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Performance of Smart Homes for participating in Electricity Markets

MESTRADO INTEGRADO EM ENGENHARIA ELETROTÉCNICA E DE COMPUTADORES

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Resumo

Os consumidores residenciais tornaram-se participantes ativos nas transações do mercado elétrico local devido ao recente avanço das tecnologias de redes inteligentes e dos sistemas de armazenamento de energia. Tendo isso em mente, esta tese propõe um modelo estocástico de duas fases, incluindo os mercados do dia seguinte e em tempo real de energia, com o objetivo de programar equipamentos domésticos, tendo em conta a incerteza na variabilidade da geração de micro turbinas eólicas, geração fotovoltaica e dos próprios eletrodomésticos.

A contribuição do veículo elétrico e da bateria no fornecimento de flexibilidade adicional por meio do comércio de energia bidirecional foi investigada considerando padrões de mobilidade determinísticos. Portanto, um programa de resposta à procura (DR) baseado numa taxa em tempo real pode afetar suas decisões. Além desta consideração, o modelo inclui outras cargas como do frigorífico e máquinas de lavar roupa e loiça.

Nesse sentido, é feita uma análise comparativa do desempenho de uma casa inteligente para participação no mercado de energia elétrica, com o principal objetivo de determinar um programa ótimo de DR. Os resultados alcançados mostram que a casa inteligente comprou e vendeu energia elétrica para o mercado local do dia seguinte e de tempo real usando uma tarifa simples.

Além disso, observou-se que usando uma tarifa simples, em comparação com a tarifa em tempo real (RTP), faz com que o sistema consuma mais energia no mercado de eletricidade do dia seguinte e produza mais no mercado elétrico em tempo real. Os resultados relativos à tarifa Critical Price Picking (CPP) indicam melhor lucro em comparação com a tarifa de preço em tempo real, no entanto, a utilização de uma tarifa simples proporciona resultados ligeiramente melhores.

Finalmente, a energia transacionada no dia seguinte obtida das tarifas simples, RTP e CPP são comparadas para avaliar o desempenho do modelo. Concluindo, a tarifa CPP é a tarifa que provoca ao sitema um comportamento mais volátil, enquanto o RTP faz com que haja mais equilíbro no seu comportamento. As tarifas simples e CPP são as que fazem a casa inteligente vender mais energia, e a tarifa em tempo real não compra energia do mercado em tempo real.

A participação da casa inteligente em ambos os mercados de eletricidade (do dia seguinte e em tempo real) proporciona benefícios à gestão do lado da procura, melhorando assim, o fluxo da energia ao longo da rede elétrica.

Palavras-chave: Casa Inteligente, Rede Inteligente, Sistemas de Gestão e Armazenamento de Energia, *Internet of Things*, *Demand Response*, Programação estocástica

Abstract

End users have become active participants in Local electricity Market (LM) transactions due to the growth of the smart grid concept and Energy Storage Systems (ESS). In this thesis, a two-stage stochastic model is proposed considering the day-ahead and real-time electricity market data to have the scheduling energy need for a Smart Home (SH), considering the uncertainty wind and Photovoltaic (PV) generation and different appliances stated as loads.

For this study, the application of Electric Vehicle (EV), together with the battery-based energy storage systems, which allow the increase of the necessary for the bidirectional energy transaction, together with the well-known features of mobility of the EV, will be considered. Hence, in addition to the above, Demand Response (DR) programs, which consider market prices in real-time and can affect the scheduling process, it is also included in this study.

A comparative analysis on the performance of a SH for participating in the electricity market is driven out with the objective of determining an optimal DR program. The achieved results show that the SH both purchased and sold electricity for the day-ahead and real-time local markets at a flat-rate price.

Moreover, it was concluded that a flat rate price, in relation to Real-Time Price (RTP), makes the system consume more energy in the day-ahead electricity market and produce more in the real-time LM. The results related to the Critical Price Picking (CPP) tariff indicate better profit in comparison to RTP, however, using a flat rate tariff provides slightly better results.

Finally, the day-ahead transacted energy obtained from flat rate, RTP and CPP tariffs are compared in order to evaluate the performance of the model. The CPP is the tariff that has a more volatile behaviour, while the RTP tariff provokes a more balanced behaviour. Also, the results showed that both CPP and flat-rate tariffs are the rates that make the SH sell more energy, and RTP does not purchase energy from the real-time LM.

Smart home participation in both electricity markets (day-ahead and real-time) provides demand-side management benefits, thus improving the flow of electrical energy along the electricity grid.

Keywords: Smart Home, Smart Grid, Energy Management System, Energy Storage System, Internet of Things, Demand Response, Stochastic Programming

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Pedro Silva

"If you're afraid to fail,
then you're probably going to fail."

Kobe Bryant

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Abbreviations

CPP	Critical-Peak Pricing
DLC	Direct Load Control
DR	Demand Response
EDRP	Emergency Demand Response Program
EM	Electricity Market
EP	Expected Profit
ESS	Energy Storage System
EV	Electric Vehicle
HVAC	Heating, Ventilating and Air Conditioning
IBDR	Incentive-Based Demand Response
IoT	Internet of Things
LM	Local Market
MILP	Mixed integer linear programming
PBDR	Price-Based Demand Response
PLC	Power Line Communication
PV	Photovoltaic
RFID	Radio Frequency Identification Devices
RTP	Real Time Pricing
SG	Smart Grid
SH	Smart Home
SOC	State of Charge
TOU	Time of Use
V2G	Vehicle to Grid

Nomenclature

A. Indexes

t	Index of time periods
ω	Index of scenarios
ξ	Index of EV mobility scenarios

B. Parameters

λ_t^{da}	Day-ahead electricity price
$\lambda_t^{sold,rt}$	Sold electricity price in the real-time market
$\lambda_t^{pur,rt}$	Purchased electricity price in the real-time market
π_ω	Probability of scenarios
π_ξ	EV's mobility probability of scenarios
V^S	Spillage cost
$VOLL^{sh}$	Space heater lost load
$VOLL^{swh}$	Storage water heater lost load
γ_b	Battery flexibility coefficient
γ_{ev}	EV flexibility coefficient
$L_t^{sh,pred,da}$	Space heater load prediction of day-ahead
$L_t^{swh,pred,da}$	Storage water heater load prediction of day-ahead
$L_t^{mrs,pred,da}$	Must-run services load prediction of day-ahead
f_{max}	Maximum power capacity of the distribution line
$P_t^{wind,pred}$	Predicted wind power generation
$P_t^{pv,pred}$	Predicted PV power generation
η_{H2B}	Battery charging efficiency
η_{B2H}	Battery discharging efficiency

C_i^b	Battery available energy at $t = 1$
P_b^{max}	Battery maximum storage level
P_b^{min}	Battery minimum storage level
ω_b^{max}	Battery's state of charge maximum ramping rate
ω_b^{min}	Battery's state of charge minimum ramping rate
η_{H2V}	EV's charging efficiency
η_{V2H}	EV's discharging efficiency
C_i^{ev}	EV's state of charge at $t = 1$
P_{ev}^{max}	EV's maximum storage level
P_{ev}^{min}	EV's minimum storage level
δ^{ev}	Consumption of EV for one mile driving
ω_{ev}^{max}	EV's state of charge maximum ramping rate
ω_{ev}^{min}	EV's state of charge minimum ramping rate
$P_{t\omega\xi}^{wind,scen}$	Different scenarios of power generation from wind
R	Thermal resistance of SH walls
$\theta_{t\omega\xi}^{out,pred}$	Predicted outdoor temperature
θ_i^{in}	Initial indoor temperature
θ_{des}^{in}	Desired indoor temperature
L_{sh}^{max}	Space heater maximum consumption
L_{swh}^{max}	Storage water heater maximum consumption
U_{swh}^{max}	Storage water heater daily energy consumption
$P_{t\omega\xi}^{light,rt}$	Amount of power used by lighting system in real time
$P_{t\omega\xi}^{wm,rt}$	Power consumption of washing machine in real time
$P_{t\omega\xi}^{dm,rt}$	Power consumption of dishwasher machine in real time
$P_{t\omega\xi}^{fridge,rt}$	Power consumption of fridge in real time
$P_{t\omega\xi}^{other,rt}$	Amount of power used by other appliances in real time
η	Coulombic coefficient
$SOC_{initial}$	Initial value of SOC
C_{cap}	Maximum capacity of the battery
I^{pv}	Installed capacity of PV power plant
I^{wind}	Installed capacity of wind power plant

C. Variables

EP	Expected Profit
$P_t^{net,da}$	Day-ahead transacted energy
$P_{t\omega\xi}^{sold,rt}$	Sold energy to the real-time market
$P_{t\omega\xi}^{pur,rt}$	Purchased energy to the real-time market
$S_{t\omega\xi}^{w}$	Wind micro-turbine spilled power
$S_{t\omega\xi}^{pv}$	PV system spilled power
$S_{t\omega\xi}$	Total spilled power of renewable sources
$L_{t\omega\xi}^{shed,sh}$	Space heater load shedding
$L_{t\omega\xi}^{shed,swh}$	Storage water heater load shedding
$P_t^{wind,da}$	Wind power generation for the day-ahead
$P_t^{pv,da}$	PV generation for the day-ahead
$P_t^{b,dis,da}$	Battery discharged power for the day-ahead
$P_t^{ev,dis,da}$	EV discharged power for the day-ahead
$P_t^{b,ch,da}$	Battery charged power for the day-ahead
$P_t^{ev,ch,da}$	EV charged power for the day-ahead
$C_t^{b,da}$	Battery stored energy for the day-ahead
$u_t^{b,da}$	Battery discharging commitment binary variable for the day-ahead
$C_t^{ev,da}$	EV stored energy for the day-ahead
Mob_t^{da}	EV mobility discharging variable for the day-ahead
Dis_t^{da}	Day-ahead stage driving distance
$u_t^{ev,da}$	EV discharging commitment binary variable for the day-ahead
$P_{t\omega\xi}^{wind,rt}$	Wind power generation in real-time
$P_{t\omega\xi}^{pv,rt}$	PV generation in real-time
$P_{t\omega\xi}^{b,dis,rt}$	Battery discharged power in real-time
$P_{t\omega\xi}^{ev,dis,rt}$	EV discharged power in real-time
$P_{t\omega\xi}^{b,ch,rt}$	Battery charged power in real-time
$P_{t\omega\xi}^{ev,ch,rt}$	EV charged power in real-time
$L_{t\omega\xi}^{sh,rt}$	Space heater load in real-time
$L_{t\omega\xi}^{swh,rt}$	Sstorage water heater load in real-time
$L_{t\omega\xi}^{mrs,rt}$	Must-run services load in real-time
$C_{t\omega\xi}^{b,rt}$	Battery stored energy in real-time
$u_{t\omega\xi}^{b,rt}$	Battery discharging commitment binary variable in real-time
$C_{t\omega\xi}^{ev,rt}$	EV stored energy in real-time
$u_{t\omega\xi}^{ev,rt}$	EV discharging commitment binary variable in real-time
$Mob_{t\omega\xi}^{rt}$	EV mobility discharging variable in real-time
$Dis_{t\omega\xi}^{rt}$	Driving distance in the real-time stage

$\theta^{in}_{t\omega\xi}$	Indoor temperature
$L^{wm,rt}_{t\omega\xi}$	Washing machine load in real-time
$L^{dm,rt}_{t\omega\xi}$	Dishwasher machine load in real-time
$L^{light,rt}_{t\omega\xi}$	Lighting system load in real-time
$L^{fridge,rt}_{t\omega\xi}$	Fridge load consumption in real-time
$L^{oth,rt}_{t\omega\xi}$	Other services load in real-time
I^{batt}	Battery's current
SOC	State of charge rate
$S\dot{O}C$	First derivative of SOC rate
P^{wind}_t	Wind power output from formulation
CF^{wind}_t	Wind capacity factor
P^{pv}_t	PV power output from formulation
CF^{pv}_t	PV capacity factor

Chapter 1

Introduction

The next chapter presents an overview of the developed work during this dissertation. Initially, in order to contextualize the chosen topic, a brief introduction will be carried out. Then, it will be presented the motivation that gave rise to the interest and development of this thesis, together with its objectives. Finally, the structure of this thesis and some relevant information will be presented.

1.1 Context

Smart home consumers' behaviour is being studied in the last years, aiming at optimal energy efficiency and consumption. Also, it has become more relevant to optimize residential electricity consumption in order to reduce costs. The concept of Smart Home emerges at this stage.

The Smart Home (SH) is defined in [1] as a technology where energy-consuming appliances and devices such as heating, ventilation and air conditioning (HVAC), dishwashers, washers and dryers, can be controlled and monitored in different areas by end-users, depending on the use of networks. SH can bring many advantages such as energy cost-saving and a better comfortable lifestyle.

Nowadays, Electricity Market (EM) has been much more competitive due to the integration of SH within Smart Grids (SG). Clients are capable of buying electricity from the grid when its price is worth it, for the consumer view. Therefore, it is important to create a module focused on the better matching of demand with supply. From the integration of SH with SG, there is also the concept of renewable energy sources, which helps in providing a better future environment and alternative options for energy production.

According to the U.S. Energy Information Administration's (EIA) Monthly Energy Review, U.S. annual renewable energy sources consumption exceeded coal consumption for the first time since before 1885, in 2019. An interesting curiosity that reflects the ongoing growth in renewable energy, mostly from wind and solar is graphically shown in figure 1.1.

With the advanced renewable energies usage, such as PV panels and wind micro-turbines, smart homes can also produce their energy to use, store or sell to the grid, making the client a producer beyond being a consumer.

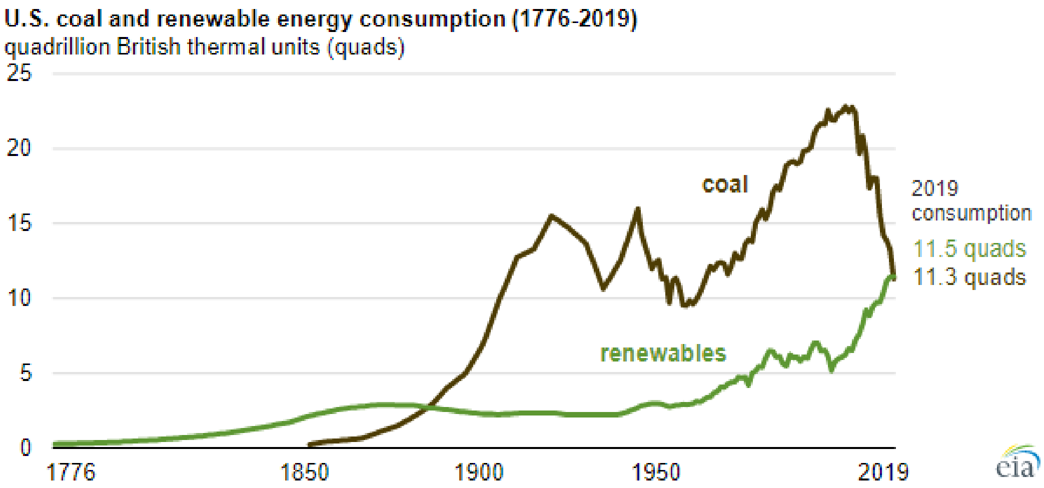


Figure 1.1: US coal and renewable energy consumption from 1776 to 2019 (Source: U.S. Energy Information Administration's [2])

Therefore, clients can role an important position in the local market. It is verified that the development of smart devices, systems for home energy management and storage (battery systems and EV), provided consumers to start taking relevant decisions on demand-side management.

The integration of EV and renewable sources are being encouraged by governmental associations, regarding an ecological future, such as incentives per renewable energy unit usage and lower costs on electric car charging stations.

The development of digital devices, like sensors, actuators, smartphones and smart devices that address the Internet of Things (IoT) concept has increased, since, through the Internet, the interconnection and communication between all devices is made possible [3].

Through advanced automation systems, residential customer has access to complete supervision and control of the house equipment. This leads to a bigger complexity on SH modules, forcing them to have integrated prediction mechanisms, decision making algorithms, wireless networking interfaces, amongst other features [4]. Basically, any device connected to the grid can be controlled by the user.

