, the algorithm is not capable of overcome the penalization and will continue considering the period with lower cost.

Chapter 6

Conclusions

The change of paradigm that is taking place in electrical power systems has been enabling the transformation of the currently passive distribution networks into fully active networks by strengthening the relation between services and costumers through demand side management and demand response. This change has created a new range of challenges and opportunities in the context of energy management, more specifically in the residential sector, in order to improve the energy efficiency and comfort standards of the end-users. Many works have been exploiting the benefits of optimization models in this context. Is in this scope that this work was carried out. Hence, this chapter intends to present a general analysis about the work developed in this dissertation, as well as highlight some open topics and guidelines for future work.

6.1 Work Analysis and Discussion

The work presented in this dissertation provides a combinatorial optimization methodology to solve the problem of the electricity consumption scheduling. The methodology is based on a general structure that was developed using the cross-entropy method for optimization. The structure is validated with a well-known NP-complete combinatorial optimization problem, and all the steps necessary for the experimental validation and the expected results are provided.

The model implemented in the algorithm considers two types of loads, designated in this work as *shiftable* and *thermal* appliances. The shiftable appliances are modelled in a simple way, only considering the maximum power, average duration cycle and number of times for operation. This allows an easier integration in the discrete formulation. Given the current interpretation of the EV as a supporting element in the planning and management of the new paradigm of distribution networks, a model to consider the EV was developed as well. This model considers the charging of the EV as a shiftable load by converting the intended driving range in the number of times that the load needs to be activated, with fixed duration cycles. The model is very simple and can be used as a starting point for the modelling of more sophisticated combinatorial optimization methodologies that consider the scheduling of the EV charging. The thermal loads were modelled according to PBLMs, that revealed to be a good approach for this type of discrete optimization.

The algorithm developed in this work is detailed in a step-by-step approach and is based on the formulation of a single objective function that includes the influence of all the variables in the problem. The collection of the data to determine this function follows a vertical structure that integrates two other sub-structures – one to collect the data for the shiftable appliances and another for the thermal ones. The data collected consists on the costs of appliances, considering or not the PV self-consumption, and on the respective penalizations according to the characteristics of the appliance, consumer patterns and preferences of the user. Since all the values that are used in the objective function are determined in different ways, it was necessary to perform a normalization of these values. The method used for this purpose was the *min-max* method. This approach can provide some flexibility to the algorithm in terms of including different types of variables, models or constraints in the problem, but also raise some difficulties when creating and adjusting the weights of the individual functions. Moreover, the resulting single objective function will depend directly on the penalties that are being applied.

The formulation of the penalizations was without any doubt the most challenging part of the work. First it was necessary to find a way to determine the value of the penalty – that is usually made by calculating the excess between the value being tested and the acceptable one –, and then the formulation of an adequate function to add in the single objective function. In the case of the shiftable appliances, the difficult part was to determine a penalty that could guarantee the number of activations inside the desired timeframe when a start and deadline were established. The function for the performance was easily obtained with the quadratic and linear approaches. The contrary happens with the thermal appliances, where the penalties are easily calculated with the surpluses, but the function and the respective weights require more than the same shiftable approach to be adjusted.

Although the algorithm takes more than ten minutes to perform a scenario with at least five appliances, it gives fast and optimal results in a matter of minutes or even seconds when considering less appliances, namely if all are shiftable. The increase in the running times is mainly related with the thermal appliances, since it is necessary to obtain the temperatures for each period, of each sample, in each iteration, with the thermal equations. Furthermore, these appliances also have a larger range for possible activations than the shiftable ones, due to the type of constraints associated (maintain temperature inside limits). Other factor that tampers with the running time is the type of tariff being used. With more dynamic tariffs, such as the PVPC used in the Spanish cases, the algorithm converges faster and usually with much less probability of being penalized.

The tests performed in the different scenarios shows that the algorithm is capable of converging to optimal and near optimal results practically all times. In all the scenarios tested with the crude Monte Carlo, the worst number of non-convergences was *13* out of *1000*, and only happened because it was a scenario considering the EV, all the appliances with deadlines defined and the less floating tariff (bi-hourly TOU tariff). This indicates that the scheme for the penalization should be improved to adapt according to the number and type of appliances, or even with the type of tariff being used.

6.2 Open Topics and Future Work

There are some aspects in this work that were not correctly addressed given the limited timeframe, and other aspects that should be improved. Since the structure of the algorithm to obtain the single objective function is flexible enough to be changed, it is possible to add, remove or alter the steps in order to enhance its performance.

In the same way that the number of samples *N* is adjusted in this work according to the number of appliances to reduce the running time, other parameters could be also adjusted to improve time and performance. For instance, an auto-adaptive smoothing parameter, mainly to be applied in the generation of the random samples of the thermal appliances. This parameter was not correctly explored, but it was noticed that its influence is greater on the thermal appliances rather than on the shiftable ones.

The development of some sort of training for the penalization schemes in order to determine the best weights to be applied in the single objective function. Moreover, this weights for the functions could be dynamic and applied according to the evolution of the results over iterations – auto-adaptive weights.

The function that considers the PV self-consumption and the remuneration could be improved in order to have the option of changing the optimization criteria to PV self-consumption maximization and not only minimization of the costs. Furthermore, a battery model could be easily implemented to support both the criterions, by saving energy in periods were the electricity prices are lower to be used in periods were the prices are higher.

In the case that the algorithm is to be applied in a platform that schedule the appliances not only for the day ahead but also for the rest of the current day, there are some interesting applications that could use the penalization scheme implemented for the time frame of the AC. For instance, the platform form home energy management could receive inputs from the smartphone of the user based on its location and adjust the scheduling of the AC activations for the remaining time of the day.

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Appendix A

Case Scenario – Winter

The scenario discussed in this appendix uses the internal data presented in the sector 5.3 – *3* shiftable and *2* thermal appliances – and the external data presented in the sector 5.4 of the *Chapter 5 – Operation Scenarios and Simulations*. It is assumed that all the *3* shiftable appliances only operate once during the day and without any deadline, *i.e.*, timeframe of *24* hours. The climatological conditions for both Portuguese and Spanish cases concern the temperatures of a winter day, and the criteria inputs for the optimization are the respective price tariffs. The PV generation and EV are not included in this analysis.

