Techno-economic analysis of charging posts to be installed in a hub for electric vehicles

Catarina Gião Beja Ventura

Thesis to obtain the Master of Science Degree in

Energy Engineering and Management

Supervisors: Prof. Carlos Augusto Santos Silva

Engº Pedro Miguel Ferreira

Examination Committee

Chairperson: Profª. Susana Isabel Carvalho Relvas

Supervisor: Prof. Carlos Augusto Santos Silva

Members of the Committee: Drª. Patrícia De Carvalho Baptista

December 2019

Acknowledgments

This page is devoted to express my gratitude to the people who made this work possible.

Firstly, I would like to express my sincere gratitude to my advisor Prof. Carlos Silva for his insightful comments regarding my doubts and way of looking at problems from another point of view, for the valuable inputs for the energy management model development as well as to help me understand how to aggregate the whole model. Also, for his endless and continuous encouragement and placed trust in me. Additionally, thank you for accepting my thesis proposal as I really wanted to work on this topic and for helping me understand how I could develop in accordance with the EDP enterprise requirements. Last but not the least, thank you for encouraging me on pursuing my desire of having a teaching volunteering experience abroad even so I was developing my thesis and the opportunity to appreciate the good person he is.

Likewise, I would like to thank Pedro Miguel Ferreira, my advisor from EDP Inovação, for let me work on the topic in cooperation with EDP as well as the constant willingness to provide answers to my questions, welcoming in his workplace and for helping me with the data used for the economic analysis.

A great thanks also goes to Carlos Miguel Diogo from IN+ Center from Innovation, Technology and Policy Research for the valuable inputs while working on my models in the python program, who always managed to clear my doubts as well as for the unconditional willingness to critically discuss and share ideas which usually went far beyond the topic of this thesis.

Finally, I want to express my gratitude to my family and friends, for the excellent people they are, for giving me support throughout my studies and for encouraging me in everything I want to pursue.

Abstract

Electric mobility is expanding at a rapid pace. Now that battery capacity and price are lesser issues, charging facilities will inevitably become the focus of attention. The integration of renewable energy sources is paramount to approach a more carbon-free mobility future in the transportation sector. Therefore, E-Hubs will emerge as completely solar-powered fast-charging stations. Ideally, E-Hubs are places where electric vehicle owners let their car recharge while performing other activities such as grocery shopping, going to the gym, etc. The aim of this thesis is to perform a techno-economic analysis of three different scenarios. Firstly, a fast-charging station using solely the national grid network for the charging facilities, secondly a photovoltaic based fast charging station together with the national grid network, and lastly a photovoltaic based fast charging station together with a storage system and the grid. Using an optimization method, the genetic algorithm, the model is analyzed for Lisboa, Faro and, Porto, in order to obtain the optimal number of charging posts, batteries and solar panels where the net present value is maximized. Its main conclusion is that the optimal scenario always resorts to a storage system and PV panels. Likewise, such E-Hubs use around 5000 PV panels, 12-14 charging posts, and 4-7 batteries for the storage system providing charging infrastructure for electric vehicles with NPV maximum values within the range of 6.315.087€ and 6.349.288€.

Keywords: Energy Management, Electric mobility, E-Hub, Fast charging station, Net Present Value

Resumo

A mobilidade elétrica está a expandir muito rapidamente. Agora que a capacidade das baterias e os preços são problemas cada vez menores, os postos de carregamento vão inevitavelmente tornar-se o foco da atenção. A integração de fontes renováveis é fundamental para uma mobilidade futura mais livre de carbono. Assim, os E-Hubs vão emergir como estações de carregamento rápido completamente alimentadas por energia solar. Idealmente, os E-Hubs são espaços onde os veículos elétricos carregam enquanto os proprietários realizam outras atividades, i.e. ir às compras de supermercado, ir ao ginásio, etc. O objetivo desta tese é realizar uma análise tecno-económica em três cenários diferentes, o primeiro uma estação de carregamento rápido utilizando apenas a rede elétrica, o segundo cenário utilizando painéis fotovoltaicos juntamente com a rede nacional elétrica e o último cenário, utilizando painéis fotovoltaicos juntamente com um sistema de armazenamento e a rede elétrica. Utilizando um método de otimização, o algoritmo genético, o modelo é analisado para Lisboa, Faro e Porto, com o propósito de obter o número ideal de postos de carregamento, baterias e painéis fotovoltaicos em que o valor atual líquido é maximizado. A conclusão principal é que a solução ideal é sempre o cenário que inclui o sistema de armazenamento e os painéis fotovoltaicos. Da mesma forma, os E-Hubs utilizam cerca de 5000 painéis fotovoltaicos, 12-14 postos de carregamento rápido, e 4-7 baterias para o sistema de armazenamento de modo a ter uma infraestrutura para veículos elétricos com valores máximos de NPV entre 6.315.087€ e 6.349.288€.