Some applications already developed are associated with lighting, home security, thermostat regulation, medical treatment and data processing. With the development of new sensing technologies, communication tools, IoT concepts and management optimization software, smart homes proved to be a profitable case study to be invested in.

Many studies have already shown multiple benefits of SH to both suppliers and costumers [5][6]; mainly, a SH can improve a consumer lifestyle in various ways. As already mentioned, SH aims to reduce energy costs and consumption, but also facilitates users' lifestyles, providing comfort and life quality. Furthermore, healthcare for individuals [7] and accurate market prices information can be provided [8].

Communication between supplier and consumer is very relevant to make suppliers and consumers' decision-making easier, giving real-time information about energy prices among different energy market mechanisms [3]. These facts help to evolve our current grid to a more efficient one, making it smarter than before.

To make this grid smarter it is relevant to have two-way communication between the local grid and consumer, for a possible exchange of information between these actors, beyond the energy transaction. From this perspective, demand-side management and demand response programs can be a great solution for many barriers.

Electricity consumption in the residential sector has the highest rates among other sectors [9] (industry, transport, services and others), especially nowadays, because of COVID-19 regulations, people spend more time at home.

It is fair enough to say that the residential sector plays a huge part in this rising electric energy consumption [9]. Thence, there is a need for new strategies to overcome this increasing electricity demand economically and ecologically.

Figure 1.2 illustrates the evolution of world electricity consumption by sector in past times until 2018, with a growth forecast for incoming years, mostly on residential, industrial and commercial sectors.

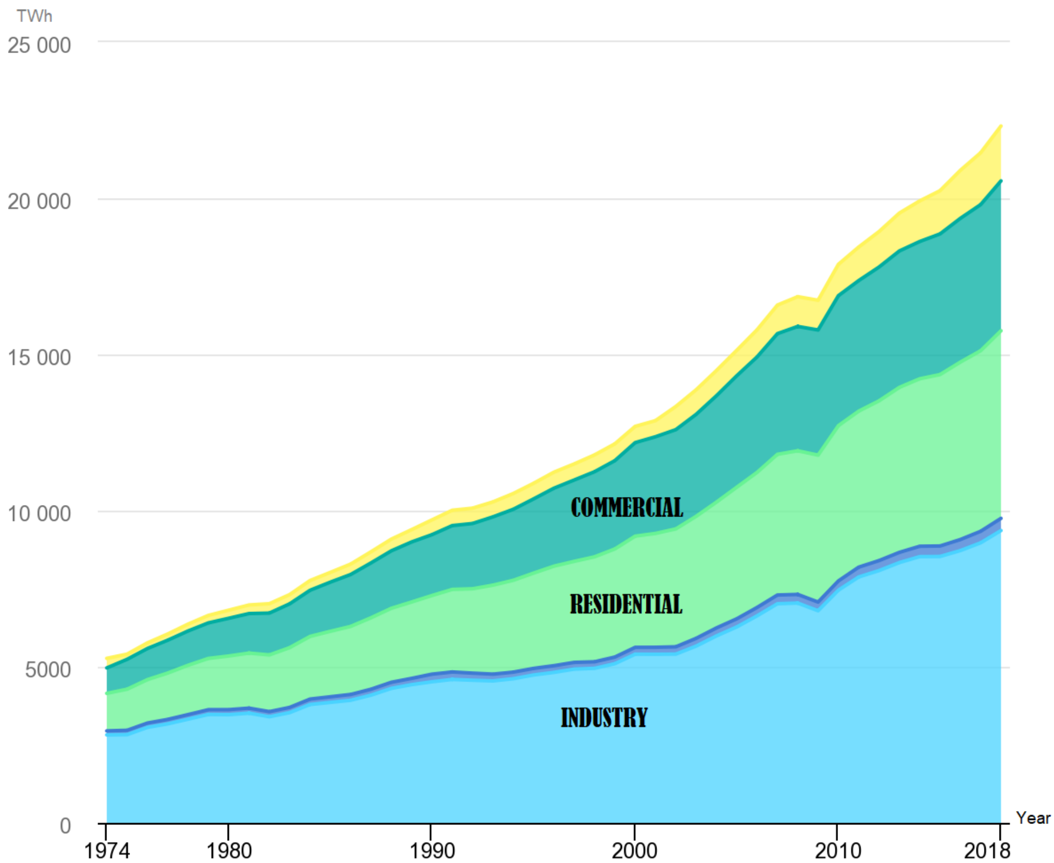


Figure 1.2: Electricity consumption by sector, worldwide, 1974-2018 (Adapted from [9])

Demand Response (DR) programs are becoming a relevant strategy to overcome high-peak demand periods, shifting energy consumption to low price hours [8]. Also, many studies point to residential consumers becoming more active participants in the local market because of the growth in the integration of DR programs and smart technologies.

Regarding residential energy management systems, renewable sources like wind and solar are predictably uncertain. Other roots of uncertainty are weather forecasting, deregulated energy market and client's behaviour/demand variations [10]. Dependency on technologies and electricity networks are some risks associated with SHs. Some other problems for SH systems are related to privacy and security policies as well as DR barriers that are being studied to compete against [3].

In light of this, stochastic and probabilistic programming is helping DR programs taking better predictions on these uncertain variables. However, it is important to mention that computational challenges increase with model complexity, in other words, the larger number of variables and equations, the more computational challenges we will have.

In [10], three types of solution approaches have been studied to control unit commitment considering a variety of uncertainties; one of the main ones is stochastic programming, a well-known solution for optimizing systems with unpredictable variables.

Smart homes aim at maximizing their profit from buying energy at a low price and selling surplus electricity to the local market. In this thesis, the optimal behaviour of smart homes in the electricity market will be investigated, improving SH performance in the EM considering client satisfaction and cost reduction with an improved demand management program [11].

1.2 Motivation and Goals

Despite the various benefits associated with renewable energies, this type of energy production presents some problems concerning its integration into the electricity market (EM). The biggest challenges are related to wind and solar energy production, due to its stochastic and unpredictable nature.

Consumers' behaviour is also unpredictable and the study of each type of consumer help to schedule and optimize the whole system. One step to helping answer these problems is by consumers actively participating in the system through DR programs, and, in this way, increase the flexibility of the system.

Nevertheless, to implement these types of solutions, some changes to the grid and home need to be fulfilled, in order to make them smart. Keeping this in mind, this thesis seeks to improve the performance of a smart home system, by increasing flexibility and model a system to decrease energy costs, taking for guarantee optimal consumer comfort.

The growth of renewable energies integration, and the rising model techniques for management of the energy demand side, allows a more sustainable environment and lower electricity prices for consumers. However, with the integration of uncertainty in the system, new and innovative modelling techniques are needed, which allow the model to optimize different conflicting objectives, operation costs and environmental restrictions.

The objectives defined for the project are based on three steps:

- The development and improvement of a source code to allow demand management of a Smart Home, including renewable energy generation, electric vehicle and other possible smart appliances;

- Specific case study analysis considering general public domain data such as client satisfaction, electricity tariffs and price variation;

- Validate and compare the developed model with different models presented in the literature review.

1.3 Structure

The structure of this thesis is divided into five chapters. Chapter 1 presents a general overview, where the context, motivation, goals, additional information regarding software and used tools are presented. Chapter 2 corresponds to a brief introduction in the literature review, in which the concepts of Electricity Market and Smart Home are introduced, following a keyword mindset.

Starting with Smart Grid and renewable energy concepts, with detail review on energy generation, where wind turbines and photovoltaic panels are reviewed; then, energy storage systems and their need, is studied, together with Electric Vehicles and their implementation results on Smart Homes. Also, a short brief about the Internet of Things concepts with communications and automation systems is reviewed and then, some stochastic and probabilistic programming is studied. Finally, some similar works related to this project are presented.

Chapter 3 is composed of the problem's mathematical formulation, including objective function, day-ahead and real-time stage constraints. Maximize the Expected Profit of the home energy management system is the objective of the model, regarding the constraints and limitations of the local grid and smart home system, with renewable energy sources, energy storage systems and smart appliances.

In Chapter 4, the case studies are presented, where each of the different case's results is studied. First, a brief review of the test system and data used for the study is presented. Furthermore, a comparative analysis between price tariffs and previous work is performed afterwards. Finally, some general conclusions future work proposals are presented in Chapter 5.

This project uses the notation and the abbreviations which are usually accepted by the scientific field. Also, figures, tables and mathematical information are numbered sequentially (y), related to the chapter (x), and restart their numbering when a new chapter starts, called, respectively, "Figure x.y", "Table x.y", "Equation (x.y)".

1.4 Information and used tools

To solve these problems the SH model was improved through the development and improvement of a source code proposed by authors in [11], using the program, General Algebraic Modeling System (GAMS), and the data specifications and results obtained were handled using Microsoft Excel.

The implementation was performed on a desktop with 16 GB RAM, AMD A10-7800 Radeon R7, 12 Compute Cores 4C+8G 3.50 GHz. Also, this thesis was written using the LaTeX document preparation system.

Chapter 2

Literature Review

In order to make the best decisions on the implementation of the proposed model in this thesis, it is required to acquire knowledge of its related concepts and technologies, as well as previous work and research. In this chapter, the goal is to describe with more detail some relevant information associated with the state of the art and theme's keywords.

2.1 Smart Grid

Our electric grid was created many years ago when electricity demand was much different from nowadays. The grid was built with a limited one-way interaction with power suppliers and consumers, which was causing trouble with the rising energy needs of the 21st century.

So, the smart grid presents a two-way connection, making able the exchange of both electricity and information between producers and end-users. Among many tools and smart technologies, this network of communications aims for making the grid more sustainable, more flexible, more efficient and more secure.

The Smart Grid (SG) is defined as an electrical grid that can supply the electricity in an intelligent and controlled way, from the place where it is produced to the customers. It uses communication technology to study suppliers and consumers' behaviour. With this, the use of a SG allows to improve efficiency, economic reliability and sustainability, and it allows the integration of renewable energy resources [12].

SG also allows the integration of bidirectional communication, where each customer has a smart meter that communicates with electricity companies and others consumers. In this way, customers can obtain information about the price of electricity and thus have the ability to control their consumption according to fluctuations of the electric market price [13].

Authors from [13] have divided SG into four groups as it's presented in figure 2.1. All these groups have bidirectional energy flow as it is highlighted with two arrows within the SG and each group.

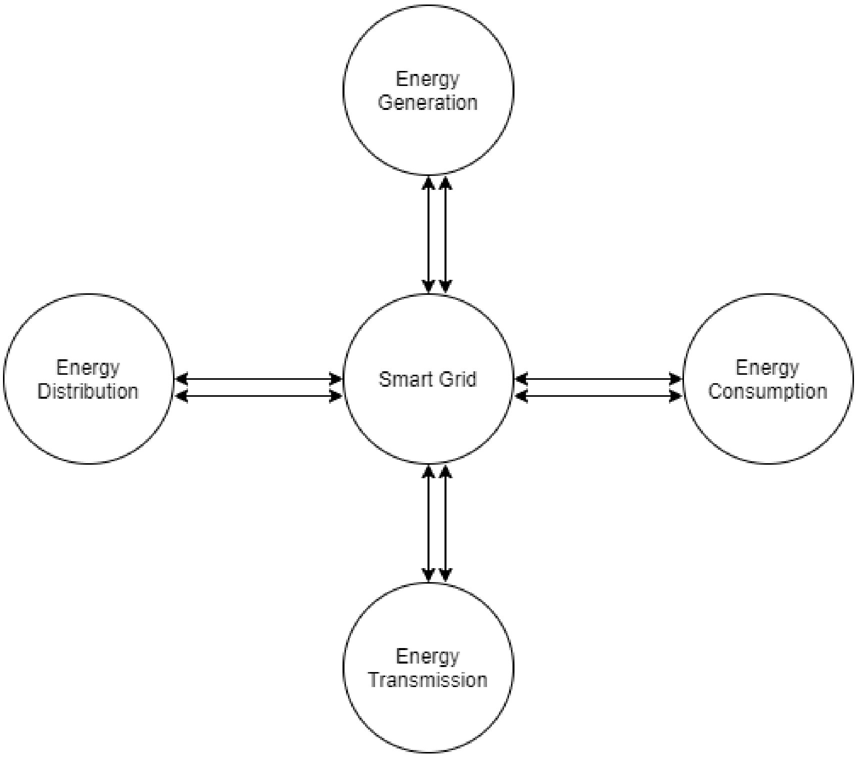


Figure 2.1: Smart Grid Structure Example

Energy Generation consists of all energy sources including (non-)renewable ones. Energy Distribution has transformers, smart meters and power controllers. Energy Transmission has all the mechanisms needed to make it possible to share energy with consumers, like power transformers, switches, capacitors and transmission lines. Energy Consumption consists of all types of loads that will consume energy from the grid, like houses, batteries, factories and electric vehicles.

Another aspect is the evolution of techniques and mechanisms on each group presented before. The advances in those areas have increased distributed generation utilization. In contrast, classical electrical distribution has always used a centralised distribution. Figure 2.2 shows a draw of these two types of energy generation and distribution.

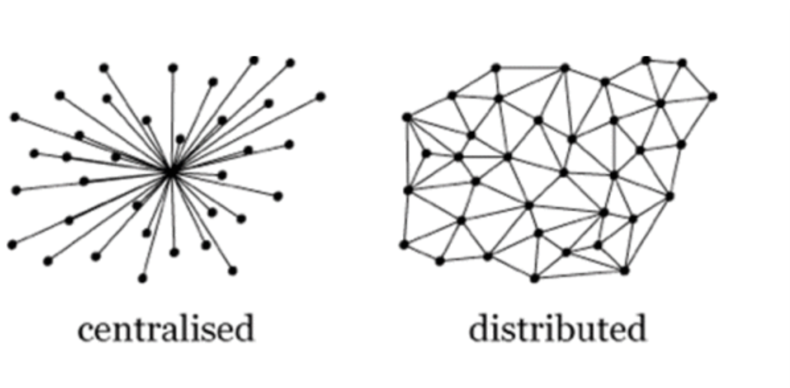


Figure 2.2: Types of Energy Generation

Table 2.1: Conventional and Smart Grid differences (Adapted from [15])

Conventional Grid	**Smart Grid**
Electromechanical	Digital
One way communication	Bi-directional communication
Centralised Distribution	Distributed Generation
Manual monitoring and restoration	Self monitoring and healing
	Lack of power quality

A large study around the benefits of converting the typical grid to a smart grid has already been made and it's possible to achieve some positive aspects, such as:

1. Providing enough energy for the raised demand;

2. Decreasing losses in transmission and distribution lines;

3. Enabling the integration of renewable energy sources to the system.

In short, a SG can bring many advantages to the whole energy grid system, making its power quality better, providing and supporting distributed generation systems with bidirectional energy and communication and making it much easier to maintain and operate due to remote measurement of automation and electrical meters [14]. In table 2.1, there is resumed some main features adapted from our conventional grid to create the smart grid.

2.2 Renewable energies

Fossil fuels are non-renewable energies very limited, having a higher cost. These energy sources play an important role in economics. However, to reduce greenhouse gas emissions and future environmental impact, renewable energy is increasingly being used.

This is a market that has evolved significantly and has great support from political and economic mechanisms. Also, due to the recent increase in energy demand, renewable energies give an alternative for energy production, allowing the reduction of production costs while using ecological ways. The authors from [16] define several positive impacts (socially, environmentally and economically) of integrating renewable energy sources with the grid system.

In terms of social impact, with the rising of energy sources, every person could have their energy source and, this way, use their source when there is any power failure within the grid, or even sell extra energy and decrease monthly costs of energy bills. Also, there are other social positive aspects, which provide health improvement, technological progress and consumer decision [17].

Integrated renewable energy plays a main role in environmental fields by creating alternative options for producing energy, decreasing the CO2 emissions from fossil fuel power generation plants.