Portugal

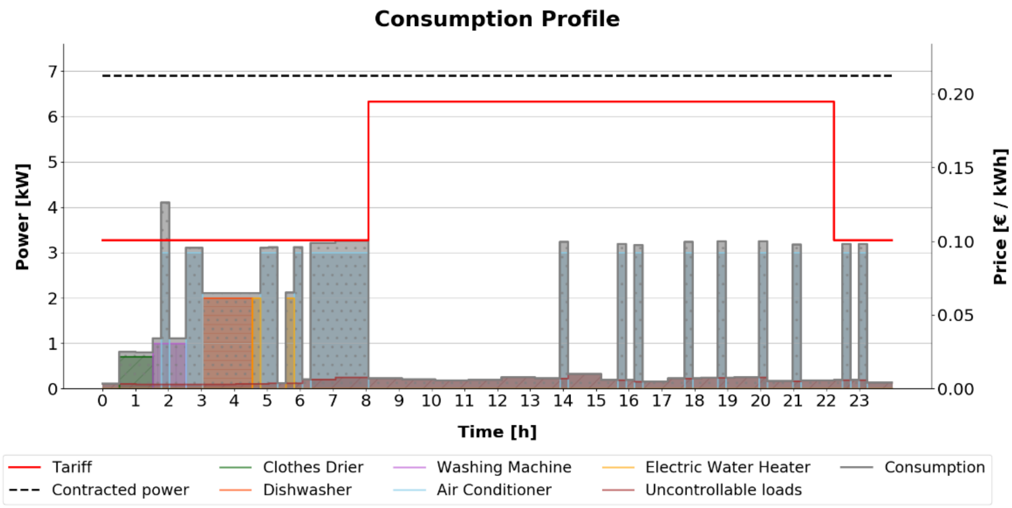

Figure A.1: Consumption profile for the day ahead – Portugal

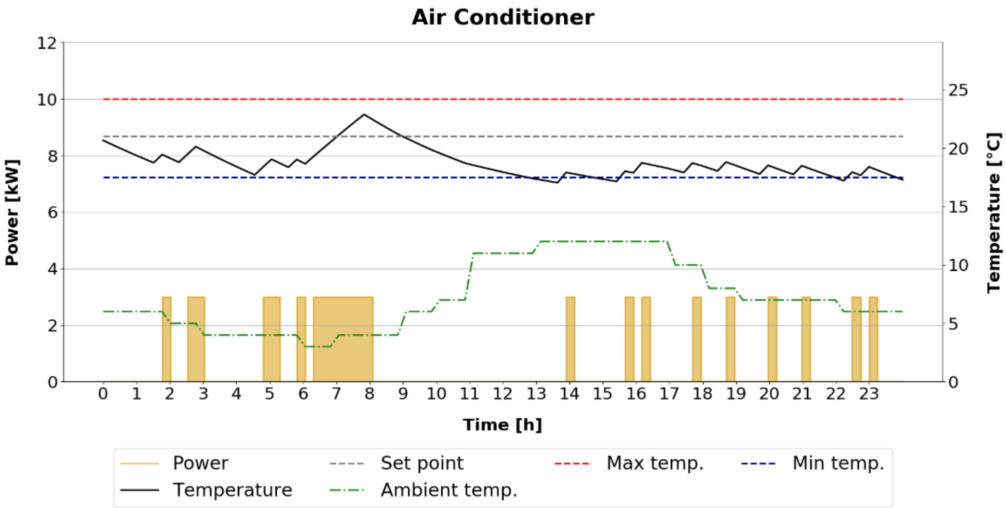

Figure A.2: Temperature profile for the AC – Portugal

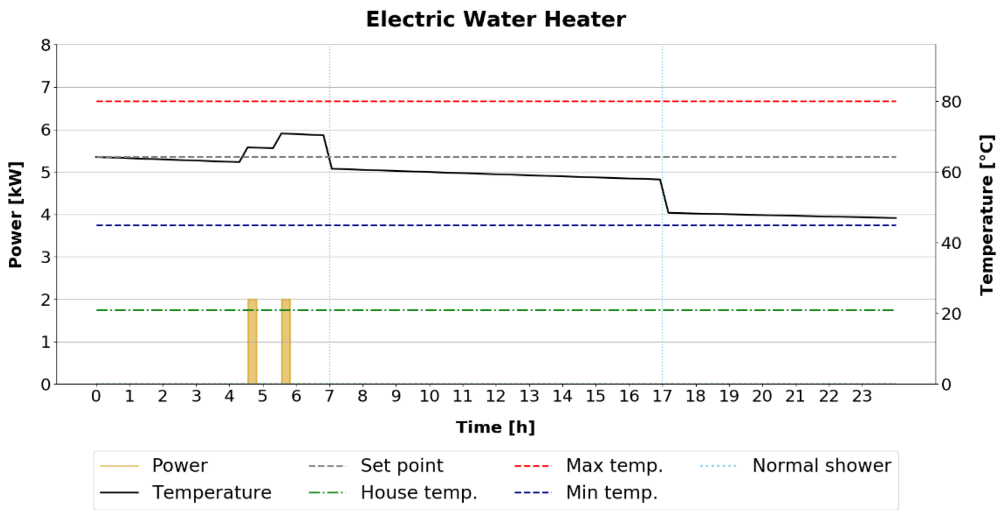

Figure A.3: Temperature profile for the EWH – Portugal

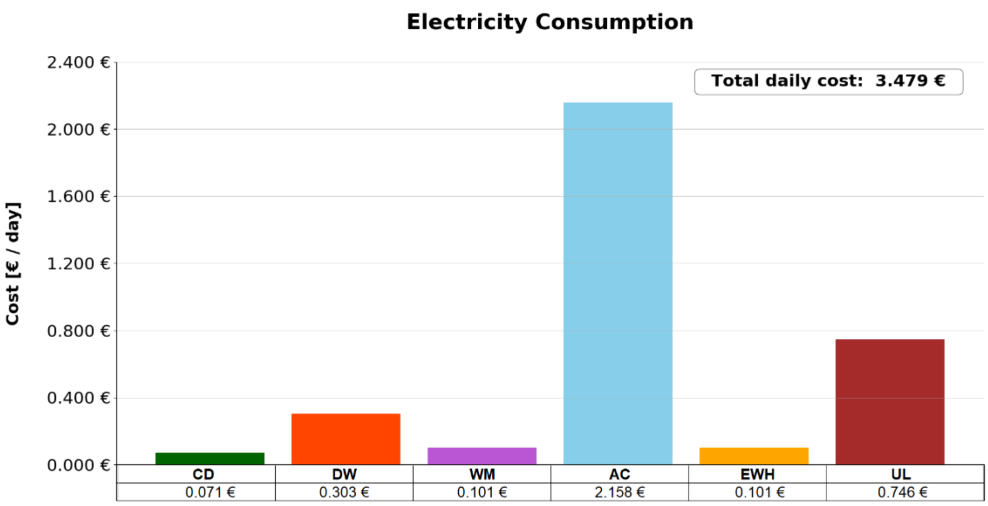

Figure A.4: Individual electricity costs – Portugal

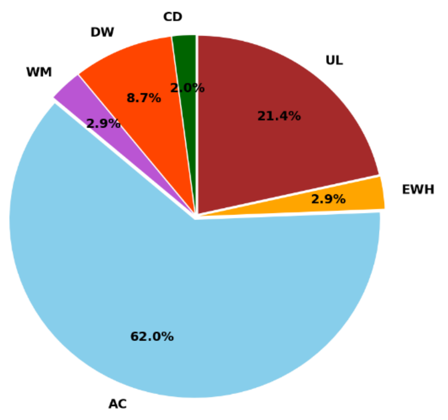

Figure A.5: Share of total daily cost – Portugal

Table A.1: Results for the Crude Monte Carlo method – Portugal

	Iterations	Performances	Running Time [min]	Total Cost [€]
Best result	36	159,848	13,632	3,479
Worst result	100	2884,837	56,033	4,199
Average	44,90	330,77	20,08	3,79
Variance	39,53	139180,59	14,34	0,02
Standard Deviation	6,29	373,07	3,79	0,14

Spain

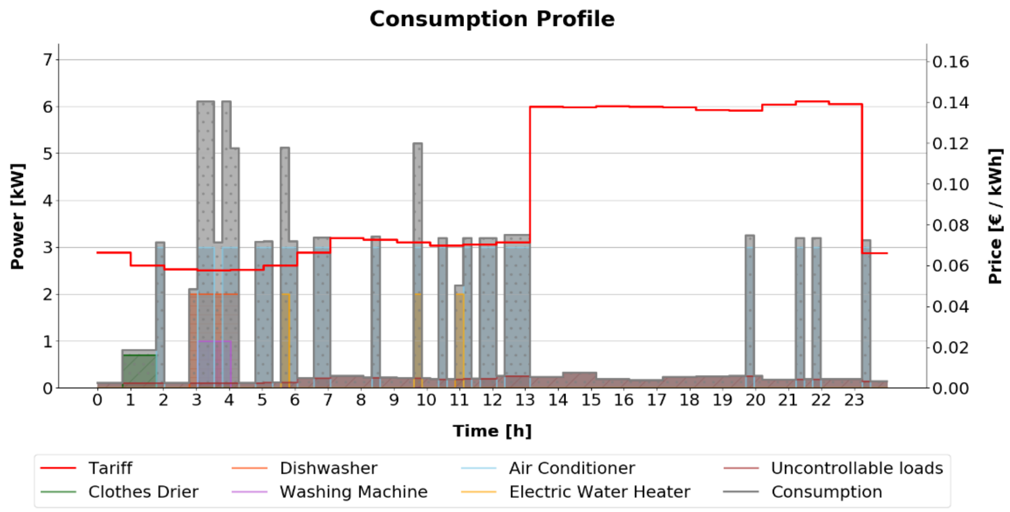

Figure A.6: Consumption profile for the day ahead – Spain

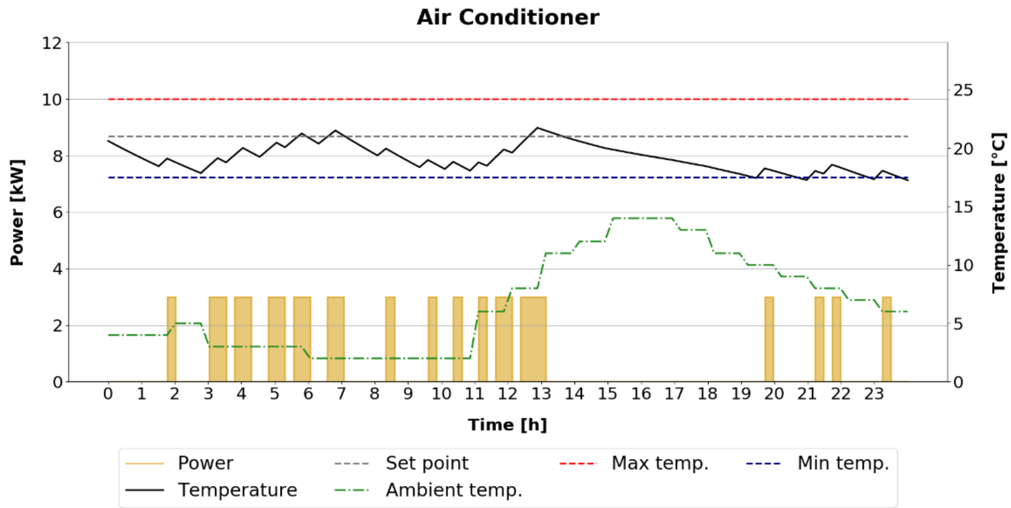

Figure A.7: Temperature profile for the AC – Spain

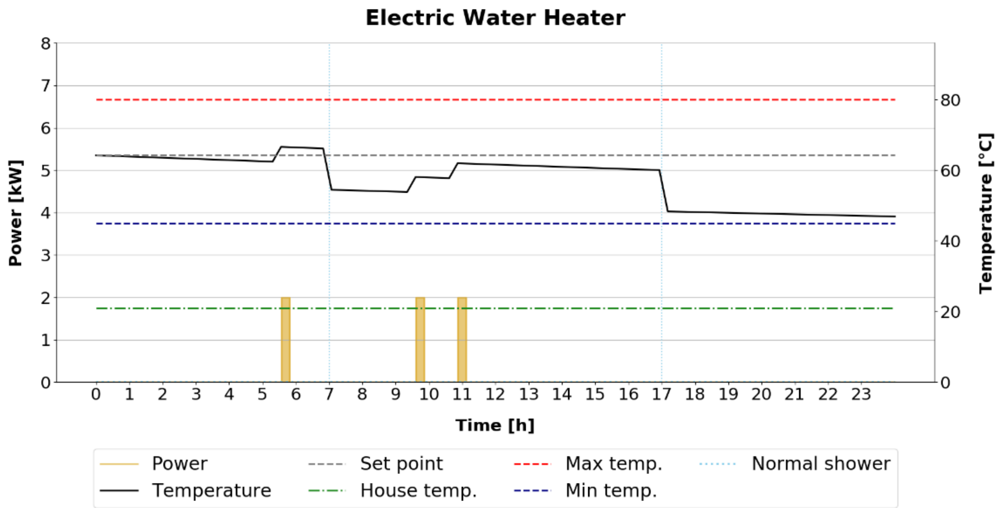

Figure A.8: Temperature profile for the EWH – Spain

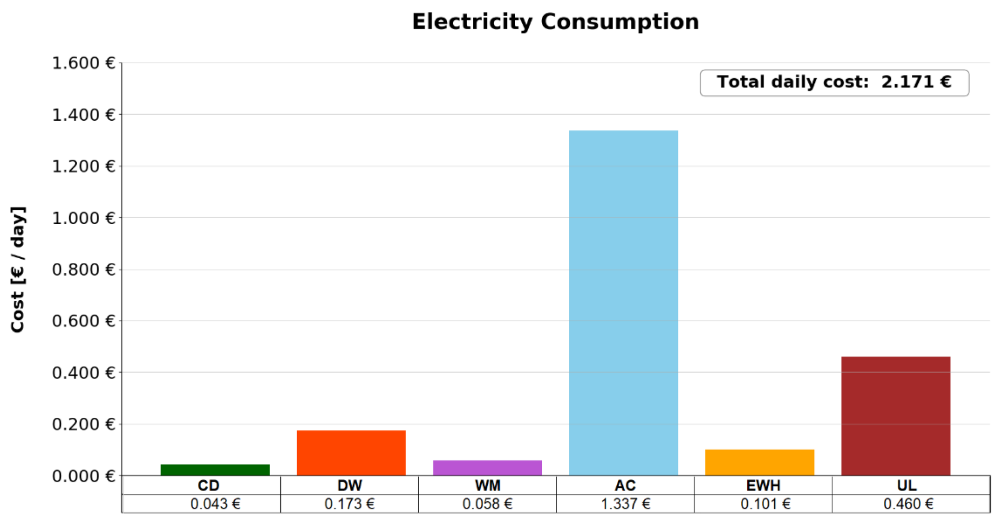

Figure A.9: Individual electricity costs – Spain

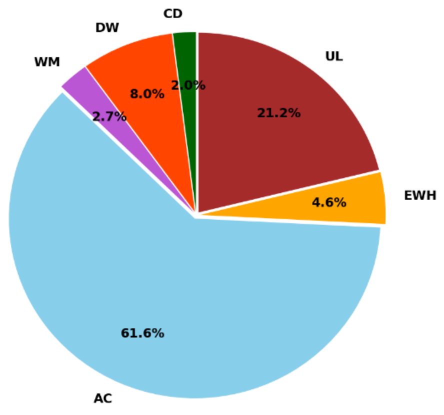

Figure A.10: Share of total daily cost – Spain

Table A.2: Results for the Crude Monte Carlo method – Spain

	Iterations	Performances	Running Time [min]	Total Cost [€]
Best result	37	184,987	8,817	2,171
Worst result	100	291,366	32,203	2,302
Average	45,17	273,45	15,25	2,23
Variance	15,80	126,08	24,15	0,00
Standard Deviation	3,98	11,23	4,91	0,02

Appendix B

Case Scenario – PV Self-Consumption

The scenario discussed in this appendix uses the internal data presented in the sector 5.3 – *3* shiftable and *2* thermal appliances – and the external data presented in the sector 5.4 of the *Chapter 5 – Operation Scenarios and Simulations*. It is assumed that all the *3* shiftable appliances only operate once during the day and without any deadline, *i.e.*, timeframe of *24* hours. The climatological conditions for both Portuguese and Spanish cases concern the temperatures of a summer day, and the criteria inputs for the optimization are the respective price tariffs. The PV generation considered in this scenario is based on the PV forecast of 28th May 2018 in Porto-Portugal, for a PV system with 1.5 kWp. The EV is not included in this analysis.