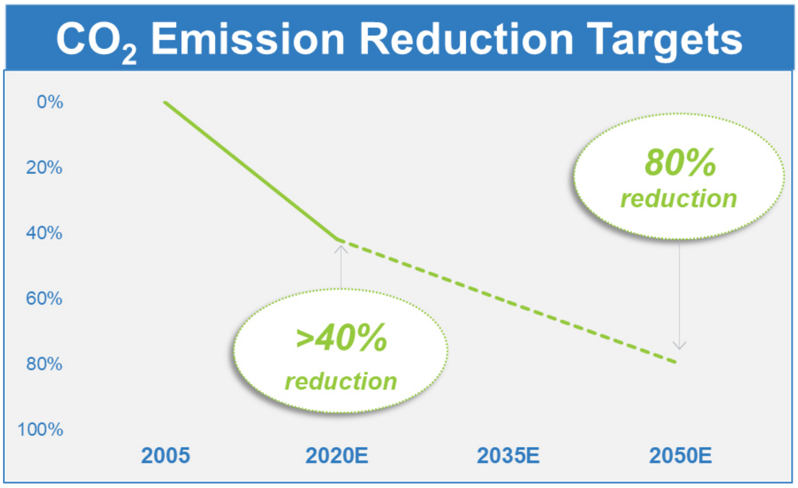


Figure 2.3: CO2 Emission Reduction Targets (Source: Business Wire [18])

According to Business Wire [18], Evergy, an energy producer company serving in Kansas and Missouri, announced that, by 2050, its carbon dioxide emissions would be lower by 80 percent, which is a commitment agreeing with the Paris Climate Accord. In light of this, by the end of this year, as predicted in figure 2.3, Evergy will already have accomplished an approximated 40 percent reduction in emissions.

Economically, renewable energy resources integrated into a grid system enables new job opportunities [19] and economic development. Besides, energy prices are lower for renewable energy [20].

In [21], it is shown a mechanism aimed at reducing SH electricity cost and maximizing renewable energy usage. This study presented positive results, but it was considered constant values of energy consumption of all appliances, thus, it isn't reliable for real application purposes.

However, there is a risk associated with the integration of renewable energies on the smart grid, such as frequency and voltage fluctuations and energy losses. Therefore, there are some technical implications and several challenges associated with the installation of renewable energy sources in distribution networks.

Renewable sources mainly depend on weather conditions and hence change their potential according to weather situations [22]. This fluctuation in voltage level deteriorates the system stability and control. As wind and solar resources are variable in nature, sometimes they generate more than sufficient required energy and sometimes are unable to produce enough energy to fulfil the demand; for example, solar energy can't be generated during the night.

Related to power generation, wind and solar generation forecasting are difficult, because of the variability and unpredictability of the weather. Also, with these restricted climate conditions to provide better efficiency of those renewable sources, make their location pretty relevant and, consequently, it will affect their costs [16].

To address these challenges, there are many solutions presented along with the literature, like more efficient predictive algorithms for wind and solar, an improvement on energy storage and energy management, through demand response the renewable energy integration can help load shifting and balancing [23].

2.2.1 Wind Turbines

When the sun warms the Earth's surface, the air in contact with it also warms and rises. This movement initiated it's called wind. The wind can be used to rotate the blades of a turbine, which, connected to an electromagnetic generator, produce electricity.

The larger the turbine dimension and the intensity of the wind, the more electricity is produced. The small turbines, with three to ten meters of rotation diameter, can feed generators up to one hundred kW of power. They are designed to inject electricity into a home or network in an isolated community.

Wind energy is a very profitable alternative to fossil energy sources; it is renewable and thus, helps in the reduction of greenhouse gases emissions. The authors from [24] concluded that electricity produced by wind is barely cheaper compared to other renewable sources. Furthermore, there are represented in table 2.2 some advantages and disadvantages of wind energy generation.

There are two main types of wind energy generation that can be integrated with homes: horizontal and vertical wind microturbines. The main difference is, horizontal turbines are only capable of generating energy from wind from one direction, while vertical wind turbines can receive wind from all directions and, possibly, generate more energy [26]. In terms of a market survey of wind turbines, figure 2.4 shows one example of each type of wind micro turbine available to purchase.

The power generated by horizontal wind turbines is related to the area of the rotor, thence, it will provide more power with larger blade diameters. Still, blades' size is limited due to their needed resistance to wind forces. On the other hand, vertical wind turbines power generation is related to the rotor's height and radius, consequently, a larger height and a larger radius provide more power [29].

Table 2.2: Characteristics of Wind Energy Generation (Adapted from [25])

Advantages	**Disadvantages**
Design and install time are low	Wind variation is high
Emissions are low	Limited resource sites
Different modular size	Audible and visual noise
	Low generation during peak-load demand periods
	Low safety for birds

(a) Horizontal wind micro turbine

(b) Vertical wind micro turbine

Figure 2.4: Wind micro turbine examples (Sources: [27] [28])

Furthermore, equation 2.1 presents the wind power output (P_t^{wind}) formulation, where I^{wind} is the wind power plant installed capacity, and CF^{wind} is the capacity factor of the wind, which is related to the average wind speed per time period and depends on the area swept by micro turbine's blades [30].

$$P_t^{wind} = I^{wind}\, CF_t^{wind} \tag{2.1}$$

In addition to power generation, results from simulations on [29] state that the average maximum power of the horizontal wind turbine is greater than in the vertical one. Increasing the number of blades make the maximum power generated increase, only in vertical ones.

Recently, many researchers have studied bladeless wind turbines, this is a new concept to generate power using wind without blades. It has a simple design, various operation speeds, low cost, it's safer for birds and the environment, providing less audible and visual noise. The power generated is low compared to the main wind turbine types, nonetheless, it's a concept already proven that outputs power [31] [32].

2.2.2 Photovoltaic Panels

Photovoltaic (PV) solar panels are made up of photovoltaic cells, which can be used in spaceships, buildings, power plants in autonomous systems and gadgets such as portable calculators. The cells are made of semiconductor materials. Solar panels are used for converting solar energy into electricity.

Moreover, in equation 2.2 it is presented the formula for PV power output (P_t^{pv}), where I^{pv} is the PV power plant installed capacity, and CF^{pv} is the PV's capacity factor, which is related to the average global horizontal irradiance per time period and depends on the area swept by the panels [30].

$$P_t^{pv} = I^{pv}\, CF_t^{pv} \tag{2.2}$$

PV panels can be installed on the floor, on the roof, on the walls, on specific fixed structures or even floating on water surfaces. The assembly can also be using a solar tracker to track the movement of the sun because solar panels can reach greater performances when the sunlight is perpendicular to the panels surface. Thus, sometimes, even self-consumption and centralized production of energy to the grid are the goals of these PV systems.

A weakness of solar PV systems is their efficiency, which is very low. Moreover, only 30-40% of the solar energy is converted into electricity by the PV system. For a high performance of the panels, it is needed a system capable of adjusting panels orientation towards the sun. Keeping this in mind, there are two types of solar energy orientation systems [29]:

1. Single-axis orientation - placed on north to the south axis will orient the sun from east to west, simply structured with an efficiency coefficient of 34 % and lower costs (maintenance, installation);

2. Dual-axis orientation - will orient the sun from east to west and north to south, complexity structured with an efficiency coefficient of 37 %.

There may also be hybrid thermal photovoltaic solar collectors that simultaneously convert solar radiation into thermal and electrical energy. Some PV systems use mirrors to focus sunlight on small solar cells, thereby achieving superior photovoltaic power. Some advantages and disadvantages of PV generation are shown in table 2.3.

In [33], reflectors and solar tracking are used in order to analyse and improve the performance of a solar PV system. The authors concluded that the energy provided by the solar PV panel with tracking, during certain hours, is stable and maximum when comparing with the PV without tracking. They also concluded that using a plane mirror reflector results in better performance, at certain hours.

Despite the fact rooftop PVs are becoming more popular, mainly due to the increase of electricity prices and environmental discussions, one of the main challenges of integrating them is related to voltage fluctuation and profile. Smart grid infrastructure needs to improve and become ready to support high penetrations of distributed generations [34].

Furthermore, it is found that demand-side management takes an important role in smoothing load profile, reducing voltage fluctuations and mitigating power flow problems caused by PV [35]. In this way, renewable generation consumption is encouraged.

Table 2.3: Characteristics of Photovoltaic Energy Generation (Adapted from [25])

Advantages	**Disadvantages**
Size and site are very flexible	High costs
Simple operation	Large area required
Neither audible nor visual noise	Low efficiency
Low maintenance	Low availability during high demand periods
Design and install time are low	Low capacity factor
No emissions	

In short, both wind and solar energy generation have low availability during high demand periods, which is a problem. Also, these energy resources, when integrated as distributed generation, leads to uncontrollable output power due to the injected power by these technologies being fluctuating [36]. Thence, energy storage systems can be used as distributed energy storage to smooth out the fluctuating production of electricity and to improve the stability of the power system.

2.3 Energy Storage Systems

Distributed Generation offers the possibility of load reduction, which is a benefit to the EM. Generally, electric producers can use distributed generation for peak load reductions, to provide reactive power support and to improve its quality. Lin [37] shows an example of the reduced load in the EM because of distributed generation.

Despite all the advantages related to distributed generation, integrating PV and wind energy into the local electrical systems leads to some drawbacks as already seen in the previous section. One of the most appropriate solutions for this problem is Energy Storage System (ESS), enabling better power system management.

Nowadays, energy storage technologies are used to capture the energy and store it for later use, there are some technologies already considered in previous works, like batteries and pumped-storage hydropower. According to data from the U.S. EIA, in 2019, both technologies operated with high-efficiency percentages, as shown in figure 2.5, obtaining fewer losses in the storage process.

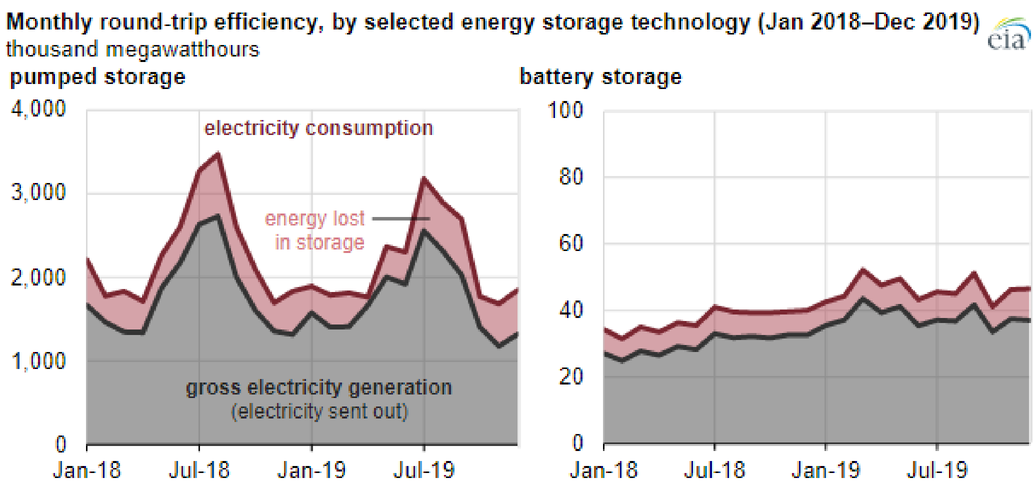


Figure 2.5: Monthly round-trip efficiency by selected energy storage technology (Source: U.S. Energy Information Administration's [38])

Table 2.4: Characterization of each battery type

Battery Types	**Characteristics**					
	Cell voltage (V)	Lifetime (years)	Energy (Wh/Kg)	Efficiency	Overload tolerance	Cost
Pb-Ac	2	5-15	30 - 40	50% - 92%	-	Low
Ni-Cd	1.2	10-20	40 - 60	70% - 90%	Very good	High
Ni-MH	1.2	10-15	30 - 80	66%	Good	High
Li-Ion	3.3	2-7	130 - 200	90% - 95%	Very bad	High

The author from [38] also highlights that batteries have become the second-largest source of electricity storage due to the rapid growth of utility-scale battery capacity while battery costs have decreased.

In [36], ESS operation is categorized in two modes: charging mode and discharging mode. During off-peak intervals, ESS is in the charging mode and absorbs the power surplus in the system. At peak load, the system is in the discharging mode and generates energy to make up for the lack of power in the system. Normally, electrical energy has a higher price during this period.

References [39]-[40] propose optimal control strategies of battery energy storage systems, for peak load shifting and peak load shaving applications on power systems, respectively. In [40] the charging schedule developed optimizes the energy costs while satisfying battery physical constraints.

Batteries can work both as a generator or load. Other technologies for the energy storage paradigm besides batteries are presented in [36]. It is important to have criteria in the energy storage system selection, taking into account its lifetime, response time, application, size and costs.

According to [41], the most common battery types used for renewable energy and energy management applications are Lithium-Ion (Li-Ion), Nickel-Metal Hydride (Ni-MH), Sodium Sulfide (Na-S), Nickel-Cadmium (Ni-Cd) and Lead-Acid (Pb-Ac). Table 2.4 displays a brief characterization of each battery type mentioned, adapted from [41].

In light of this, battery systems should be designed and implemented regarding the capacity needed, the physical area available and the cost. Observing the different benefits and disadvantages for all types, the best for a wide range of applications is the Li-Ion, due to the high power density, lifetime, high voltage per cell. Weaknesses of this type are its charging system and its cost.

To improve the energy storage system's performance and lifetime, specific requirements should be studied, such as charging or discharging control, thermal management, battery protection and state of charge control [42].

State of Charge (SOC) refers to the level of an electric battery relative to its total capacity, it's a very important variable to be balanced within all units of ESS. According to [43], energy storage systems configuration can be divided into three types:

- Parallel - used for decentralized or distributed control, SOC information is acquired to change frequency reference;
- Cascade - dependent on a centralized controller and adopted to acquire high voltage level;
- Hybrid - use a mix of parallel and cascade connections, authors from [43] developed a SOC balancing method for this type of ESS.

The battery's SOC value is based on load changes taking into account the current flow of the battery cell, either if it is charging or discharging. It was estimated using the Coulomb counting method [44], which is presented in equations 2.3 and 2.4. It should be notice that SOC modelling depends on the specific battery which is being studied.

$$SOC = SOC_{initial} - \frac{1}{C_{cap}} \int_0^t \eta \ I^{batt} \, dt \tag{2.3}$$

$$S\dot{O}C = -\frac{\eta \ I^{batt}}{C_{cap}} \tag{2.4}$$

With η representing the coulombic coefficient, which is a constant value defining charging and discharging of the battery. $SOC_{initial}$ is the initial value of SOC just before the current (I^{batt}) flow into or from the battery cell, and C_{cap} is the maximum battery capacity to store current.

In this perspective, energy storage management systems can provide better system flexibility due to their potential of smoothing out the fluctuating output of renewable energy generators [45]. These systems also allow customers to reduce the cost of energy purchased from the grid since it is loaded during low peak periods and discharged during high peak periods.

In its background, this type of storage system needs complex decision making management to optimize it. Also, different batteries have different limitations on the rate at which they can be charged due to their chemistry and structure conditions. Those limitations have to be considered in the developed ESS. The use of electric vehicles or hybrids may be one of the main contributions to increase storage capacity.

As renewable energy sources are rapidly increasing, more non-renewable energy sources are being replaced. Traditional gasoline-based vehicles tend to be replaced by electric vehicles. The use of Electric Vehicles (EVs) has been increasing and more companies besides Tesla and BMW, are becoming interested in this market, as their qualities are surpassing internal combustion engine vehicles.

EVs are considered to be the future of transportation due to their efficiency, reduced costs (producing and supplying electricity has fewer costs than gasoline) and fewer carbon emissions. However, they have a limited driving range (theoretically, near 300 km on a single charge) because the current charging infrastructure still isn't capable of overcoming this problem [46].

A detailed review of available methods to improve the driving range is presented in [47]. Driving range can be increased by using advanced techniques and materials to improve converter and motor efficiency, using good driving practices and the highest impact on the effective driving range is related to the improvement in the storage capacity.

Nowadays, there are quite a few charging stations, making the EVs market less convenient and reliable for the consumer view. Furthermore, the time taken to recharge an EV (1-2hours), is much longer, compared to refuelling a gasoline-based vehicle.

In terms of a Smart Home, electric vehicles have decentralized and autonomous decisions in energy management and they can be seen as a load. They also can help to balance supply and demand by valley filling and peak shaving by actively participating in transactions with the local market [48].

Vehicle to Grid (V2G) systems are characterized by their bidirectional communication, in other words, an electric vehicle can be connected to the grid and its battery is charging up or it may be also used as a buffer to other smart homes appliances or renewable energy sources. By storing energy produced during low demand periods and selling it to the grid during high demand periods [49].

Regarding all of this, the implementation of EVs in a SH is not so simple, due to their charging unpredictability including start time, stay duration, and energy demand. Prediction models and probabilistic methods are being studied by many researchers to solve this problem.

In short, the integration of electric vehicles on a distribution network allows energy demand and supply stabilization, as well as the use of V2G systems, provides a better transition to a smart grid. Hence, with the integration of Internet of Things technologies into the vehicle, with more sensors on the vehicle operation, the chances of errors are much less, the efficiency of the vehicle can be improved and consequently, it will improve the driving range further [47].

2.4 Communications and Automation

2.4.1 Communication Systems

The rise of the Internet of Things (IoT) and its potential abilities brought answers to some questions on the Smart Home paradigm. Considering the evolution of smart devices and wireless communications, IoT concepts emerge when it is needed to interconnect all these devices in order to achieve a respective objective.

In this field, remote control and remote monitoring systems are two relevant topics in order to provide a more safe and secure work environment aiming at earlier fault detection, health risk assessment, energy management, among others [50] [51]. Lighting and small-scale appliances from home, electronic equipment, real-time audio and video monitoring are some examples of devices that can be integrated with a smart home.

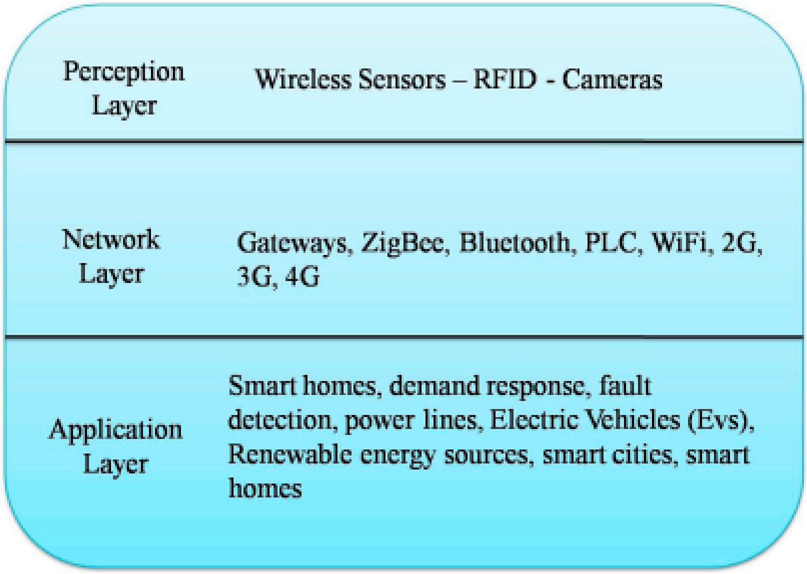


Figure 2.6: Internet of Things layers (Adapted from [3])

According to [3], the main IoT applications on smart homes are demand response, temperature monitoring, fire detection, the social network supporting and security systems. The sensors of these appliances take care of the supervision of home conditions and environment, which enables the end-user to control the home, even from outside thanks to the connection of smart devices to the Internet.

As it shows in figure 2.6, IoT comprises three layers. The perception layer includes all smart meters and sensors, Radio Frequency Identification Devices (RFID), cameras and all devices capable of detecting or gather information within the Internet communication networks.

The network layer has the function of sending data from the perception layer to the application layer, under all devices, network and applications' constraints. The application layer includes demand response management, power line communication network, renewable energy sources management, EV charging schedule.

IoT systems use, for short-range networks, communication technologies such as Bluetooth and ZigBee which are used to send the information from the top layer to the bottom; for long-distance networks, Internet technologies such as Wi-Fi, 3G, 4G and PLC can trade the information between layers.

A SH with smart lighting, heating and air conditioning systems, smart entertainment audio and video systems and security camera systems, all components interconnected to share the data with each other; and also able to be controlled and monitored remotely, provides SH users energy efficiency, more security and comfort, and better quality of life [52].

Thus, a SH might have intelligent and automated systems which extend home control levels, such as automatic doors with smart locks, smart light control system with object motion sensors, remote mobile control, automated temperature setting, notification system and appliances scheduling, providing benefits in energy efficiency and home security [53].

The use of cloud computing brings a platform for data storage and processing [54]. Access to the information to each home energy management system's component is ensured by IoT devices and the integration of different techniques allows the data storage and processing to happen locally, avoiding excessive data traded to the cloud, providing a solution to the big data problem.

2.4.2 Automation Systems

Smart Home automation technology in the past few years has shown an impressive increase in development. These days, world researchers are also working on integrating smart technology in home automation to make devices more intelligent.

Home automation systems are integrated with multiple devices, such as sensors to measure relevant information data, controllers, actuators, communication buses and interfaces. More recent automation systems are already integrating advanced communication platforms in terms of Wi-Fi and IoT.

With smart home automation technology, everything can be controlled remotely, all the commands can be given via smartphones and, this way, providing comfort to the users [54]. Also, to manage all kinds of facilities needed in a modern home, it is necessary a home automation system [55]. Hereafter, it is presented in table 2.5, some advantages and disadvantages of home automation systems, with a more detailed explanation below.

These automation technologies also give users a guarantee of security and energy-saving, providing real-time cameras access via the Internet and automatically switching off appliances that are wasting energy. The development of smart meters also took a huge step in improving comfort and energy costs reduction for the users.

However, behind these highlights from automation systems, there is a pretty complex coding and circuits integration, as well as high equipment's costs, are some issues behind home automation implementation.

According to [56], these are the four main problems that can create difficulties in network operation and control: voltage control, load flows, network security and fault levels.

In short, a home energy management system include sensors, smart meters, communication infrastructure and smart controllers with the respective analyses of data. These components associate control, monitoring, management, and fault detection functions for energy systems, enabling consumers to control and schedule appliances.

Table 2.5: Home Automation systems advantages and disadvantages

Advantages	**Disadvantages**
User comfort	Architecture complexity
Security	Equipment's costs
Cost effectiveness	Inflexible interface
Flexible control	Equipment's damage

2.4.2.1 Smart Metering

Smart Homes can record the consumption of different electrical appliances during the day by use of a smart meter. Smart meters proved to be an efficient technological device due to their capability of storing information data about all sensors available inside the house such as cameras and light and temperature sensors. Some of the advantages related to data obtained from smart meters are [15]:

- More accurate information about power consumption and energy costs;
- Improved client safety and risk reduction;
- Relevant data for the development of efficient grid systems.

With this in mind, smart meters are an important development for home energy management system, because it provides reliable and real-time information of loads, making it easy for the system to ensure consumer's comfort and security, to extend equipment's lifespan and provide energy savings.

2.4.2.2 Load Management

Every appliance can be set as a load and has different types of operation which can be divided into critical loads and controllable loads, illustrated in table 2.6.

The controllable loads are, for instance, HVAC, water heating, dishwashers, dryers and EV, and can be divided into thermostatically controlled (a set temperature needs to be chosen) and non-thermostatically controlled. Critical loads are lighting, refrigeration and freezing. [1].

Authors from [58] classify electrical loads into shiftable and/or controllable, or even must-run services. Shiftable loads are all appliances that may change their consumption during the time but are uninterruptible, controllable loads are the units that can control their power consumption in time.

Thus, consumer loads are required to be reduced or shifted in order to achieve better energy efficiency and less costs. Furthermore, load scheduling techniques are used to find the best operational timings for each appliance, considering peak demand times and user preferences.

Table 2.6: Residential load types (Adapted from [57])

Controllable loads		**Critical loads**
Thermostatically controlled	Non-thermostatically controlled	
HVAC's	Dish washers/washers	Lighting equipment
Water heating	Dryers	Refrigeration
	Plug-in hybrid electric vehicle	Freezing

There is some uncertainty regarding the predictions for load scheduling, in this way, several optimization techniques are used in the literature to find an optimal load scheduling. Mathematical optimization techniques based on constraints have been used for the scheduling of appliances. When it involves a large number of constraints and variables, they are computationally expensive, though.

Linear programming models constraints between variables as linear functions to maximize or minimize a certain objective. Similar to this technique is the Mixed Integer Linear Programming (MILP) approach, however, it mixes integer and binary variables within the constraints [54].

To fight the computational problem, heuristic approaches are used, which uses high-level criteria to select a subgroup of better candidates within a search space that is likely to contain the optimal solution. Some examples are genetic programming and particle swarm optimization.

Other load scheduling techniques are based on a rule system, such as fuzzy logic controller and game theory methods; also, machine learning and artificial intelligence modelling techniques are used to create complex models for forecasting to maximize an objective function through trial and error.

2.5 Demand Response

DR programs allow the consumer to play a pertinent role in terms of fluctuations in the electricity price at different times of day, encouraging variations in the pattern of consumer's daily consumption. Customers change their consumption of electricity, both due to the increase in the price of electricity and when the reliability of the grid is called into question. They also allow end-users to reduce electricity consumption when its price is high and also allow them to schedule appliances in their homes in order to achieve energy efficiency.

In an electricity market, a DR program can help producers minimizing risk by sending incentives to the end-users for changing their demand. Real-time prices will make end users behave economically, in comparison to fixed tariffs [59]. DR is divided into two groups, namely price-based programs (PBDR) and programs incentive-based (IBDR), both presented in figure 2.7.

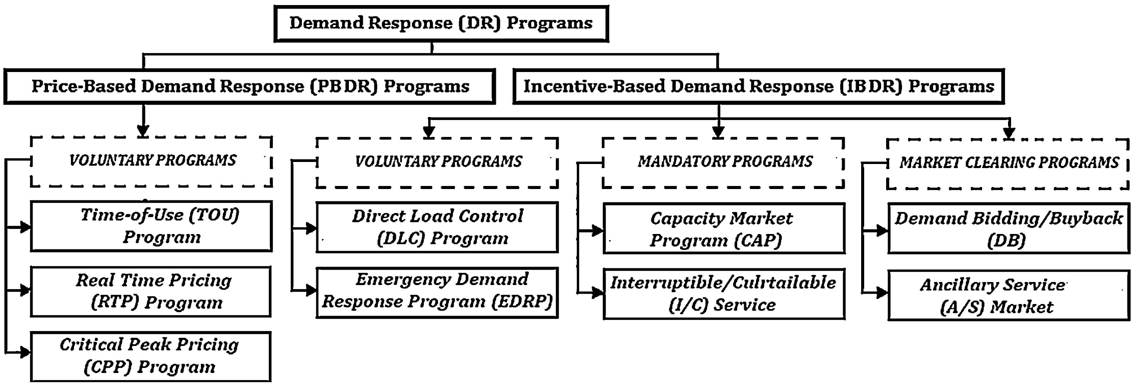


Figure 2.7: Demand Response programs (Adapted from [60])

PBDR are all programs that allow customers to change or reduce electricity consumption concerning the electricity price changes. So, if the difference in electricity price at certain times of day is relevant, customers can adjust their loads for periods where the tariff is lower. These include several programs such as [60]:

- Time-of-use (TOU) Program - daily rates that are differentiated both during peak and off-peak periods, prices are higher when energy consumption is high, and lower outside peak load;

- Real-Time Pricing (RTP) Program - interconnected with the market price, having variations during the day according to different tariffs in real-time;

- Critical Peak Pricing (CPP) Program - corresponds to a fusion of TOU tariffs or fixed prices, it is used when the reliability of the power system is compromised and it uses real-time pricing when the peak load is high.

Incentive-based demand response programs induce consumers to modify their demand in exchange for a specific incentive. These are classified as voluntary, mandatory and market clearing programs. Voluntary programs are divided into two different programs:

- Direct Load Control (DLC) Program - direct charge control program, implemented in a short period of time, where the system operator disconnects the customer's electrical equipment with short notice, in exchange for a payment or incentive;

- Emergency Demand Response Program (EDRP) - provides its end users with incentives to reduce their loads during certain events.

2.6 Stochastic and Probabilistic module

Due to the uncertainty associated with renewable energy sources and load variations on the demand side, stochastic optimization programming modelling has started to been integrated into Smart Home environments.

The two-stage stochastic programming is a well-known proposal to model uncertainty problems, amongst researchers. The uncertainty associated with wind power as well as EV mobility justifies the stochastic programming problem structuring into two stages.

However, the complexity of the optimization problem can increase if it includes a large number of scenarios. Thus, the use of algorithms that provide the reduction of scenarios is really important because of the reduced number of variables and equations, allowing solutions to be reached with greater efficiency [61].

In [11], a two-stage stochastic model is presented for the home energy management problem. In the first stage, the problem of the day-ahead transaction between the home energy management system and the local market is defined. In the second stage, real-time energy transactions problem with both energy management system and local market is modelled, considering both wind power generation and EV mobility uncertainties.

As it can be seen in figure 2.8, the model presented work to achieve optimal energy consumption generation and also load consumption, while controlling transactions with the local electricity market.

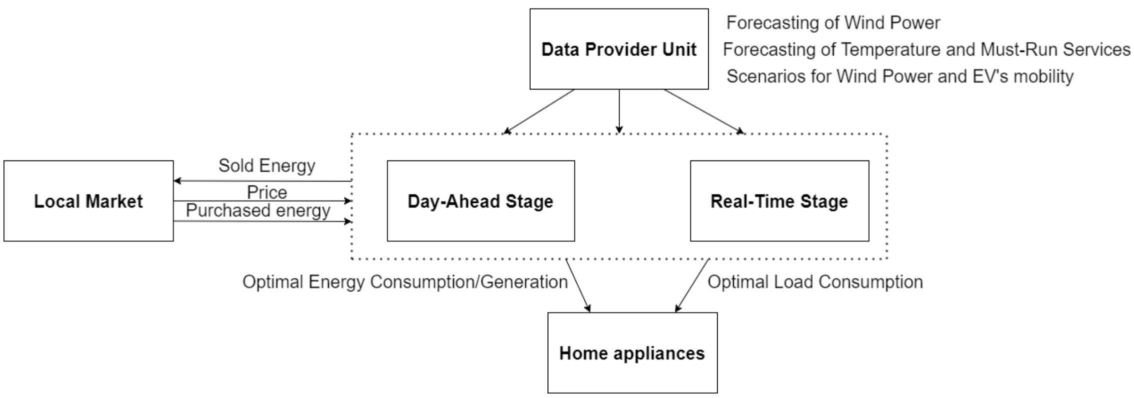


Figure 2.8: Physical features of home energy management system in [11]

2.7 Related work

In this chapter, it is presented some previous work already investigated within the thesis' theme. New specific control strategies and optimized models for managing energy service of home energy management systems were deeply developed in the last years since many home appliances induce power consumption variations during their operational cycle.

For instance, different control approaches to optimize energy flow management in a smart home were studied in [62]. A MILP approach was carried to solve the optimization problem between binary variables for representing as ON/OFF status of critical loads or continuous variables, mainly used to model energy storage systems.

Generally, MILP is efficient in terms of the objective function (minimizing total energy cost for the consumer view), however, it requires higher computational time than other control approaches, due to the typically large number of variables and constraints in the system model.

The problem of scheduling of different SH appliances' operation is also formulated in [63], where is proposed a solution to minimize electricity cost and the maximum peak-load. Based on the MILP technique and given a load demand profile, SH appliances, such as dishwasher, clothes washer and dryer, refrigerator, air-conditioner, oven and EV, were scheduled for minimizing cost.

It was proven the effectiveness of the proposed solution regarding the objective functions. Furthermore, it was added a PV panel into the model and it showed that also provided profit to the consumer, lowering electricity bills by using energy from the PV or selling it to the grid.

In [64], an optimal home energy management system also with appliance operational dependencies is proposed. It considers both real-time pricing and demand charge tariff, and each appliance operational constraint is defined taking into concern the consumer's lifestyle. In fact, demand charge tariff has become, recently, a new type of tariff for residential customers, which is defined as a one-off tariff based on the maximum demand recorded during a month.

Therefore, this paper shows that this tariff creates a relevant impact on the system and it should be considered in this type of system. Numerical studies also illustrate that appliance operational management is relevant to secure better user-oriented home energy management systems.