Portugal

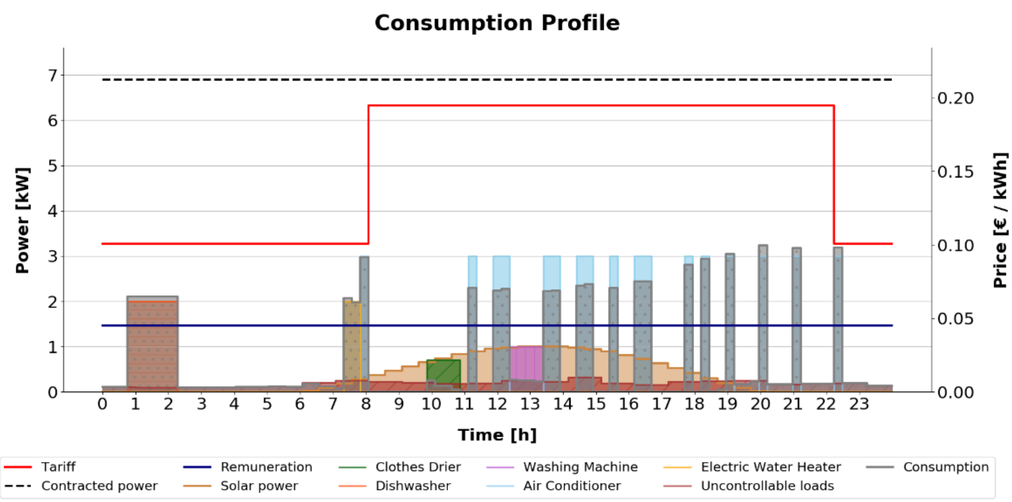

Figure B.1: Consumption profile for the day ahead – Portugal

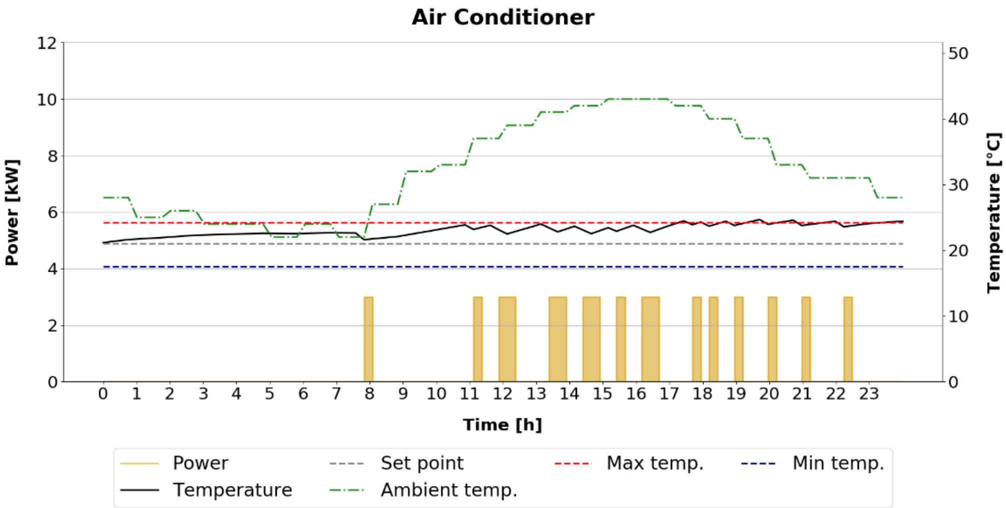

Figure B.2: Temperature profile for the AC – Portugal

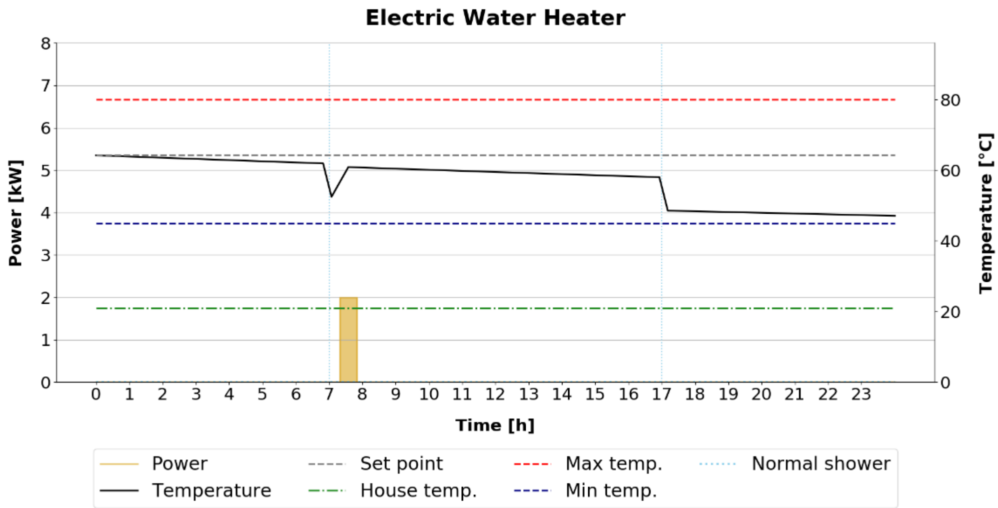

Figure B.3: Temperature profile for the EWH – Portugal

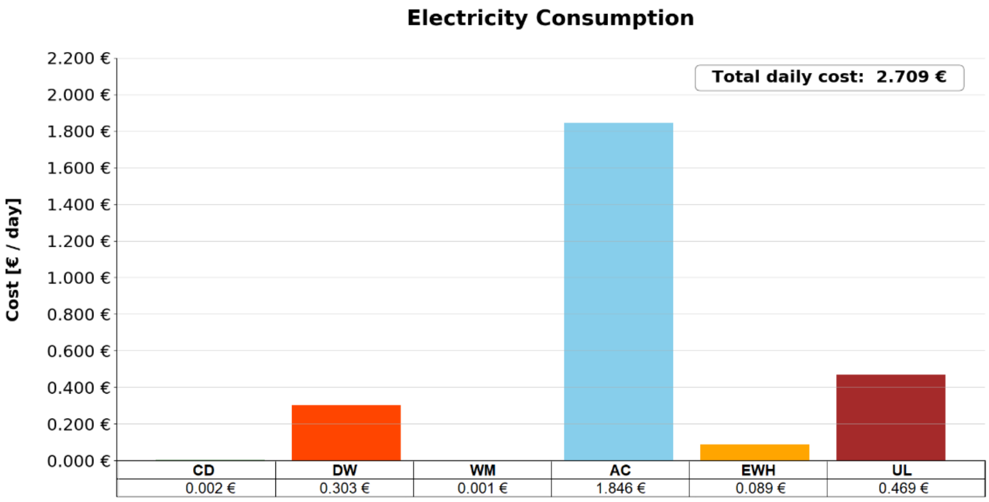

Figure B.4: Individual electricity costs – Portugal

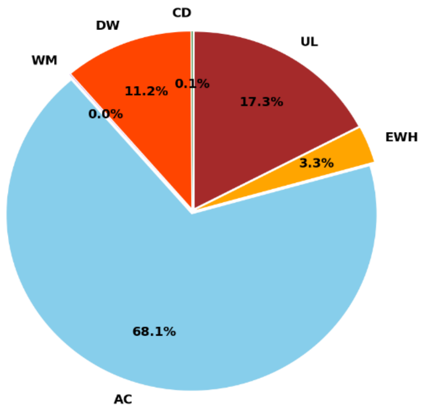

Figure B.5: Share of total daily cost – Portugal

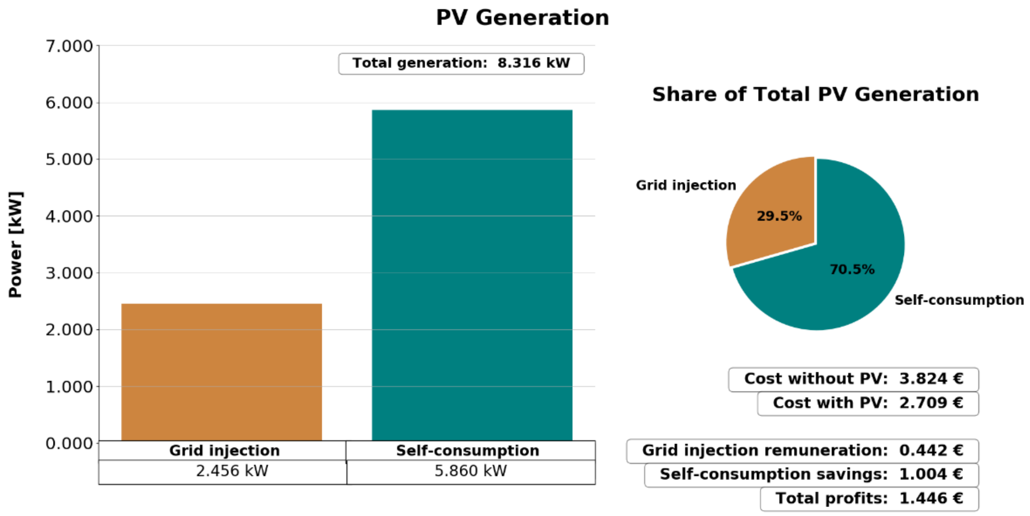

Figure B.6: PV information – Portugal

Table B.1: Results for the Crude Monte Carlo method – Portugal

	Iterations	Performances	Running Time [min]	Total Cost [€]
Best result	34	150,156	13,26	2,709
Worst result	100	4687,204	66,946	3,204
Average	40,92	495,92	23,99	2,97
Variance	14,16	314347,68	23,67	0,01
Standard Deviation	3,76	560,67	4,87	0,07

Table B.2: Results for the Crude Monte Carlo method (PV information) – Portugal

	Grid Injection [kW]	Self-Consumption [kW]	Remuneration [€]	Savings [€]
Best result	0,664	5,171	0,119	0,839
Worst result	3,145	7,652	0,566	1,434
Average	1,85	6,47	0,33	1,15
Variance	0,20	0,20	0,01	0,01
Standard Deviation	0,45	0,45	0,08	0,11