In addition to providing a high level of comfort to end-users, residential energy management systems should handle the practical difficulties of uncertainty and limitations. To this end, a two-stage model considering the uncertainties of residential load and small-scale renewable energy generation is proposed in [65], with the purpose of day-ahead and real-time energy management and regulation.

Based on forecasted values of uncertain parameters, the authors proposed an optimal scheduling solution for the day-ahead stage. An adaptive neuro-fuzzy inference system is used on the real-time stage to regulate errors between real values and forecasted ones.

The proposed model showed that, for real-time management, the algorithm can optimize the control of the output power of the battery and controllable loads in comparison with ideal results. However, the model does not have complete success and requires special strategies to improve its rate.

Another control strategy for home energy management systems is used in [66], which is a stochastic model predictive control strategy designed for a smart residential building. This article aims for the reduction of electricity cost and EV's battery degradation cost and the predictive home energy management system ensures that all constraints regarding PV system, EV system, consumer's comfort and load demand.

Additionally, the stochastic model predictive control minimizes the error between forecasted and real data, hence, it provides the home energy management system with more reliable value and closer to real data. The results of the model system proposed showed that the system managed to reduce electricity costs.

As already described, various studies have been concerned with energy management systems and optimization algorithms for energy cost and peak-load reduction. None of the papers gives a relevant study on the utilization of electricity bought from the LM and the electricity sold back to the grid.

In [67], it is proposed a new structure with small-scale renewable energy sources and energy storage systems where is taken into account the use of the grid's electricity and the electricity selling. Particle swarm optimization is used to optimize mathematical formulas for energy cost and peak ratio.

In comparison to previous work on this topic, the home energy management system developed by the authors achieved the goal of energy cost reduction. Still, it is important to comment that in this paper user comforts, such as thermal comfort and load schedule, are not considered within the problem's constraints.

Chapter 3

Mathematical Formulation

3.1 Objective Function

The objective function of the model developed is to maximize the Expected Profit (EP) of the home energy management system related to day-ahead and real-time local markets. This system is capable of buying and selling energy to and from the LM and it is divided into two stages, according to with [11], which are presented in equation 3.1.

$$
\begin{aligned}
Maximize\ EP = \sum_{t} \lambda_t^{da} P_t^{net,da} + \\
+ \sum_{\omega} \pi_\omega \sum_{\xi} \pi_\xi \sum_{t} [\lambda_t^{sold,rt} P_{t\omega\xi}^{sold,rt} - \lambda_t^{pur,rt} P_{t\omega\xi}^{pur,rt} - V^S S_{t\omega\xi} - VOLL^{sh} L_{t\omega\xi}^{shed,sh} - VOLL^{swh} L_{t\omega\xi}^{shed,swh}]
\end{aligned}
\tag{3.1}
$$

First-line refers to the EP based on energy transactions with the day-ahead LM, depending on the day-ahead price tariff (λ_t^{da}) and the day-ahead transacted energy ($P_t^{net,da}$), which is positive when there is energy sold by SH to the LM, and negative when it buys from the LM.

Furthermore, the second part denotes the EP based on energy transactions in real time, that includes energy revenue and cost ($\lambda_t^{sold,rt} P_{t\omega\xi}^{sold,rt} - \lambda_t^{pur,rt} P_{t\omega\xi}^{pur,rt}$), wind and PV systems cost from losses ($V^S S_{t\omega\xi}$) and value of lost load of the space heater ($VOLL^{sh} L_{t\omega\xi}^{shed,sh}$) and the storage water heater ($VOLL^{swh} L_{t\omega\xi}^{shed,swh}$).

The following sections describe the corresponding constraints of each SH component for the two stages studied.

3.2 Day-Ahead Stage Constraints

Here, the day-ahead stage constraints are specified without considering the wind power and PV generation uncertainty. Equation 3.2 defines the day-ahead power balance equation, depending on the following variables (note that every variable presented below stands for the day-ahead stage):

- Wind micro-turbine power generated ($P_t^{wind,da}$);
- Power output generated by PV system ($P_t^{pv,da}$);
- Discharged and charged power of the battery ($P_t^{b,dis,da}$ and $P_t^{b,ch,da}$, respectively);
- Discharged and charged power of the EV ($P_t^{ev,dis,da}$ and $P_t^{ev,ch,da}$, respectively);
- Energy transacted with the LM ($P_t^{net,da}$);
- Point forecasting of loads ($L_t^{sh,pred,da} + L_t^{swh,pred,da} + L_t^{mrs,pred,da}$).

$$\begin{aligned} P_t^{wind,da} + P_t^{pv,da} + \gamma_b P_t^{b,dis,da} + \gamma_{ev} P_t^{ev,dis,da} = \\ = L_t^{sh,pred,da} + L_t^{swh,pred,da} + L_t^{mrs,pred,da} + \gamma_b P_t^{b,ch,da} + \gamma_{ev} P_t^{ev,ch,da} + P_t^{net,da} \end{aligned} \tag{3.2}$$

As seen in equation 3.2, obtained from [11], γ_b and γ_{ev} are parameters to define home energy management system flexibility, that can take values between 0 and 1, representing if ESS is being used one or both stages. For example, if γ_{ev} is null, the home energy management system only utilizes the EV system for the real-time stage; however if the γ_b equals one, it utilizes the batteries in the day-ahead stage.

The limitation of the end-user distribution line is defined in equation 3.3. Here, f_{max} represents the maximum power capacity of the distribution line, securing that the energy transacted will not surpass this value.

$$-f_{max} \leq P_t^{net,da} \leq f_{max} \tag{3.3}$$

The power generation from the wind micro-turbine and the PV system equals wind and solar point forecasting in the day-ahead stage and it is represented in equations 3.4 and 3.5.

$$P_t^{wind,da} = P_t^{wind,pred} \tag{3.4}$$

$$P_t^{pv,da} = P_t^{pv,pred} \tag{3.5}$$

3.2.1 Battery System

Next, equations 3.6-3.9 represent day-ahead constraints regarding the battery system [11]. In equation 3.6 is stated a sequence to calculate the day-ahead stored energy in the battery ($C_t^{b,da}$), the initial value of available energy in the battery is C_i^b; η_{H2B} and η_{B2H} are battery efficiency coefficients, where it is used the same values for different flow directions, from home to battery (H2B) or from battery to home (B2H).

$$\begin{cases} C_t^{b,da} = C_{t-1}^{b,da} + P_t^{b,ch,da}\eta_{H2B} - \frac{P_t^{b,dis,da}}{\eta_{B2H}} & \forall\, \mathrm{t} \geq\ 2 \\ C_{t=1}^{b,da} = C_i^b + P_{t=1}^{b,ch,da}\eta_{H2B} - \frac{P_t^{b,dis,da}}{\eta_{B2H}} & \forall\, \mathrm{t} =\ 1 \end{cases} \tag{3.6}$$

The maximum and minimum limitations for the stored energy of the battery in real-time are defined in equation 3.7 (P_b^{max} and P_b^{min}, respectively).

$$P_b^{min} \leq C_t^{b,da} \leq P_b^{max} \tag{3.7}$$

Equations 3.8 and 3.9 represent the battery maximum charging and discharging power, respectively. Where ω_b^{min} and ω_b^{max} are the battery minimum and maximum charging/discharging rate, and $u_t^{b,da}$ is a binary variable which is representing the estimation of battery charging. If $u_t^{b,da}$ equals one, the battery is in discharging status, and if $u_t^{b,da}$ is null, it is in charging status.

$$0 \leq P_t^{b,ch,da} \leq \omega_b^{min}(1 - u_t^{b,da}) \tag{3.8}$$

$$0 \leq P_t^{b,dis,da} \leq \omega_b^{max} u_t^{b,da} \tag{3.9}$$

3.2.2 Electric Vehicle

The only difference between EV's and battery's constraints is mobility. In light of this, EV's constraints are similar to battery ones. The equations regarding day-ahead constraints for the EV are presented in equations 3.10-3.14.

In equation 3.10 is stated a sequence to calculate the day-ahead stored energy in the EV ($C_t^{ev,da}$), the initial value of available energy in the battery is C_i^{ev}; η_{H2V} and η_{V2H} are battery efficiency coefficients, where it is used the same values for different flow directions, from home to vehicle (H2V) or from vehicle to home (V2H).

$$\begin{cases} C_t^{ev,da} = C_{t-1}^{ev,da} + P_t^{ev,ch,da}\eta_{H2V} - \frac{P_t^{ev,dis,da}}{\eta_{V2H}} - Mob_t^{da} & \forall\, \mathrm{t} \geq\ 2 \\ C_{t=1}^{ev,da} = C_i^{ev} + P_{t=1}^{ev,ch,da}\eta_{H2V} - \frac{P_t^{ev,dis,da}}{\eta_{V2H}} - Mob_{t=1}^{da} & \forall\, \mathrm{t} =\ 1 \end{cases} \tag{3.10}$$

Here, mobility constraint is added to the EV's battery system equation, where Mob_t^{da} is the discharge rate of the EV in the day-ahead stage, due to driving. Whenever the EV is at home, Mob_t^{da} equals zero, if not, its value is bigger than zero. Its function is presented in equation 3.11 and it depends on the day-ahead travel distance (Dis_t^{da}) and EV's energy consumption per mile (δ^{ev}).

$$Mob_t^{da} = Dis_t^{da} \delta^{ev} \tag{3.11}$$

The limitations for the day-ahead stored energy of the electric vehicle ($C_t^{ev,da}$) are defined in equation 3.12.

$$P_{ev}^{min} \leq C_t^{ev,da} \leq P_{ev}^{max} \tag{3.12}$$

Equations 3.13 and 3.14 represent the day-ahead maximum EV charging and discharging power, respectively. Where ω_{ev}^{min} and ω_{ev}^{max} are the minimum and maximum EV charging or discharging rate, and $u_t^{ev,da}$ is a binary variable which is representing the estimation of EV charging. If $u_t^{ev,da}$ equals one, the EV's battery is in discharging status, and if $u_t^{ev,da}$ is null, it is in charging status.

$$0 \leq P_t^{ev,ch,da} \leq \omega_{ev}^{min}(1 - u_t^{ev,da}) \tag{3.13}$$

$$0 \leq P_t^{ev,dis,da} \leq \omega_{ev}^{max} u_t^{ev,da} \tag{3.14}$$

3.3 Real-Time Stage Constraints

In this stage, real-time wind power generation and EV mobility uncertainty are considered based on stochastic scenarios. Also, the SH can both purchase and sell energy with the real-time LM.

$$\begin{aligned} P_{t\omega\xi}^{wind,rt} + P_{t\omega\xi}^{pv,rt} + P_{t\omega\xi}^{b,dis,rt} + P_{t\omega\xi}^{ev,dis,rt} + P_{t\omega\xi}^{pur,rt} = \\ = L_{t\omega\xi}^{sh,rt} + L_{t\omega\xi}^{swh,rt} + L_{t\omega\xi}^{mrs,rt} - (L_{t\omega\xi}^{sh,shed,rt} + L_{t\omega\xi}^{swh,shed,rt}) + \\ + P_{t\omega\xi}^{b,ch,rt} + P_{t\omega\xi}^{ev,ch,rt} + P_t^{net,da} + P_{t\omega\xi}^{sold,rt} \end{aligned} \tag{3.15}$$

Taking that into account, equation 3.15 represents the real-time power balance equation, where each parameter is described as it follows (note that for this stage, every variable presented below stands for real-time constraint):

- Wind micro-turbine power generated ($P_t^{wind,rt}$);
- Power output generated by PV system ($P_t^{pv,rt}$);
- Battery discharged and charged power ($P_t^{b,dis,rt}$ and $P_t^{b,ch,rt}$, respectively);
- EV discharged and charged power ($P_t^{ev,dis,rt}$ and $P_t^{ev,ch,rt}$, respectively);
- Energy transacted with the LM ($P_t^{net,da}$);
- Point forecasting of loads ($L_{t\omega\xi}^{sh,rt} + L_{t\omega\xi}^{swh,rt} + L_{t\omega\xi}^{mrs,rt}$);
- Load shedding constraints, related to the lost energy of loads, such as the space heater and the storage water heater ($L_{t\omega\xi}^{sh,shed,rt} + L_{t\omega\xi}^{swh,shed,rt}$).

This model can have different real-time prices, hence, it is noticeable that in the day-ahead stage, $P_{t\omega\xi}^{pur,rt}$ and $P_{t\omega\xi}^{sold,rt}$ are representing the purchased and sold energy, respectively.

In light of this, equation 3.16 states the power distribution line limitation, taking into account the energy purchased/sold from/to the grid in the real-time and day-ahead stages, which helps problems caused by day-ahead and real-time stages to be solved at the same time. Also, the energy purchased and sold by the SH must be a positive value (equation 3.17).

$$-f_{max} \leq P_t^{net,da} + P_{t\omega\xi}^{sold,rt} - P_{t\omega\xi}^{pur,rt} \leq f_{max} \tag{3.16}$$

$$P_{t\omega\xi}^{sold,rt}, P_{t\omega\xi}^{pur,rt} \geq 0 \tag{3.17}$$

Equation 3.18 represents the wind microturbine power generated equation in the real-time, where $P_{t\omega\xi}^{wind,scen}$ is the potential wind power generation based on different scenarios, and $S_{t\omega\xi}^{w}$ refers to the spilt energy of the wind system. The limits for the spilt wind power is stated in equation 3.19.

$$P_{t\omega\xi}^{wind,rt} = P_{t\omega\xi}^{wind,scen} - S_{t\omega\xi}^{w} \tag{3.18}$$

$$0 \leq S_{t\omega\xi}^{w} \leq P_{t\omega\xi}^{wind,scen} \tag{3.19}$$

The power output generation of the PV system in the real-time stage is represented in equation 3.20, where $P^{pv,pred}_{t\omega\xi}$ is the potential PV generation based on previous studies, and $S^{pv}_{t\omega\xi}$ refers to the spilled PV power. The limits for the spilt energy of the PV system is stated in equation 3.21.

$$P^{pv,rt}_{t\omega\xi} = P^{pv,pred}_{t\omega\xi} - S^{pv}_{t\omega\xi} \tag{3.20}$$

$$0 \leq S^{pv}_{t\omega\xi} \leq P^{pv,pred}_{t\omega\xi} \tag{3.21}$$

Equation 3.22 aggregates the total spilt energy from PV and wind power sources. In the next subsection, it is presented the real-time constraints for the battery system and electric vehicle.

$$S_{t\omega\xi} = S^{w}_{t\omega\xi} + S^{pv}_{t\omega\xi} \tag{3.22}$$

3.3.1 Battery System

Here, equations 3.23-3.26 represent real-time constraints regarding the battery system, which are very similar to the day-ahead equations, but with different parameters. In equation 3.23 is stated a sequence to calculate the battery stored energy in the real-time ($C^{b,rt}_{t}$).

$$\begin{cases} C^{b,rt}_{t\omega\xi} = C^{b,rt}_{t-1,\omega\xi} + P^{b,ch,rt}_{t\omega\xi}\eta_{H2B} - \frac{P^{b,dis,rt}_{t\omega\xi}}{\eta_{B2H}} & \forall \text{ t} \geq \text{ 2} \\ C^{b,rt}_{(t=1)\omega\xi} = C^{b}_{i} + P^{b,ch,rt}_{(t=1)\omega\xi}\eta_{H2B} - \frac{P^{b,dis,rt}_{t\omega\xi}}{\eta_{B2H}} & \forall \text{ t} = \text{ 1} \end{cases} \tag{3.23}$$

The maximum and minimum capacity of battery stored energy in real-time is stated in equation 3.24.

$$P^{min}_{b} \leq C^{b,rt}_{t\omega\xi} \leq P^{max}_{b} \tag{3.24}$$

Equations 3.25 and 3.26 represent the maximum battery charging and discharging power in real-time, respectively. Where $u^{b,rt}_{t}$ is a binary variable which is representing the estimation of battery charging in real-time, with similar functionality as the day-ahead battery charging status variable. If $u^{b,rt}_{t}$ equals one, the battery is in discharging status, and if $u^{b,rt}_{t}$ is null, it is in charging status.

$$0 \leq P^{b,ch,rt}_{t\omega\xi} \leq \omega^{min}_{b}(1 - u^{b,rt}_{t\omega\xi}) \tag{3.25}$$

$$0 \leq P^{b,dis,rt}_{t\omega\xi} \leq \omega^{max}_{b} u^{b,rt}_{t\omega\xi} \tag{3.26}$$

3.3.2 Electric Vehicle

The constraints related to EV in the real-time stage are defined in equations 3.27-3.31. In equation 3.27 is stated a sequence to calculate the EV stored energy in real-time ($C_t^{ev,rt}$).

$$\begin{cases} C_{t\omega\xi}^{ev,rt} = C_{t-1,\omega\xi}^{ev,rt} + P_{t\omega\xi}^{ev,ch,rt}\eta_{H2V} - \frac{P_{t\omega\xi}^{ev,dis,rt}}{\eta_{V2H}} - Mob_{t\omega\xi}^{rt} & \forall\, t \geq 2 \\ C_{(t=1)\omega\xi}^{ev,rt} = C_i^{ev} + P_{(t=1)\omega\xi}^{ev,ch,rt}\eta_{H2V} - \frac{P_{t\omega\xi}^{ev,dis,rt}}{\eta_{V2H}} - Mob_{(t=1)\omega\xi}^{rt} & \forall\, t = 1 \end{cases} \tag{3.27}$$

Here, the mobility constraint is presented in equation 3.28, where Mob_t^{rt} is the discharge rate in real-time of the EV due to driving. Whenever the EV is at home, Mob_t^{rt} equals zero, if not, its value is bigger than zero. It depends on the real-time travel distance (Dis_t^{rt}) and EV's energy consumption per mile (δ^{ev}).

$$Mob_{t\omega\xi}^{rt} = Dis_{t\omega\xi}^{rt}\delta^{ev} \tag{3.28}$$

The limitations for the real-time stored energy of the electric vehicle ($C_{t\omega\xi}^{ev,rt}$) are defined in equation 3.29 (P_{ev}^{max} and P_{ev}^{min}, respectively).

$$P_{ev}^{min} \leq C_{t\omega\xi}^{ev,rt} \leq P_{ev}^{max} \tag{3.29}$$

Equations 3.30 and 3.31 represent the maximum charging and discharging power of the EV in the real-time stage, respectively. Where ($u_t^{ev,rt}$ is a binary variable that is representing the estimation of real-time EV's charging. If $u_t^{ev,rt}$ equals one, the EV's battery is in discharging status, and if $u_t^{ev,rt}$ is null, it is in charging status.

$$0 \leq P_{t\omega\xi}^{ev,ch,rt} \leq \omega_{ev}^{min}(1 - u_{t\omega\xi}^{ev,rt}) \tag{3.30}$$

$$0 \leq P_{t\omega\xi}^{ev,dis,rt} \leq \omega_{ev}^{max} u_{t\omega\xi}^{ev,rt} \tag{3.31}$$

3.3.3 Space Heater

Regarding electrical loads, the space heater is considered as a controllable load and it controls the indoor temperature, according to the desired temperature. For a matter of simplicity, every room of the SH is projected to have the same indoor and desired temperatures.

Equation 3.32 from [11] defines the equation between the electrical consumption of the space heater and room's temperature, where $\theta_{t\omega\xi}^{out,pred}$ is a prediction of outdoor temperature, R is the thermal resistance, and θ_i^{in} and θ_{des}^{in} are the initial indoor temperature and the desired indoor temperature, respectively.

$$\begin{cases} \theta_{t+1,\omega\xi}^{in} = e^{\frac{-1}{RC}}\theta_{t\omega\xi}^{in} + R(1 - e^{\frac{-1}{RC}})L_{t\omega\xi}^{sh,rt} + (1 - e^{\frac{-1}{RC}})\theta_{t\omega\xi}^{out,pred} & \forall\, t \geq 2 \\ \theta_{t\omega\xi}^{in} = \theta_i^{in} = \theta_{des}^{in} & \forall\, t = 1 \end{cases} \tag{3.32}$$

For comfort reasons, the temperature inside the home is limited to one more or less than a certain desired value. This statement is expressed in equation 3.33.

$$-1 \leq \theta^{in}_{t\omega\xi} - \theta^{in}_{des} \leq 1 \tag{3.33}$$

Space heater load consumption and load shedding constraints are represented in equations 3.34 and 3.35, where L^{max}_{sh} represents the space heater maximum load consumption and $L^{sh,shed,rt}_{t\omega\xi}$ is the space heater load shedding.

$$0 \leq L^{sh,rt}_{t\omega\xi} \leq L^{max}_{sh} \tag{3.34}$$

$$0 \leq L^{sh,shed,rt}_{t\omega\xi} \leq L^{sh,rt}_{t\omega\xi} \tag{3.35}$$

3.3.4 Storage Water Heater

The storage water heater is considered as a shiftable load and it stores heat in the water tank. Its load and energy consumption limitations and its load shedding constraints are represented in equations 3.36, 3.37 and 3.38, respectively. Here, L^{max}_{swh} and U^{max}_{swh} are the maximum load consumption and storage water heater maximum energy consumption in a day, respectively, and $L^{swh,shed,rt}_{t\omega\xi}$ represents its load shedding.

$$0 \leq L^{swh,rt}_{t\omega\xi} \leq L^{max}_{swh} \tag{3.36}$$

$$\sum_{\omega} \pi_{\omega} \sum_{\xi} \pi_{\xi} \sum_{t} L^{swh,rt}_{t\omega\xi} = U^{max}_{swh} \tag{3.37}$$

$$0 \leq L^{swh,shed,rt}_{t\omega\xi} \leq L^{swh,rt}_{t\omega\xi} \tag{3.38}$$

3.3.5 Must-Run Services

Must-run services include the loads that should not be interrupted, such as the lighting system, washing machine, dishwasher machine, fridge/refrigerator and others. In this project, the uncertainty of must-run services and their spillage is not considered. Equation 3.39 defines the total load consumption of must-run services as the sum of the load consumption of each appliance modelled.

$$L^{mrs,rt}_{t\omega\xi} = L^{light,rt}_{t\omega\xi} + L^{wm,rt}_{t\omega\xi} + L^{dm,rt}_{t\omega\xi} + L^{fridge,rt}_{t\omega\xi} + L^{other,rt}_{t\omega\xi} \tag{3.39}$$

3.3.5.1 Lighting

The lighting energy consumption ($L_{t\omega\xi}^{light,rt}$) is modeled as shown in equation 3.40, being equal to a constant amount of power used during a certain time period ($P_{t\omega\xi}^{light}$).

$$L_{t\omega\xi}^{light,rt} = P_{t\omega\xi}^{light,rt} \tag{3.40}$$

3.3.5.2 Washing machine and dishwasher machine

Load consumption of washing machine ($L_{t\omega\xi}^{wm,rt}$) and dishwasher machine ($L_{t\omega\xi}^{dm,rt}$) during a certain time period is represented as equal to equipment's maximum power consumption, $P_{t\omega\xi}^{wm,rt}$ and $P_{t\omega\xi}^{dm,rt}$, respectively. This statement is described in equations 3.41 and 3.42.

$$L_{t\omega\xi}^{wm,rt} = P_{t\omega\xi}^{wm,rt} \tag{3.41}$$

$$L_{t\omega\xi}^{dm,rt} = P_{t\omega\xi}^{dm,rt} \tag{3.42}$$

3.3.5.3 Fridge/Refrigerator

The fridge's electricity consumption ($L_{t\omega\xi}^{fridge,rt}$) is modeled as shown in equation 3.43, being equal to a constant amount of power used during a certain time period ($P_{t\omega\xi}^{fridge}$).

$$L_{t\omega\xi}^{fridge,rt} = P_{t\omega\xi}^{fridge,rt} \tag{3.43}$$

In fact, a typical fridge behaviour during a day is simple as turning ON/OFF an appliance within 15-minute range. Also, the fridge's electricity consumption increases with the number of times its doors are open during the day.

Keeping this in mind, for a matter of simplicity in result analysis, fridge electrical consumption is assumed to equal the total capacity of the fridge during operational periods (mode ON), which are stated as those periods when is most likely to fridge's doors be opened.

3.3.5.4 TV/PC/Others

Here, it is considered every other electrical appliance not mentioned, such as televisions, computers and other devices that consume considerable energy. Real-time load consumption of these must-run services ($L_{t\omega\xi}^{other,rt}$) is calculated from device's maximum power consumption during a certain time period ($P_{t\omega\xi}^{other}$) and it is represented in equation 3.44.

$$L_{t\omega\xi}^{other,rt} = P_{t\omega\xi}^{other,rt} \tag{3.44}$$

Chapter 4

Numerical Studies and Results

4.1 Case Study

For the purpose of evaluating the model's performance, a basic SH scenario is defined, taking into account a casual behaviour of a SH consumer and his activities at home using smart appliances. The outputs of the project are the hourly consumption, electricity bill and battery charge/discharge. It should be mentioned that a price-based comparative analysis is carried out in order to discuss SH performance.

The system used for testing the proposed model has already been used before in [11], [58] and [68]. However, it is used both PV and wind power generation and must-run services are specified as smart appliances, as it is shown in figure 4.1.

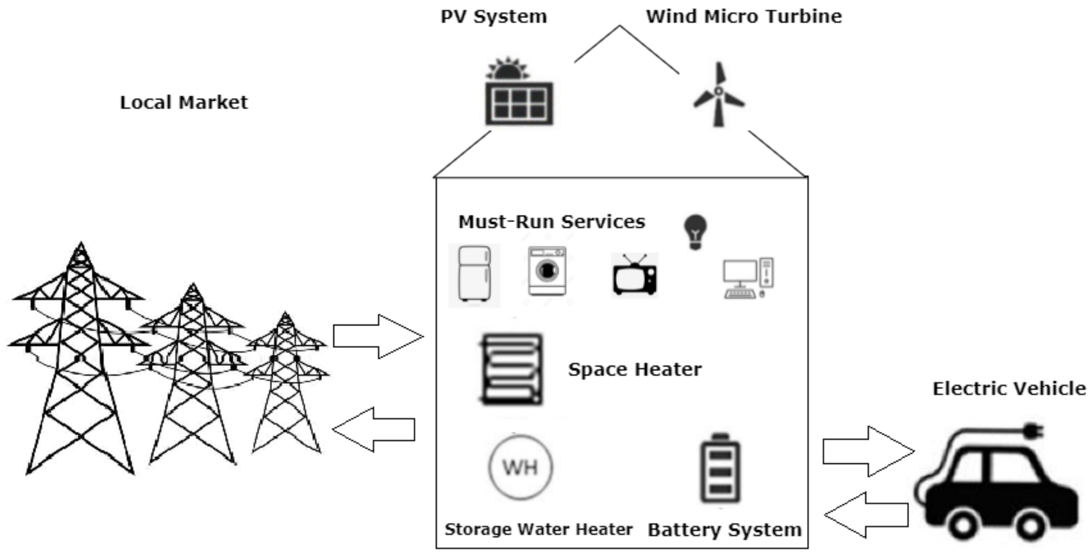


Figure 4.1: Home energy management system (Modified from [11] and [68])

Table 4.1: PV, Wind, Battery and EV specifications

PV System	Maximum energy produced: 2 kWh
Wind System	Maximum energy produced: 2 kWh
Battery System	Storage capacity: 0.48 - 2.4 kWh Maximum charging and discharging rate: 400 W Charging and discharging efficiency: 90%
EV System	Storage capacity: 1.77 - 5.9 kWh Maximum charging and discharging rate: 3 kW Charging and discharging efficiency: 90%

In this point of view, specifications for wind micro-turbine and PV systems, battery and EV systems are presented in table 4.1. The predicted data of generation energy from PV System during a day is obtained from [68] and it is graphically shown in figure 4.2.

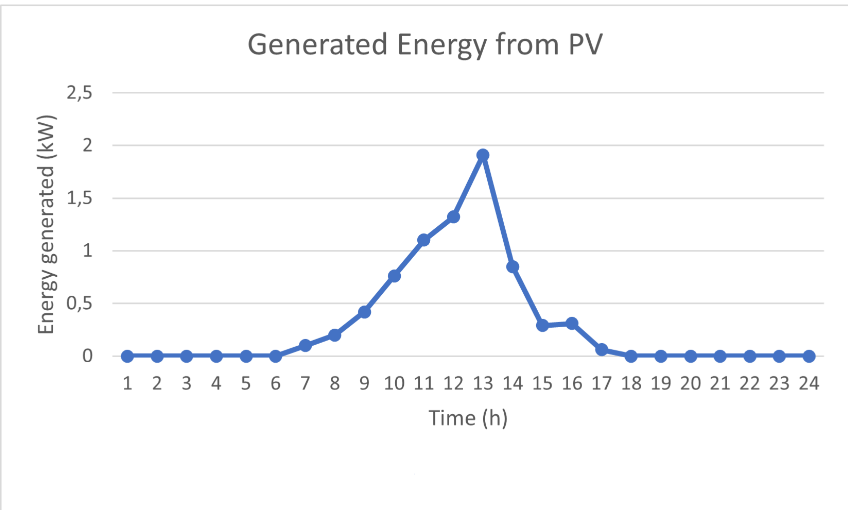


Figure 4.2: Generated energy from PV System during a day

Table 4.2: Point forecasting of wind power generation (Adapted from [11])

Time (h)	Point forecasting (kW)
1	0.139
2	0.486
3	0.826
4	1.290
5	1.491
6	1.385
7	1.564
8	1.261
9	1.275
10	0.956
11	0.979
12	0.848
13	0.644
14	0.439
15	0.600
16	0.398
17	0.271
18	0.204
19	0.165
20	0.142
21	0.179
22	0.086
23	0
24	0

Table 4.2 gives information about the forecasted data achieved from ten different wind power generation scenarios obtained from [11]. Furthermore, it is presumed that the time schedule for EV's mobility is leaving home at 7:00 AM and returning home at 18:00 PM. This scenario states that the EV charge should be full when it leaves home and it should be empty when it returns home.

Regarding load management specifications, the space heater maximum load capacity in each cycle equals 5.525 kW, and the storage water heater daily energy capacity is 10.46 kWh, having a 2 kW heating element. The home is presumed to be at the desired temperature of 23 °C. Moreover, the walls thermal resistance and C equal 18 °C/kW and 0.525 kWh/°C, respectively.

The smart home is considered to be relatively windowed, in this way, the lighting system was modelled to consume energy mostly during the night (8:00 PM - 05:00 AM); also, it is considered a 10W LED light power consumption per hour. Figure 4.3 presents the behaviour of outdoor temperature during a day, obtained with predicted stochastic data from [68]. The proposed MILP is solved in GAMS 24.1.2 [69].

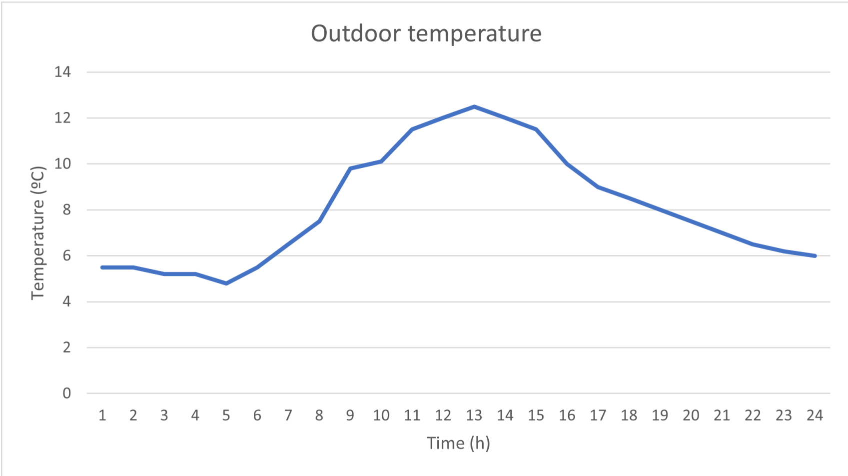


Figure 4.3: Outdoor temperature behaviour during a day

Furthermore, the washing machine consumption is assumed to equal 1.850 kW per cycle, based on equipment's electrical connection rating [70], and the dishwasher machine is considered to be energy class type C or above [71], which means, energy consumption of 1.5 kW per cycle.

Both washing and dishwasher machine schedules are presented in figure 4.4, considering the worst case of daily usage, is stated that both machines are used two times a day.