Spain

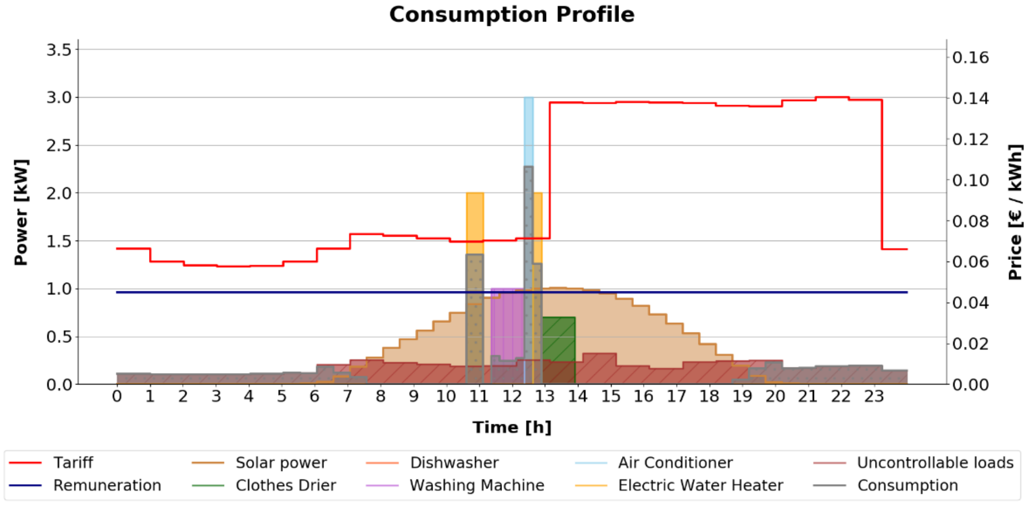

Figure B.7: Consumption profile for the day ahead – Spain

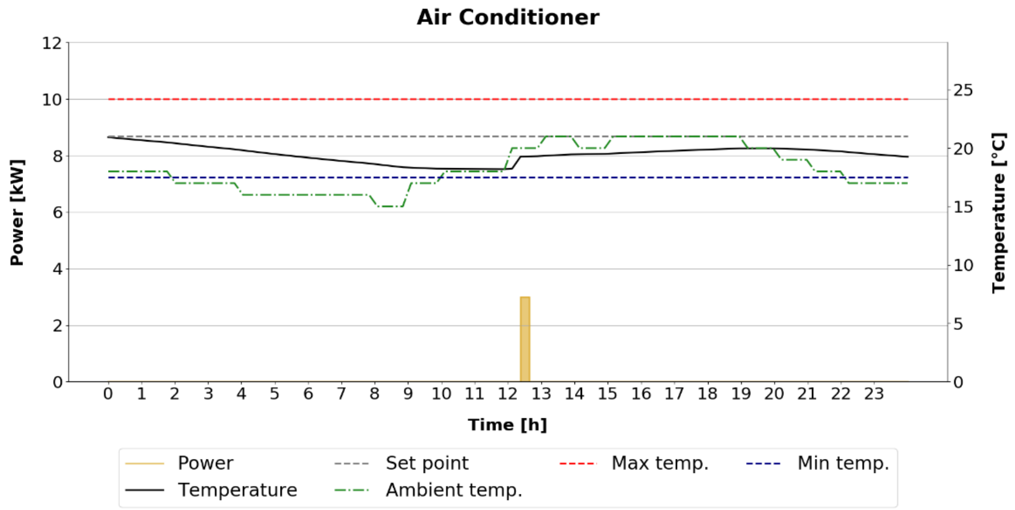

Figure B.8: Temperature profile for the AC – Spain

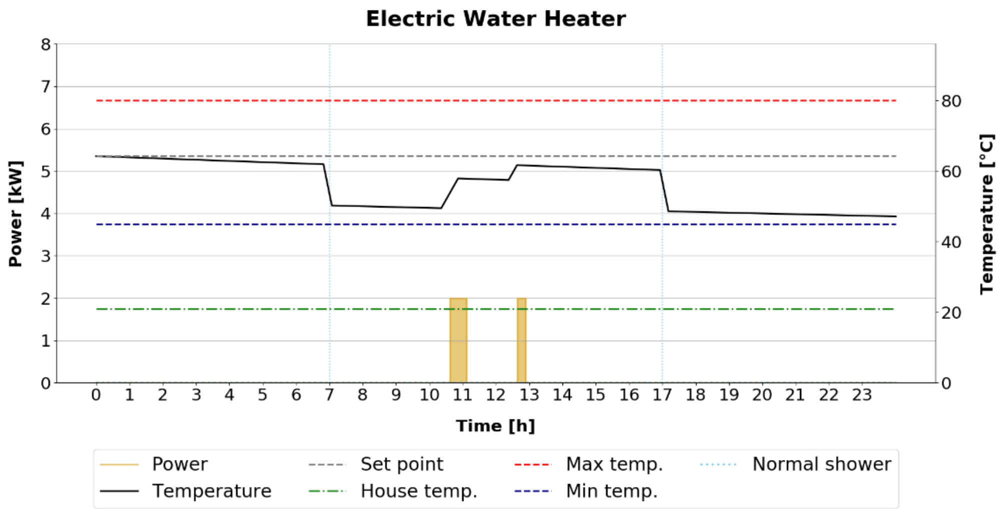

Figure B.9: Temperature profile for the EWH – Spain

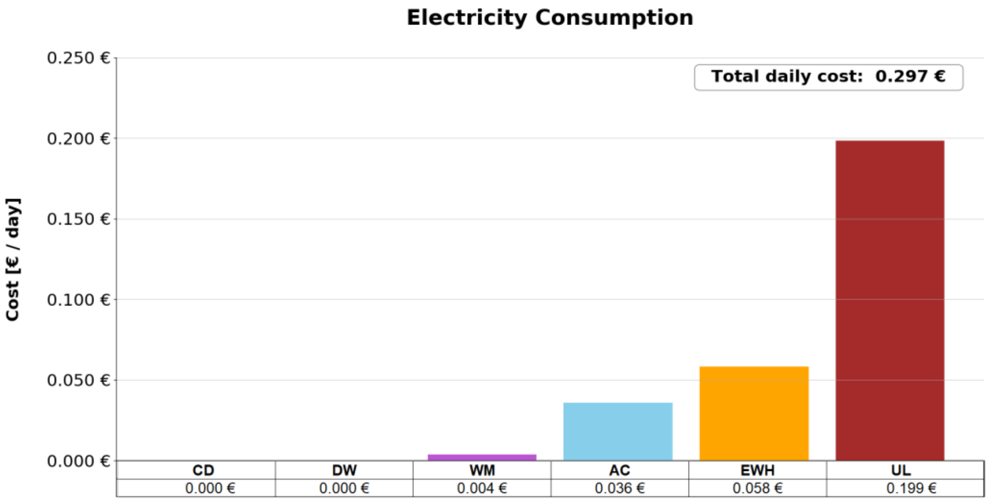

Figure B.10: Individual electricity costs – Spain

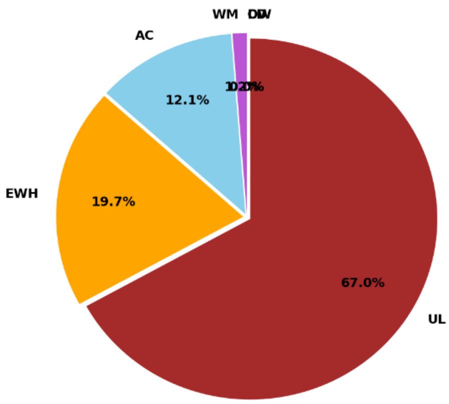

Figure B.11: Share of total daily cost – Spain

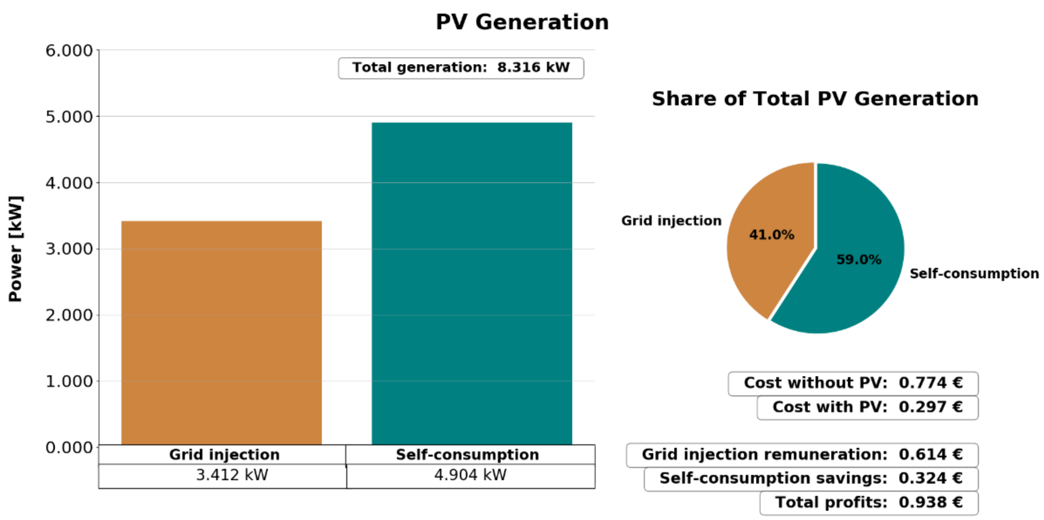

Figure B.12: PV information – Spain

Table B.3: Results for the Crude Monte Carlo method – Spain

	Iterations	**Performances**	**Running Time [min]**	**Total Cost [€]**
Best result	28	108,771	11,562	0,391
Worst result	100	339,001	45,498	1,115
Average	32,16	192,48	15,94	0,61
Variance	13,48	1367,80	5,45	0,00
Standard Deviation	3,67	36,98	2,33	0,06

Table B.4: Results for the Crude Monte Carlo method (PV information) – Spain

	Grid Injection [kW]	**Self-Consumption [kW]**	**Remuneration [€]**	**Savings [€]**
Best result	1,088	3,288	0,196	0,236
Worst result	2,024	4,223	0,364	0,393
Average	1,56	3,76	0,28	0,31
Variance	0,03	0,03	0,00	0,00
Standard Deviation	0,18	0,18	0,03	0,03

Appendix C

Case Scenario – Electric Vehicle and Appliances with Deadlines

The scenario discussed in this appendix uses the internal data presented in the sector *5.3* – *3* shiftable and *2* thermal appliances – and the external data presented in the sector *5.4* of the *Chapter 5 – Operation Scenarios and Simulations*. The EV is also considered in this scenario as a shiftable load under the conditions presented in the sub-sector *3.2.1* of the *Chapter 3 – Model for Home Energy Management*. The data related to the EV is presented in Table C.1. The remaining shiftable appliances use the consumption patterns of the Table 5.7 (*Chapter 5*), i.e., all *3* shiftable appliances have a deadline established for the operation and in the case of the DW two deadlines are defined, since the appliance operates *2* times. The climatological conditions for both Portuguese and Spanish cases concern the temperatures of a summer day, and the criteria inputs for the optimization are the respective price tariffs. The PV generation is not included in this analysis.

Table C.1: Characteristics and consumption patterns for the EV

	EV
Characteristics	
Power of the charger $[kW]$	3,7
Power consumed during the charging $[kWh/km]$	0,135
Duration cycle $[h]$	0,25
Number of activations $[\#]$	12
Consumption patterns	
User's intended range $[km]$	75
Final range $[km]$	82,2
Deadlines $[h]$	9