Additionally, as already mentioned in the mathematical formulation, the fridge's electrical consumption is 380W per operational cycle, it depends on the total amount of energy used by the fridge, which value is obtained from the annual consumption of a SAMSUNG fridge [72].

For a matter of simplicity, fridge's and washing and dishwasher machines' operational cycle is assumed to equal one hour. Figure 4.5 shows the energy consumption of the fridge during a day.

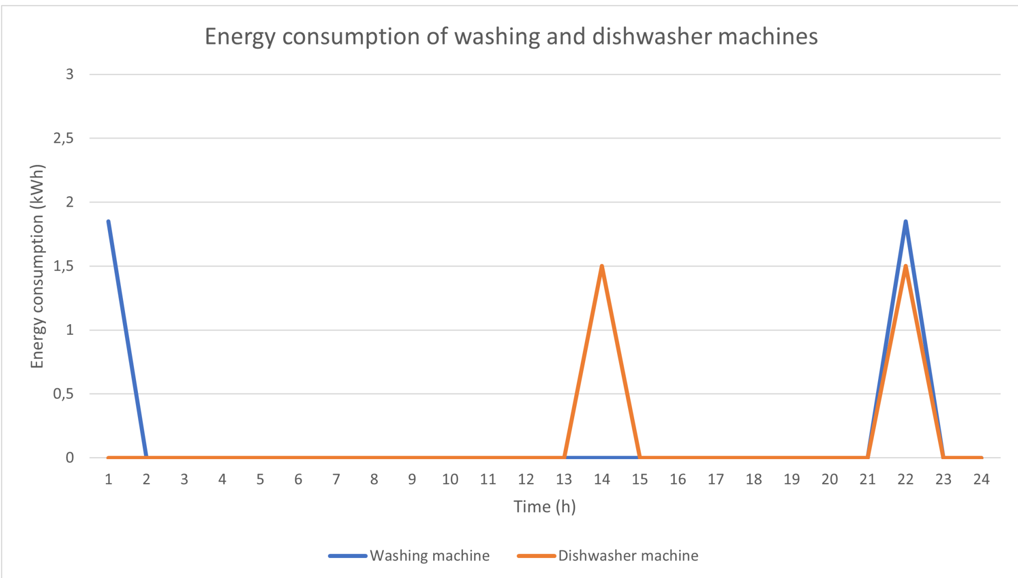


Figure 4.4: Energy consumption of the washing and dishwasher machines during a day

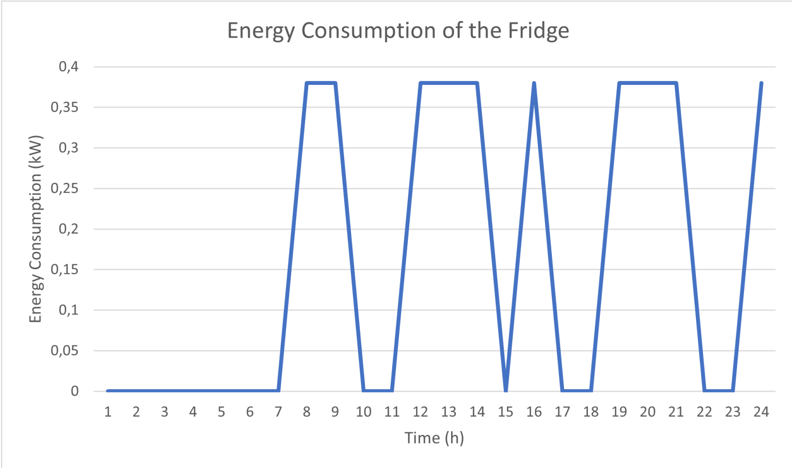


Figure 4.5: Energy consumption of the fridge during a day

In this thesis, the uncertainty of other electrical appliances is not considered. It is used predicted stochastic data for must-run services consumption obtained from [68], which is shown in table 4.3, also with a space heater and storage water heater predicted data for the day-ahead stage.

Table 4.3: Predicted data of stochastic variables (Adapted from [68])

Time (h)	Space heater (kW)	Storage water heater (kW)	Other (kW)
1	2.6	2	0.005
2	2.6	2	0.005
3	2.6	2	0.005
4	2.6	2	0.005
5	2.6	0.46	0.005
6	2.6	0	0.005
7	2.43	0	0.005
8	2.24	0	0.005
9	2.05	0	0.005
10	1.86	0	0.005
11	1.67	0	0.005
12	1.67	0	0.005
13	1.67	0	0.005
14	1.67	0	0.005
15	1.67	0	0.005
16	1.67	0	0.005
17	1.8	0	0.005
18	1.93	0	0.005
19	2.06	0	1.218
20	2.19	0	0.262
21	2.32	0	0.262
22	2.45	0	0.14
23	2.6	0	0.127
24	2.6	2	0.005

Table 4.4: Real time price and critical price picking data (Adapted from [11])

Time (h)	Real-time price ($/kWh)	Critical price picking ($/kWh)
1	0.165	0.238
2	0.177	0.238
3	0.197	0.238
4	0.220	0.238
5	0.229	0.238
6	0.241	0.238
7	0.235	0.238
8	0.232	0.238
9	0.311	0.715
10	0.280	0.715
11	0.266	0.238
12	0.262	0.238
13	0.239	0.238
14	0.229	0.238
15	0.246	0.238
16	0.247	0.238
17	0.260	0.238
18	0.314	0.715
19	0.270	0.715
20	0.257	0.238
21	0.225	0.238
22	0.209	0.238
23	0.210	0.238
24	0.199	0.238

Additionally, fixed tariff (flat-rate price), RTP and CPP are the tariffs studied in this model, table 4.4 states RTP and CPP prices per hour within a day; flat rate price is stated as a fixed value of 0.2384 $/kWh.

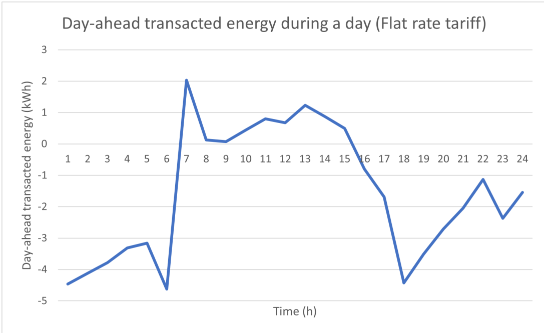
4.2 Discussion and Results

In this section, the performance of the proposed model is evaluated through a comparative analysis within the project outputs based on different price tariffs (RTP and flat-rate tariff) for the electricity market price. Furthermore, EPs from these different tariffs are discussed and compared with previous work results.

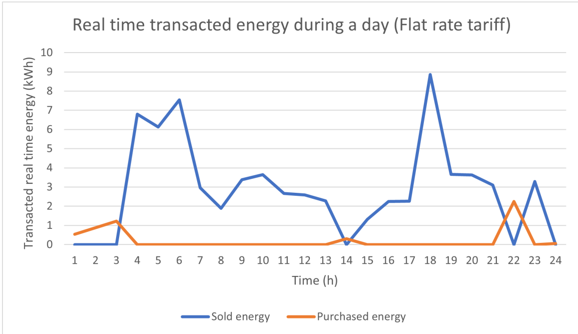
4.2.1 Flat-rate tariff

Firstly, the electricity market price is assumed to follow a fçat rate tariff, thus, next is presented results for the hourly consumption, battery charge/discharge and electricity bill.

Figures 4.6a and 4.6b show the energy traded with the day-ahead and real-time local markets, respectively. It can be seen that the system purchased and sold energy to the LM when considering a flat-rate tariff scheme.



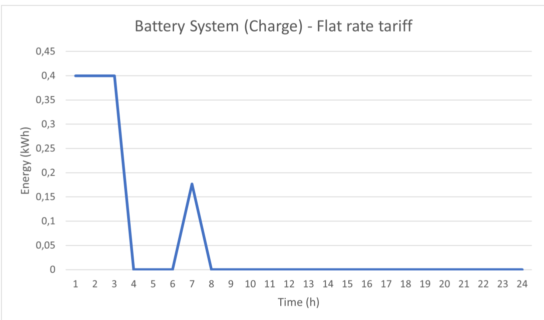
(a) Day-ahead transacted energy considering flat rate tariff



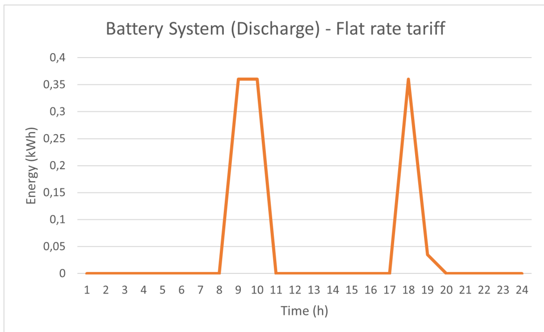
(b) Real-time transacted energy considering flat rate tariff

Figure 4.6: Transacted energy considering flat rate tariff

In figures 4.7a and 4.7b, battery's charged and discharged power are shown, respectively. The battery helps the home energy management system in time periods, $t = 9$, $t = 10$ and $t = 18$, which are peak-load time periods of the model.

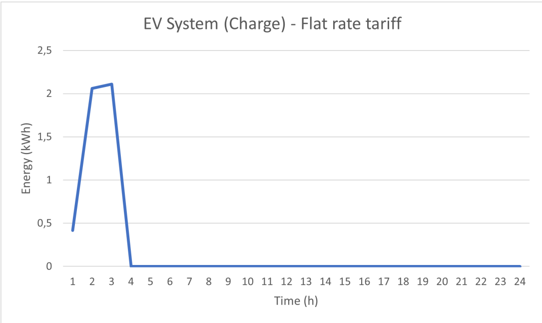


(a) Expected charged energy of the battery considering flat rate tariff

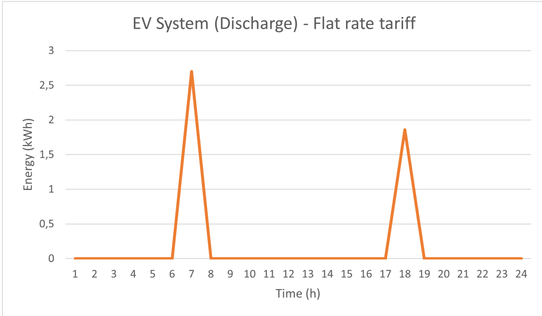


(b) Expected discharged energy of the battery considering flat rate tariff

Figure 4.7: Expected charged/discharged energy of the battery considering flat rate tariff



(a) Expected charged energy of the EV considering flat rate tariff



(b) Expected discharged energy of the EV considering flat rate tariff

Figure 4.8: Expected charged/discharged energy of the battery considering flat rate tariff

The EV is only in charging mode in $t = 2$ and $t = 3$ since it should be fully charged at 7 AM ($t = 7$). Figures 4.8a and 4.8b represent the EV's charged and discharged power, which is transacted with the system and not the discharged energy caused by EV's.

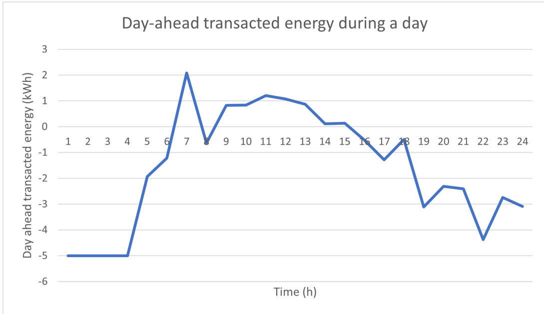
4.2.2 RTP tariff

The electricity price is assumed to follow the RTP tariff, in light of this, the last section's comparative analysis is re-studied here. Thence, the next figures present obtained results for the hourly consumption, battery charge/discharge and electricity bill, regarding a RTP tariff.

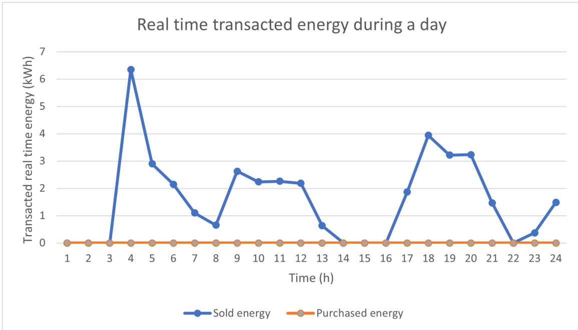
Figure 4.9a show the energy traded with the local market during the day-ahead stage. In figure 4.9b, sold and purchased real-time energy are presented. It can be seen that the system does not purchase energy from the real-time LM when considering the RTP tariff.

In figures 4.10a and 4.10b, battery's charged and discharged power are shown, respectively. The battery helps the home energy management system in time periods, $t = 9$, $t = 10$ and $t = 18$, which are peak-load time periods of the model.

However, the EV is only in charging mode in $t = 2$ and $t = 3$ due to the fact that it should be fully charged at 7 AM ($t = 7$). Figures 4.11a and 4.11b represent the EV's charged and discharged power, which is transacted with the system and not the discharged energy caused by EV's.

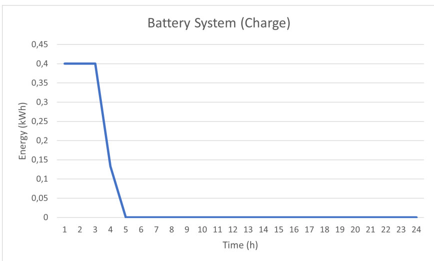


(a) Day-ahead transacted energy considering RTP

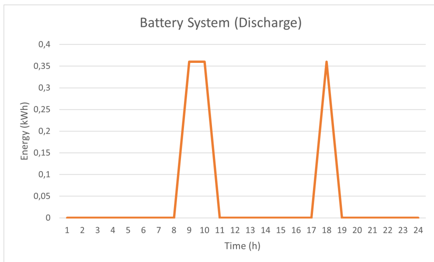


(b) Real-time transacted energy considering RTP

Figure 4.9: Transacted energy considering RTP

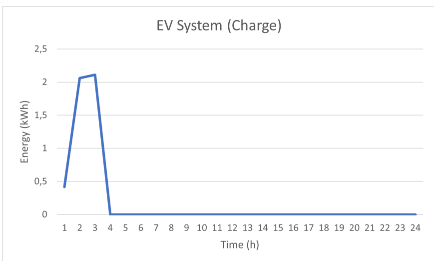


(a) Expected charged energy of the battery considering RTP

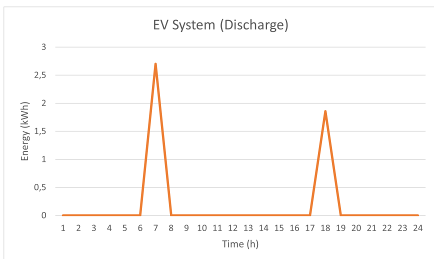


(b) Expected discharged energy of the battery considering RTP

Figure 4.10: Expected charged/discharged energy of the battery considering RTP



(a) Expected charged energy of the EV considering RTP



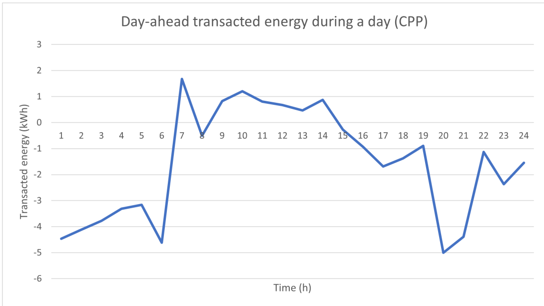
(b) Expected discharged energy of the EV considering RTP

Figure 4.11: Expected charged/discharged energy of the battery considering RTP

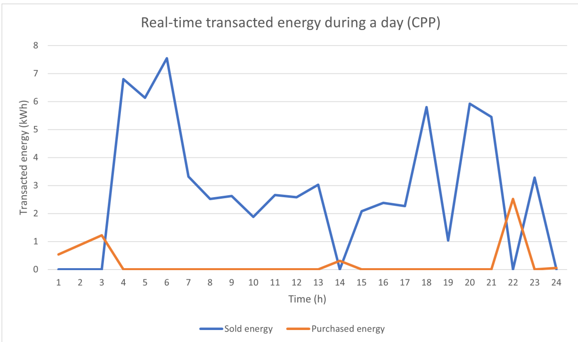
4.2.3 CPP tariff

The electricity price used here is assumed to follow the CPP tariff. Thence, next, is graphically presented the obtained results same outputs mentioned before, taking into account this specific program.