Portugal

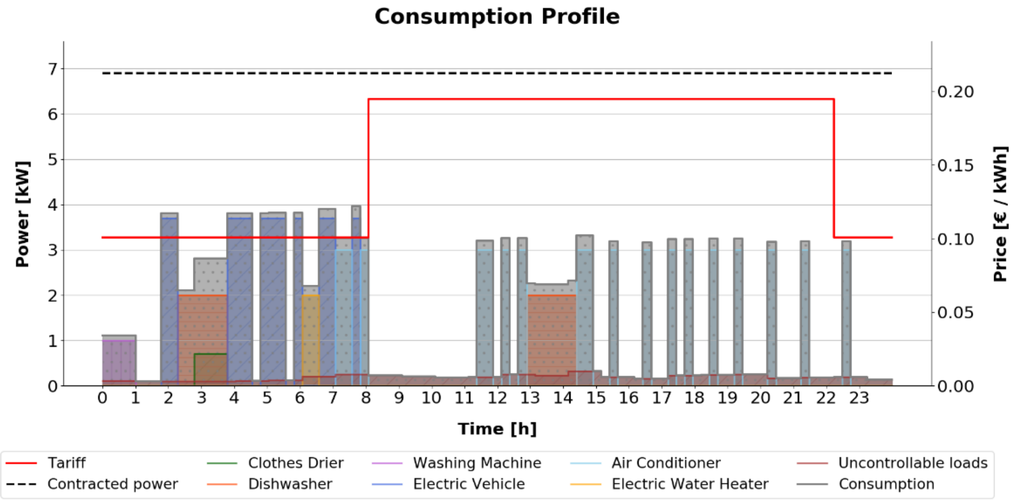

Figure C.1: Consumption profile for the day ahead – Portugal

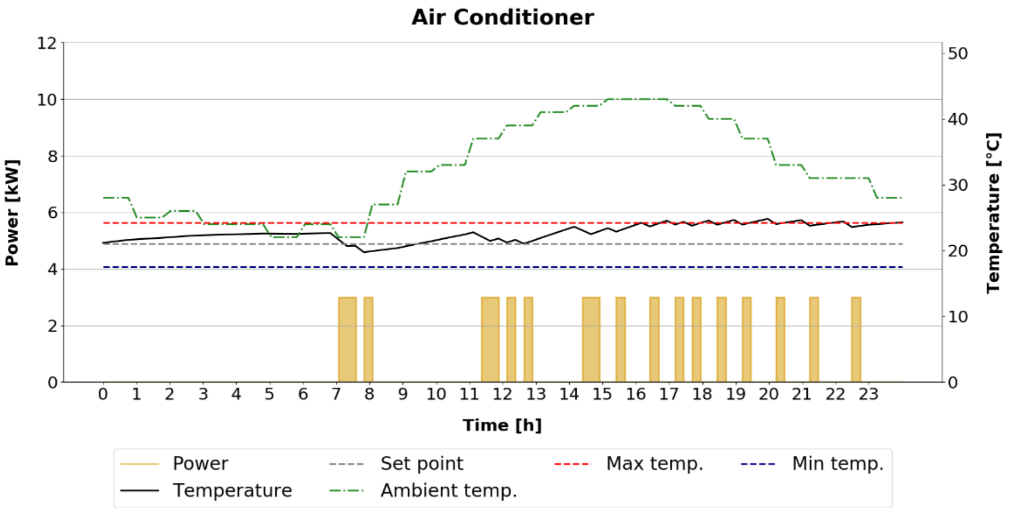

Figure C.2: Temperature profile for the AC – Portugal

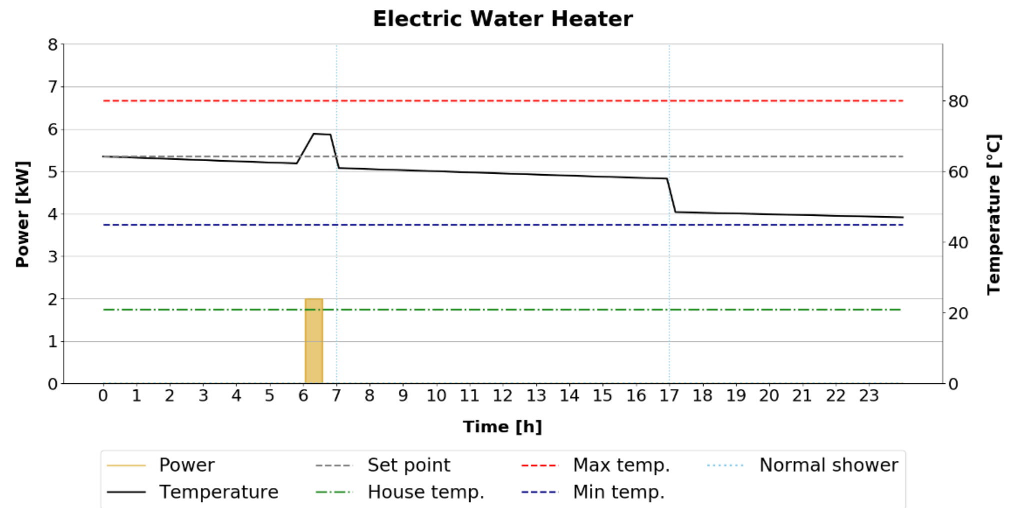

Figure C.3: Temperature profile for the EWH – Portugal

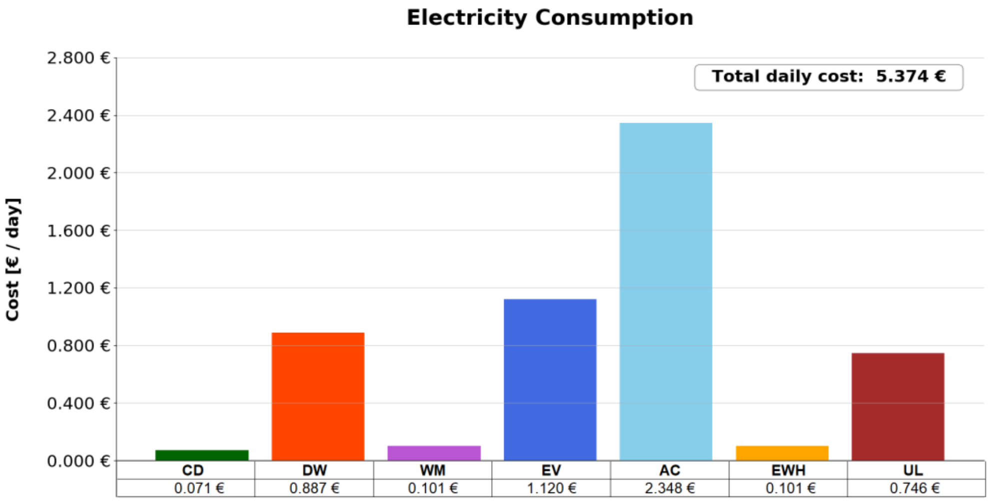

Figure C.4: Individual electricity costs – Portugal

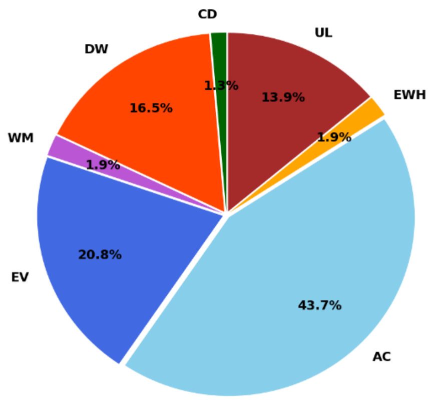

Figure C.5: Share of total daily cost – Portugal

Table C.2: Results for the Crude Monte Carlo method – Portugal

	Iterations	Performances	Running Time [min]	Total Cost [€]
Best result	41	201,5	15,547	5,369
Worst result	100	3076,505	91,108	5,951
Average	53,51	494,08	32,05	5,63
Variance	60,18	516425,21	56,35	0,01
Standard Deviation	7,76	718,63	7,51	0,08

Spain

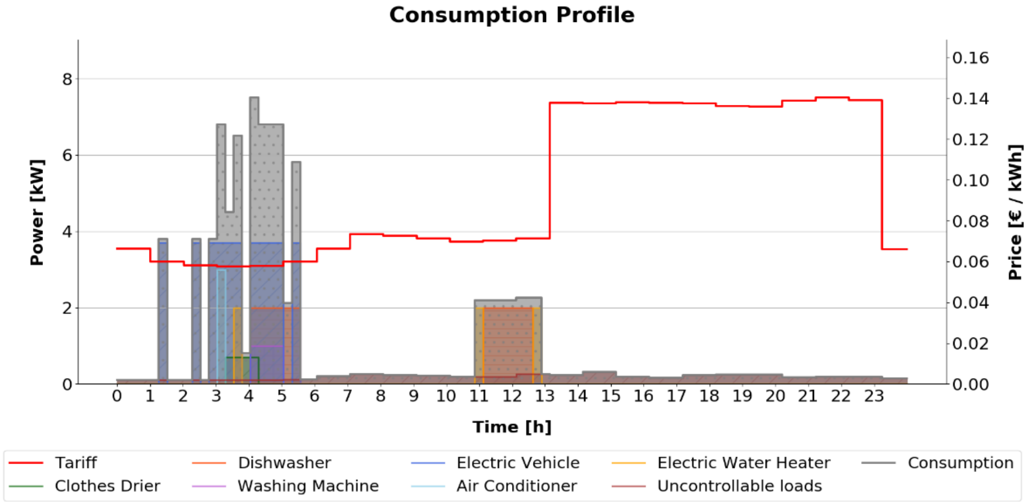

Figure C.6: Consumption profile for the day ahead – Spain

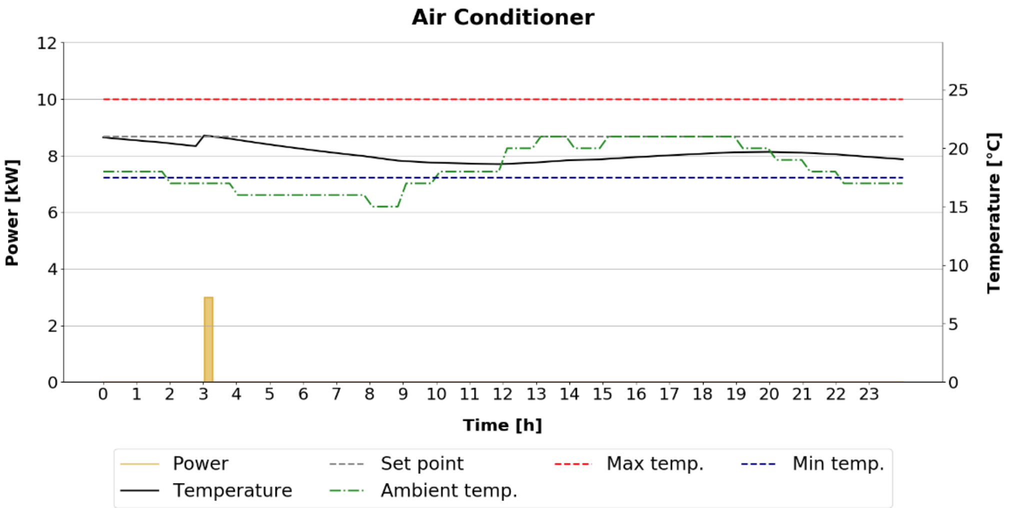

Figure C.7: Temperature profile for the AC – Spain

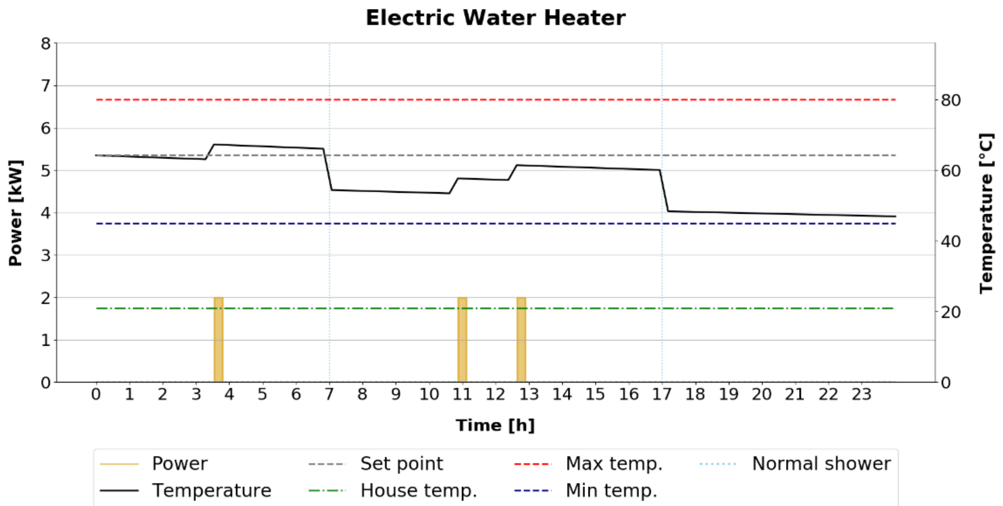

Figure C.8: Temperature profile for the EWH – Spain

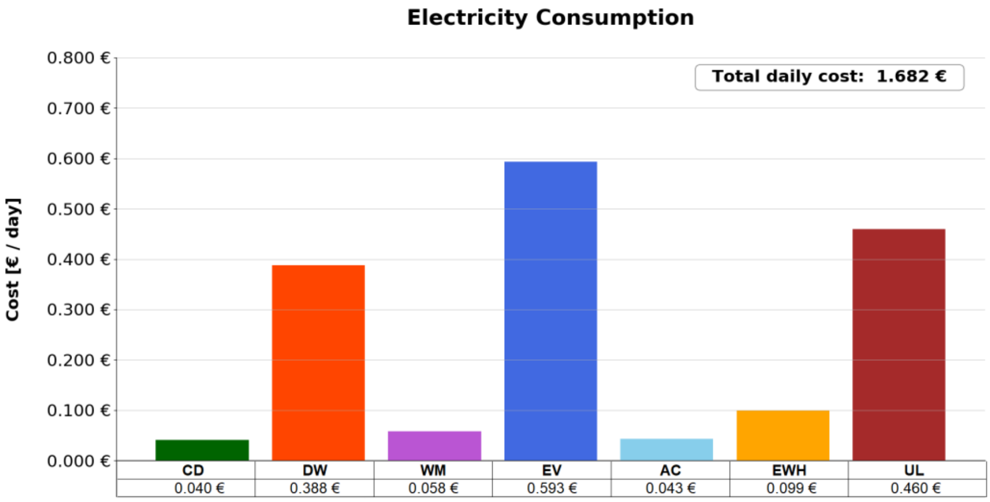

Figure C.9: Individual electricity costs – Spain

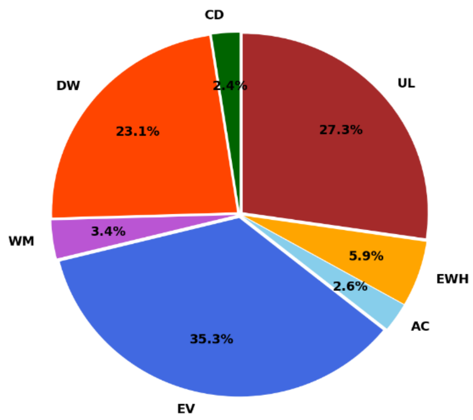

Figure C.10: Share of total daily cost – Spain

Table C.3: Results for the Crude Monte Carlo method – Spain

	Iterations	Performances	Running Time [min]	Total Cost [€]
Best result	37	139,808	11,827	1,682
Worst result	100	901,514	34,321	2,355
Average	44,09	245,27	20,45	1,84
Variance	11,82	2402,38	29,76	0,01
Standard Deviation	3,44	49,01	5,46	0,10

Appendix D

Case Scenario – Electric Vehicle and PV Self-Consumption

The scenario discussed in this appendix uses the internal data presented in the sector 5.3 – *3* shiftable and *2* thermal appliances – and the external data presented in the sector 5.4 of the *Chapter 5 – Operation Scenarios and Simulations*. The EV is considered and uses the characteristics of the Table C.1 of *Appendix C*. It is assumed that all the *3* shiftable appliances only operate once during the day and without any deadline, *i.e.*, timeframe of *24* hours. The same timeframe is applied to the EV. The climatological conditions for both Portuguese and Spanish cases concern the temperatures of a summer day, and the criteria inputs for the optimization are the respective price tariffs. The PV generation considered in this scenario is based on the PV forecast of 28th May 2018 in Porto-Portugal, for a PV system with 1.5 kWp.

Portugal

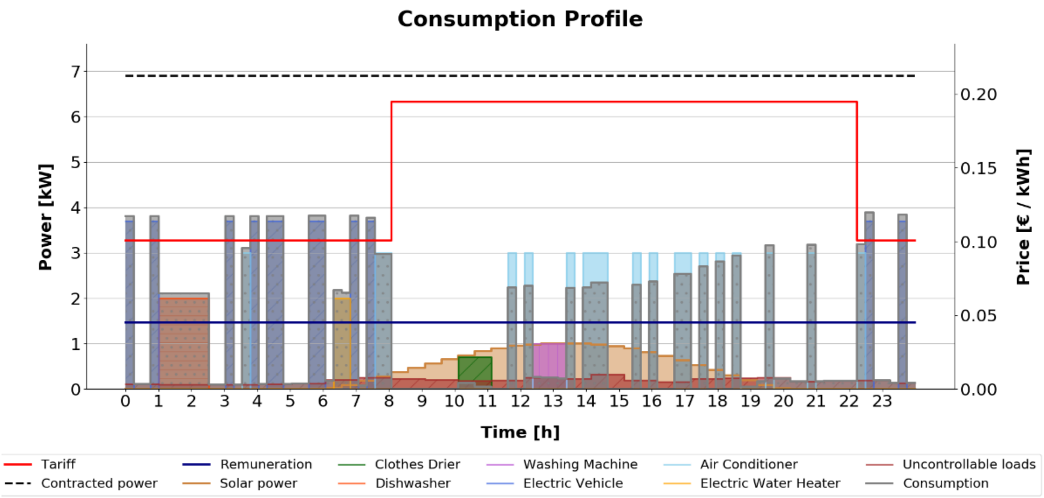

Figure D.1: Consumption profile for the day ahead – Portugal

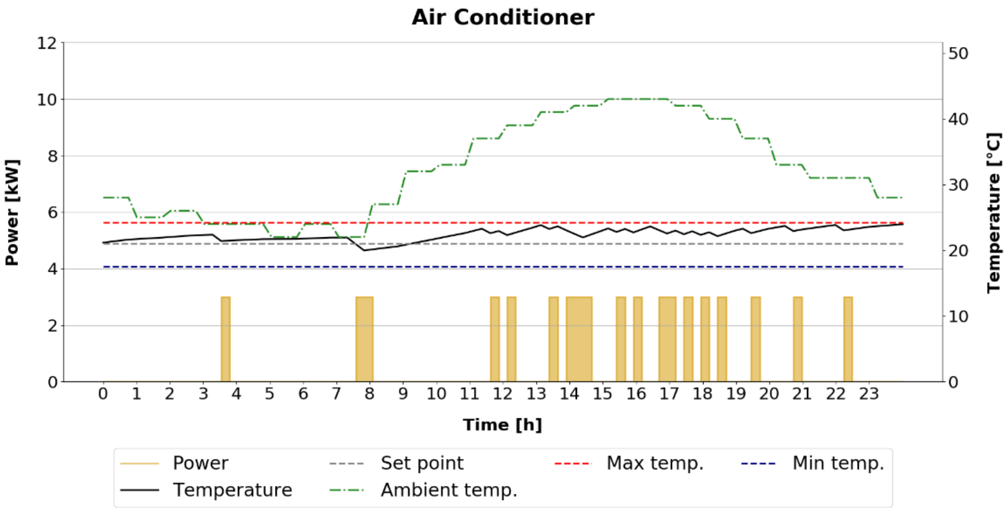

Figure D.2: Temperature profile for the AC – Portugal

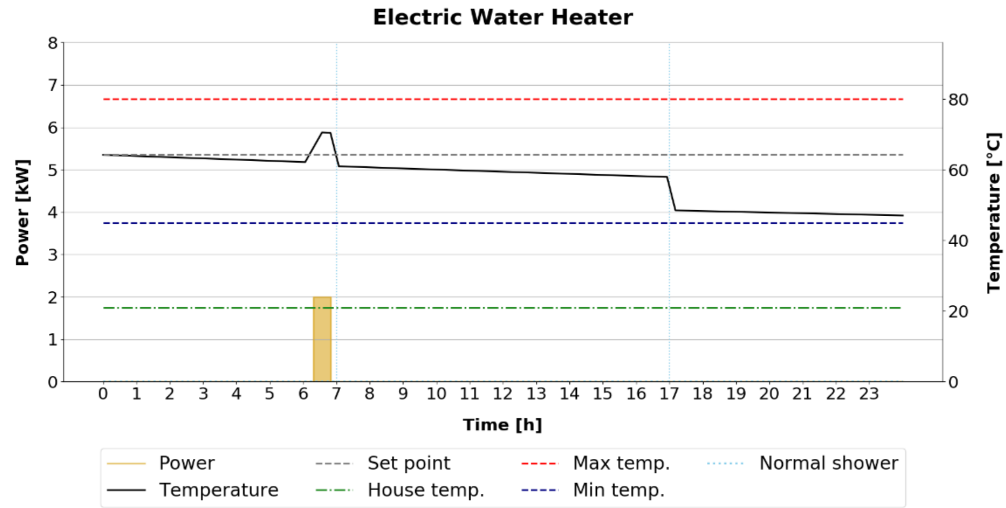

Figure D.3: Temperature profile for the EWH – Portugal

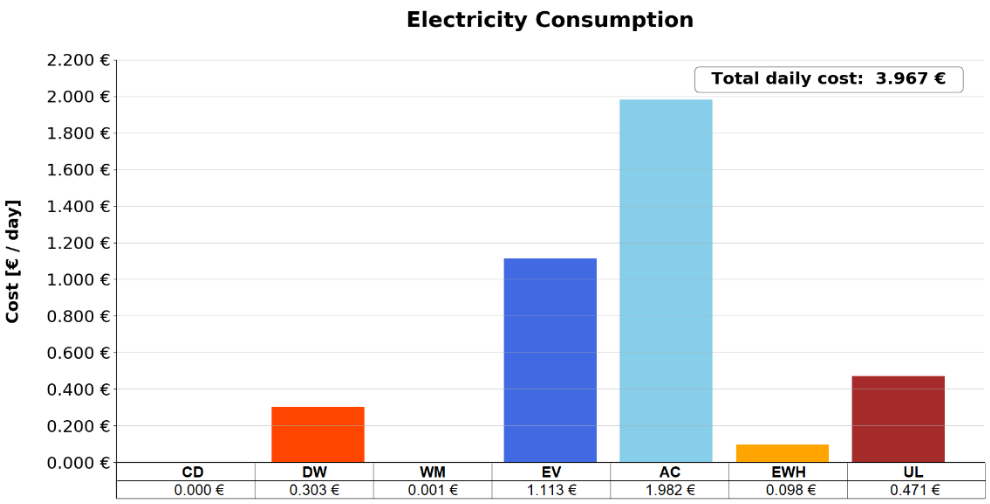

Figure D.4: Individual electricity costs – Portugal

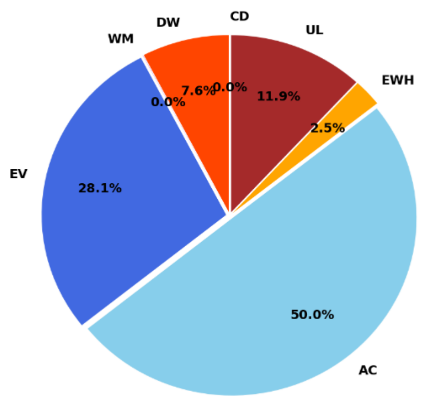

Figure D.5: Share of total daily cost – Portugal

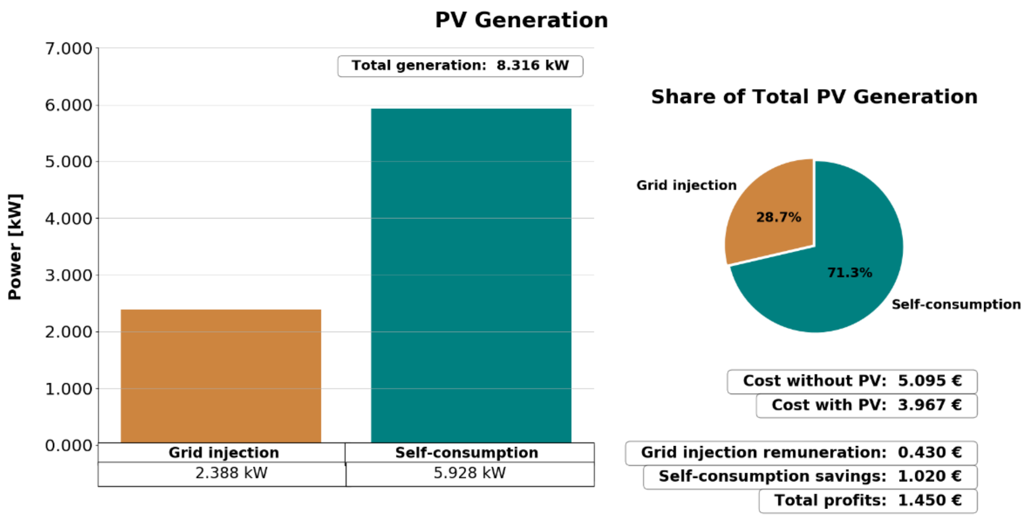

Figure D.6: PV information – Portugal

Table D.1: Results for the Crude Monte Carlo method – Portugal

	Iterations	Performances	Running Time [min]	Total Cost [€]
Best result	42	163,011	18,078	3,931
Worst result	100	3468,224	80,155	4,588
Average	52,14	421,53	34,56	4,23
Variance	43,81	142161,02	51,85	0,01
Standard Deviation	6,62	377,04	7,20	0,09

Table D.2: Results for the Crude Monte Carlo method (PV information) – Portugal

	Grid Injection [kW]	Self-Consumption [kW]	Remuneration [€]	Savings [€]
Best result	0,742	5,039	0,134	0,808
Worst result	3,277	7,574	0,59	1,416
Average	1,90	6,42	0,34	1,14
Variance	0,19	0,19	0,01	0,01
Standard Deviation	0,44	0,44	0,08	0,10