Figure 4.12a show the energy traded with the local market during the day-ahead stage. In figure 4.12b, sold and purchased real-time energy are presented. It can be seen that the system purchased and sold energy in the real-time LM when considering the CPP tariff scheme.



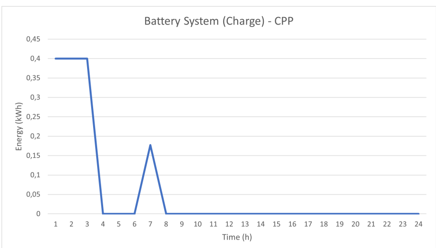
(a) Day-ahead transacted energy considering CPP



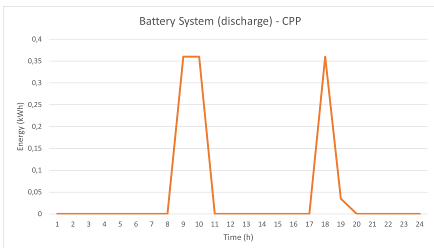
(b) Real-time transacted energy considering CPP

Figure 4.12: Transacted energy considering CPP

In figures 4.13a and 4.13b, battery's charged and discharged power are shown, respectively. Figures 4.14a and 4.14b represent the EV's charged and discharged power. Both battery and EV expected traded energy are similar to flat rate tariff results, as graphically shown below.

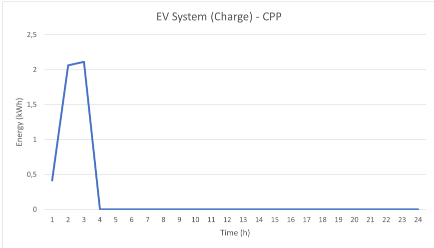


(a) Expected charged energy of the battery considering CPP

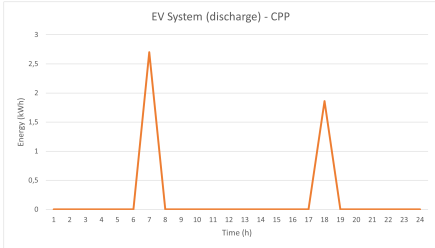


(b) Expected discharged energy of the battery considering CPP

Figure 4.13: Expected charged/discharged energy of the battery considering CPP



(a) Expected charged energy of the EV considering CPP



(b) Expected discharged energy of the EV considering CPP

Figure 4.14: Expected charged/discharged energy of the battery considering CPP

4.2.4 Expected Profit and transacted energy

Table 4.5 presents the total, day-ahead and real-time expected profits of the proposed home energy management model, considering a flat-rate price as the electricity bill, for a preliminary study. Moreover, RTP and CPP are used for a different analysis of the model, following the same concept as the previous result analysis.

As seen in table 4.5, the day-ahead EP is negative in all price tariffs, because the home consumes more than it produces when concerning day-ahead EM, therefore, it buys electricity more than it sells. However, the home produces more than it consumes in the real-time market, this way, the real-time EP is positive on the three specified price tariffs.

The model has shown that, with a fixed tariff for the electricity market price, day-ahead EP decreases in comparison to the RTP tariff scheme. Also, real-time EP is increased by, approximately, two times the RTP achieved value, in the real-time LM.

This helps to conclude that a fixed electricity price, comparing with RTP, makes the system consume more energy from in day-ahead electricity market and produce more in the real-time LM. The results from the case study with the CPP program indicate better profit in comparison to RTP tariff, however, using a fixed tariff program provides slightly better results than using a CPP program, in this model.

Next, in figure 4.15, it is compared the daily behaviour of day-ahead transacted energy between the three types of price tariffs defined: flat rate, RTP and CPP. It is noticeable that the day-ahead transacted energy in flat rate and CPP have the same behaviour between 1:00 AM and 8:00 AM, with RTP tending to transact more energy throughout the day compared to other tariffs.

Table 4.5: Expected profit of the home energy management model

Price tariff	EP ($)	Day-ahead EP ($)	Real-time EP ($)
Flat price rate	-1.405	-8.802	7.397
RTP	-3.399	-7.211	3.812
CPP	-1.902	-8.933	7.031

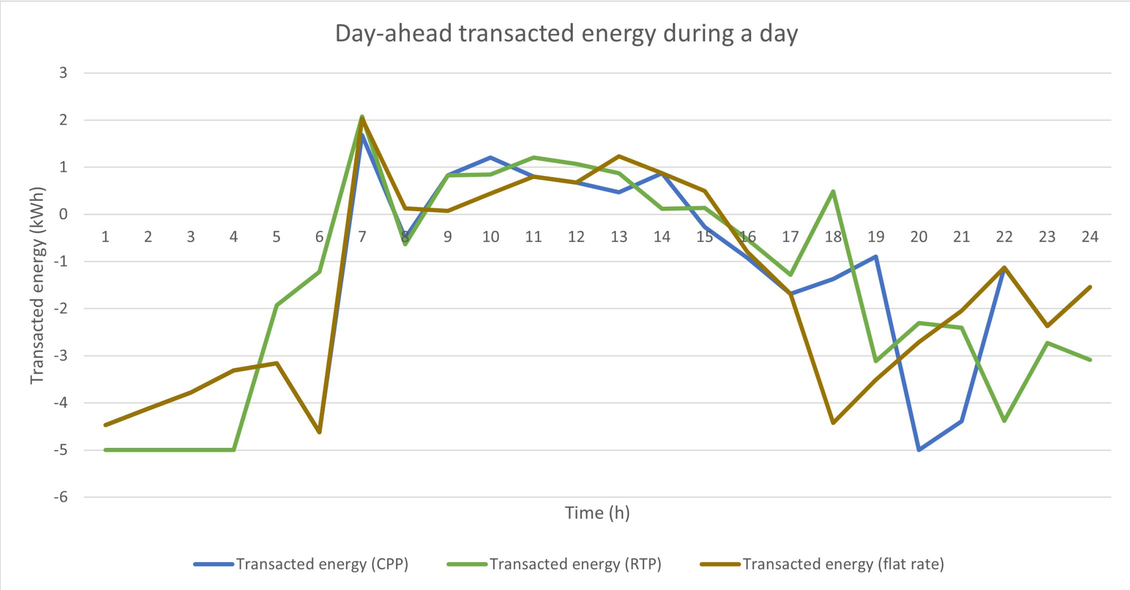


Figure 4.15: Day-ahead transacted energy during a day for different DR programs

For example, during off-peak hours, between 00:00 AM and 5:00 AM, the system is consuming energy, regarding all studied tariffs. In peak hours, RTP tends to be the one that provokes the system to sell the most to the market, especially between 5:00 PM and 6:00 PM.

On the other hand, the flat rate price makes the system deliver a lot of energy in a short time, as seen in increased transacted energy between 6:00 AM and 7:00 AM. The differences could be even more significant if, for instance, the flat rate had a value greater than RTP. Furthermore, the CPP result denotes very short peak periods, which allows the behaviour of the energy transacted to be similar to the flat rate tariff.

In general, the CPP is the tariff that has a more volatile behaviour at the end of the day, in relation to the other tariffs, whereas the RTP tariff is the one that has a more balanced behaviour.

Figure 4.16 presents the daily behaviour of real-time sold energy within the price tariffs in the study. Between 00:00 AM and 4:00 AM, all three rates have an equal increase. Throughout the day, the RTP tariff is worst rate, selling less energy to the real-time LM, in comparison to other tariffs.

The flat-rate and CPP tariffs have a pretty similar total energy sold to the LM during the day, however, the flat-rate reaches higher values of sold energy at 6:00 PM, while RTP reaches its peak two times, at 6:00 PM and between 8:00 PM and 9:00 PM (longer duration while selling more energy). It can be concluded that the tariffs which make the system sell more energy to the real-time LM during a day are CPP and flat-rate tariffs.

However, despite selling less energy, the system simulated with the RTP program showed that SH does not buy energy from the real-time LM, during the entire day. This statement can be seen in figure 4.17, which presents the daily behaviour of real-time purchased energy for each studied tariff. Also, it can be seen that both CPP and flat-rate tariffs have equal behaviours during a day when concerning real-time purchased energy from the LM.

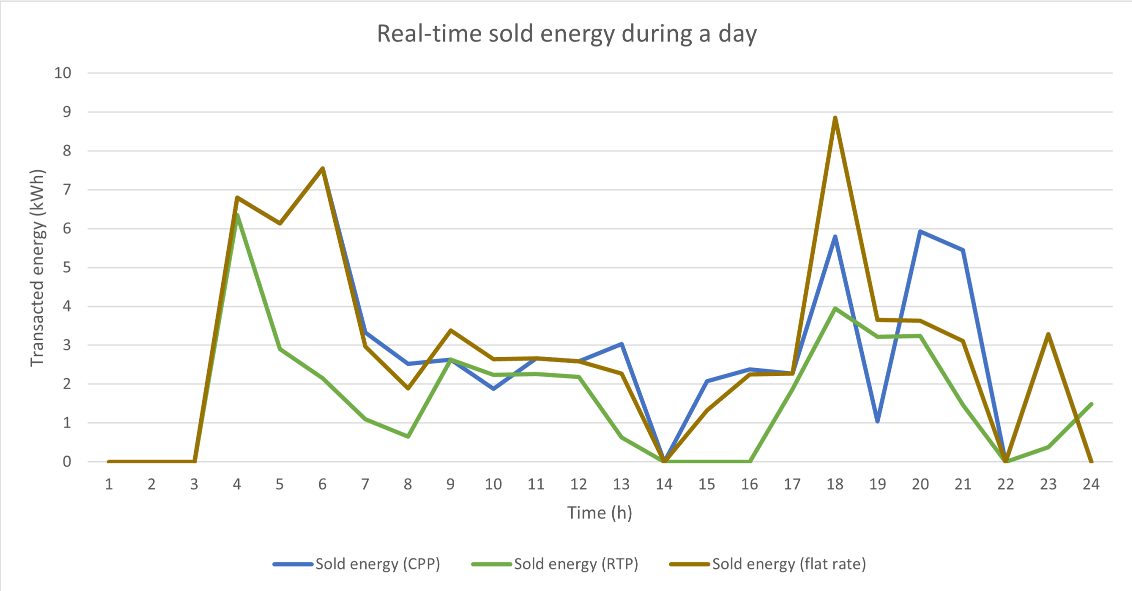


Figure 4.16: Real-time sold energy during a day for different DR programs

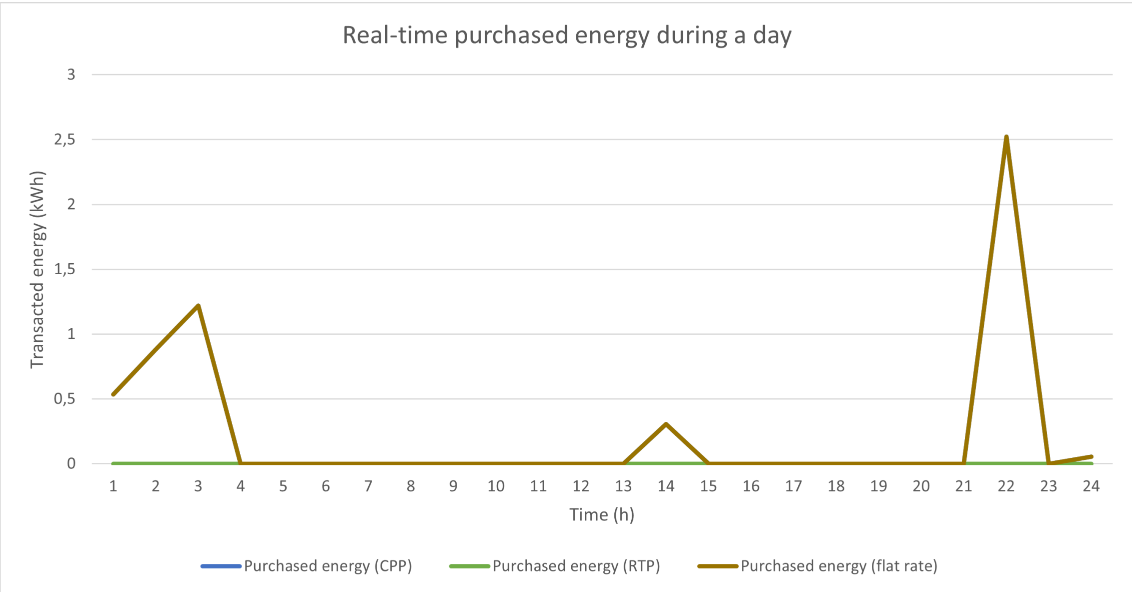


Figure 4.17: Real-time purchased energy during a day for different DR programs

Chapter 5

Conclusions and future work

5.1 Conclusion

A two-stage stochastic home energy management system has been modelled in this thesis. The system is able to trade energy with the day-ahead and real-time local markets. The problem is solved using the MILP technique.

It was presumed that the SH was allowed to buy or sell electricity from the local electricity market, store energy through energy storage systems and produce small-scale renewable energy. Furthermore, PV and wind systems are integrated into the home energy management problem as renewable sources of electricity.

Additionally, an EV and a battery system are considered as energy storage systems and there are smart appliances integrated into the problem, such as the space heater, the storage water heater, washing and dishwasher machines and other small-scale load appliances (television, computer). It should be noticeable that charging and discharging the EV and battery multiple times, may cause damages in the battery's lifetime and this is a topic that needs further researches in future.

Regarding the first stage, the day-ahead home energy management problem was simulated without considering wind power generation uncertainty. However, wind power uncertainty is considered in the real-time stage; also, in this stage, the load schedule is carefully managed to reduce energy costs.

In addition, the performance of the proposed system was evaluated based on the hourly energy consumption of the smart home system, end-users electricity bill and battery's charge/discharge rate. The simulation results show that the SH both purchased and sold electricity for the day-ahead and real-time local markets; hence, the day-ahead expected profit was negative.

Moreover, total, day-ahead and real-time expected profits are better when RTP tariff is used, obtaining a -3.399$ total EP, in comparison with results obtained from previous works. Furthermore, it was concluded that a flat rate price, in relation to RTP, makes the system consume more energy in the day-ahead electricity market and produce more in the real-time LM, with a value of -1.405$ total EP.

The results from the case study with CPP indicate better profit in comparison to RTP tariff, with a -1.902$ total EP; however, using a fixed tariff provides slightly better results than using CPP. Also, a comparative analysis of the day-ahead and real-time transacted energy obtained from different price rates is carried out.

In short, it was concluded that the CPP is the tariff that has a more volatile behaviour, in relation to RTP and flat rate, whereas the RTP tariff is the one that has a more balanced behaviour. The CPP and flat-rate tariffs are the rates that make the SH sell more energy during a day, and RTP does not purchase energy from the real-time LM.

5.2 Future Work

The model proposed in this thesis can be extended to a model which integrates several smart homes or smart buildings as one system, creating, for instance, a smart community with different role players interconnected with themselves and the local grid.

As the number of players increases, there is an increase in the number of constraints and, in turn, the MILP technique loses strength to solve the energy management problem. In this sense, it can be studied heuristic and metaheuristic approaches for this problem in order to reduce search space and better find the optimal solution, providing a more reliable model.

Furthermore, home energy management systems with more smart appliances integrated into the model can be studied to provide better distribution and total management of energy usage.

5.3 Scientific Contribution

From this Master thesis, a publication in peer-reviewed conference proceedings was accomplished.

Pedro C.R. Silva, Gerardo J. Osório, Miadreza Shafie-khah, Matthew Gough, Sérgio F. Santos, João P.S. Catalão, "Two-Stage Optimal Operation of Smart Homes Participating in Competitive Electricity Markets" in: Proceedings of the 21st IEEE International Conference on Environment and Electrical Engineering and 5th IEEE Industrial and Commercial Power Systems Europe — EEEIC 2021 / I&CPS Europe 2021, Bari, Italy, 7-10 September 2021, pp. 1-6. (accepted).

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