Spain

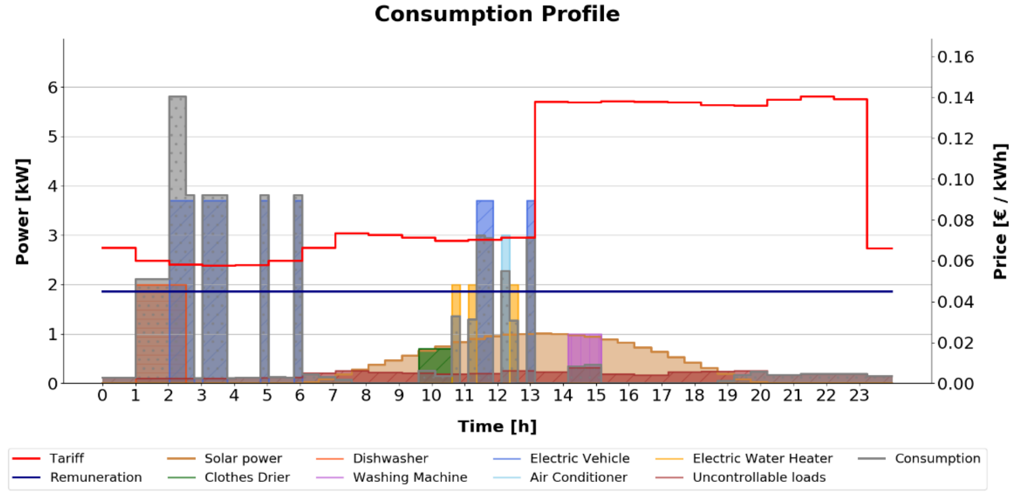

Figure D.7: Consumption profile for the day ahead – Spain

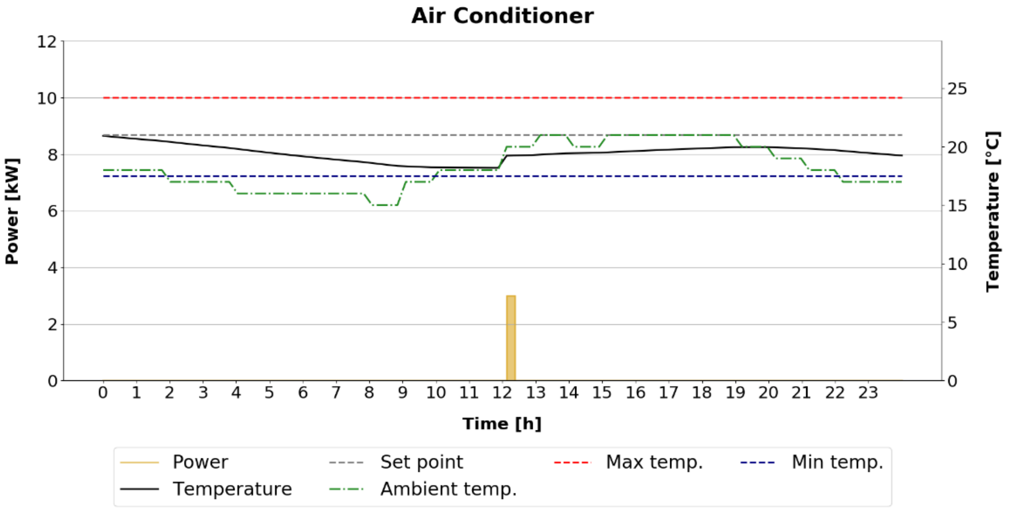

Figure D.8: Temperature profile for the AC – Spain

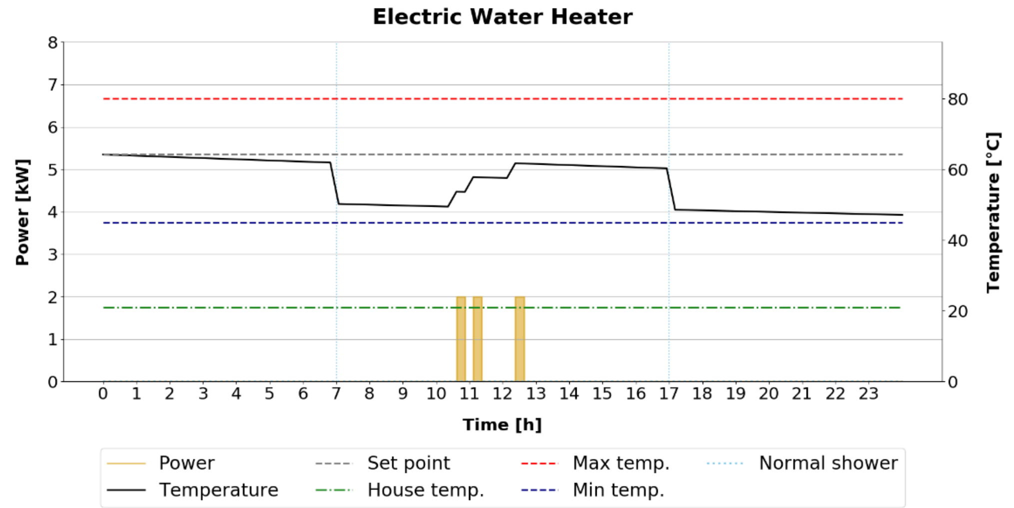

Figure D.9: Temperature profile for the EWH – Spain

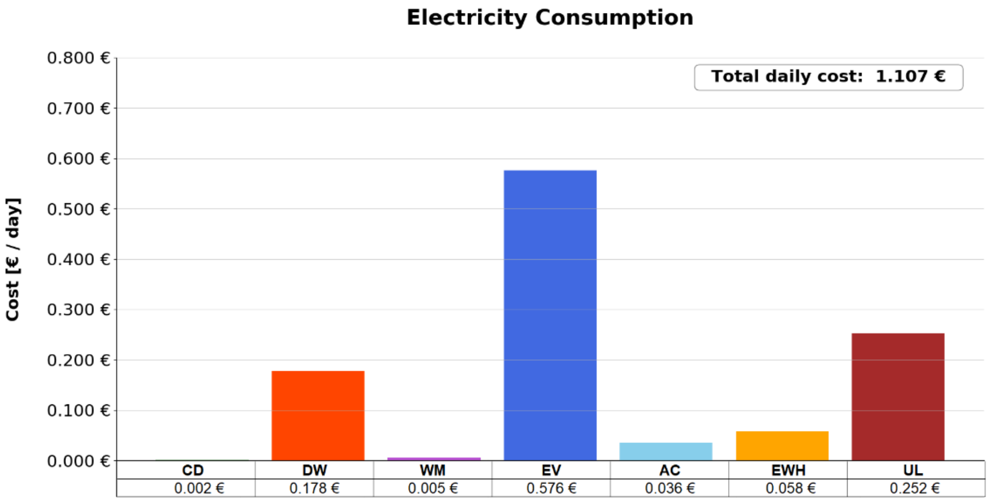

Figure D.10: Individual electricity costs – Spain

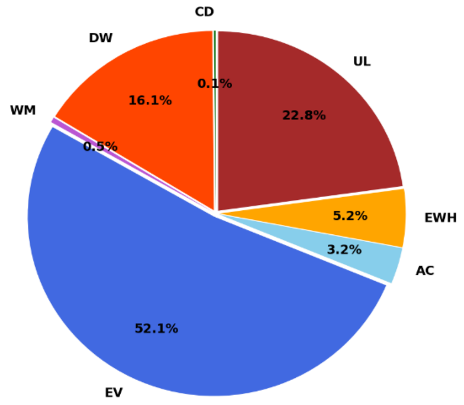

Figure D.11: Share of total daily cost – Spain

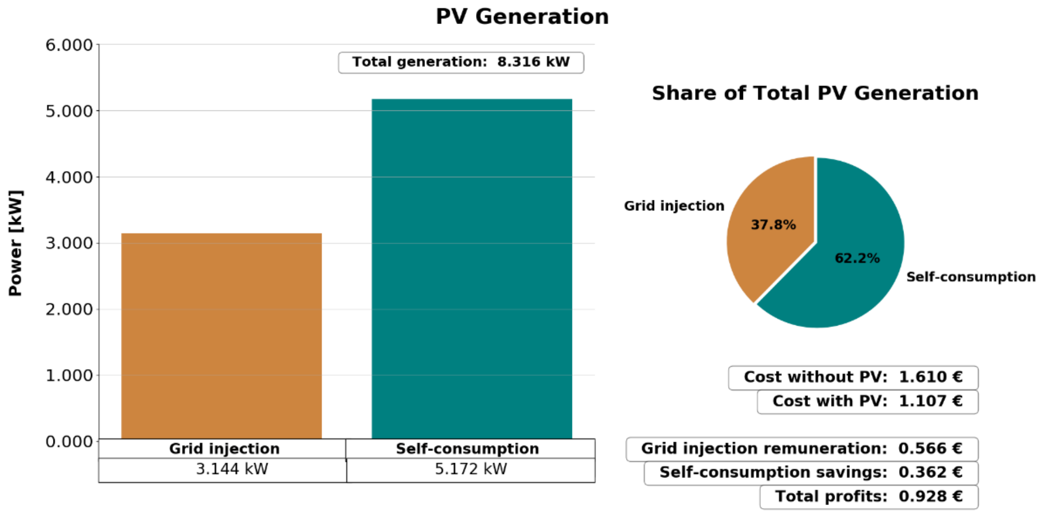

Figure D.12: PV information – Spain

Table D.3: Results for the Crude Monte Carlo method – Portugal

	Iterations	Performances	Running Time [min]	Total Cost [€]
Best result	38	147,096	12,184	1,094
Worst result	57	2740,833	34,902	1,681
Average	44,10	354,40	19,55	1,28
Variance	7,43	82778,21	31,41	0,01
Standard Deviation	2,72	287,71	5,60	0,10

Table D.4: Results for the Crude Monte Carlo method (PV information) – Portugal

	Grid Injection [kW]	Self-Consumption [kW]	Remuneration [€]	Savings [€]
Best result	0,804	3,143	0,145	0,201
Worst result	4,169	6,793	0,75	0,634
Average	2,35	4,76	0,42	0,36
Variance	0,56	0,83	0,02	0,01
Standard Deviation	0,75	0,91	0,13	0,08