Palavras-chave: Gestão de Energia, Mobilidade elétrica, E-Hub, Estação de carregamento rápido, Valor Atualizado Líquido

Contents

List of Figures

List of Tables

List of Abbreviations and Symbols

Abbreviations

AC – Alternating Current

AFI – Alternative Fuels Infrastructure

BEV – Battery Electric Vehicle

BS – Battery Storage

B2B – Business to business fleets

CCS – Combined Charging System

CAPEX – Capital Expenditure

DC – Direct Current

EVSE – Electric Vehicle Supply Equipment

EV – Electric Vehicle

EU – European Union

EVI – Electric Vehicles Initiative

EAFO – European Alternative Fuels Observatory

EREV – Extended-Range Electric Vehicle

EFTA – European Free Trade Association

EDP – Energias De Portugal

GA – Genetic Algorithm

GHG – Green House Gas

GC – Grid Connection

GHI – Global Horizontal Irradiation

HEV – Hybrid Electric Vehicle

IEA – International Energy Agency

ICE – Internal Combustion Engine

IRR – Internal Rate of Return

ISV – Isenção do Imposto sobre Veículos

IUC – Imposto Único de Circulação

NCF – Net Cash Flow

NOCT – Normal operating cell temperature

NPV – Net Present Value

OMIE – Operador do Mercado Ibérico de Energia

O&M – Operation and Management costs

OPEX – Operational Expenditure

PDF – Probability Distribution Function

PHEV – Plug-in Electric Vehicle

PLC – Power Line Communication

PV - Photovoltaic

PVGIS – Photovoltaic Geographical Information System

SE – Solar Energy

SOC – State of Charge

US – United States

UK – United Kingdom

WLTP – Worldwide Light Vehicles Test Procedure

V2G – Vehicle to Grid

Symbols

A – Anisotropy index

$Bcapacity_k$ - battery capacity of each k model car (kW.h)

$Bcapacity_{sto}$ – storage system capacity (kW.h)

Ccg_h - energy price of the grid at hour t (€)

Ccp - cost of charging point (€)

Ccp_t – maintenance of charging point at year t (€)

Cev_h - energy price station at hour h (€)

Cpv – the cost of PV panel (€)

Cpv_t - maintenance of PV panels at year t (€)

Csg_h - remuneration price of selling to the grid (€)

Csto – the cost of the storage system (€)

$Csto_t$ - maintenance of storage system at year t (€)

Ecg_h - energy consumed from the grid at hour h (kW.h)

$Ecsto_h$ - energy charged to the battery at hour h (kW.h)

$Edsto_h$ - energy discharged from the battery (kW.h)

Eev_h - energy supplied to EVs at hour h (kW.h)

Eev_k - energy supplied to every k EV (kW.h)

Esg_h - energy supplied to grid at hour h (kW.h)

$Esoc_h$ - energy level in the battery at hour h (kW.h)

$Esoc_{h-1}$ - energy level in the battery at hour h-1 (kW.h)

$Espv_h$ - energy supplied by PV at hour h (kW.h)

$Esto_c$ - energy capacity of the battery (kW.h)

G_{Bn} – beam irradiance on the horizontal surface (W/m^2)

G_{Bt} – beam irradiance on the tilted surface (W/m^2)

G_D – diffuse irradiance (W/m^2)

G_{Dt} – diffuse irradiance on the tilted surface (W/m^2)

G_{Gt} – reflected irradiance on the tilted surface (W/m^2)

G_{on} – extraterrestrial irradiance (W/m^2)

$INFLOW_h$ - cash inflow at hour h (€)

m – diode's ideality factor

N – number of panels

NCF_t - net cash flow at year t (€)

Ncp - number of charging points installed

Npv - number of PV panels installed

NPV - net present value (€)

Nsto - number of batteries

$MAXev_h$ - energy demanded by EV at hour h (kW.h)

$OUTFLOW_h$ - cash outflow at hour h (€)

Pcg_h - power consumed from the grid at hour h (kW)

$P_{charger}$ - fast charger power (kW)

Pg_{max} - power limit in the connection point (kW)

P_{MP} – maximum power point power (W)

P_{NOM} – storage system rated power (kW)

Psg_h - power supplied to grid at hour h (kw)

q – electronic charge (J/K)

R_B – ratio between tilted and horizontal beam irradiance

$SC_{battery}$ – specific cost of the storage system (€/kW.h)

$SC_{equipment}$ – battery complement specific cost (€/kW)

$SOC_{initial}$ - initial SOC of the battery (p.u)

SOC_{min} - minimum SOC of the battery (p.u)

$SOC_{initialk}$ – initial SOC of each k EV arriving (%)

SOC_{finalk} – final SOC of each k after charging (%)

SOC_{full} – full state of charge of EVs battery (%)

Tc - charging time for each EV (min)

T – cell temperature (K)

T_{amb} – ambient temperature (K)

G_t – total solar irradiance on the tilted surface (W/m^2)

I_0 – reverse saturation current (A)

I_{MP} – maximum power point current (A)

I_{SC} – short circuit current (A)

k – Boltzmann's gas constant (J/K)

I - initial investment (€)

i - interest rate

Tc_{max} - maximum charging time (min)

Tw - waiting time for each EV (min)

Tw_{max} - maximum waiting time (min)

V – voltage imposed across the cell (V)

V_{MP} - maximum power point voltage (V)

V^T – thermal voltage (V)

V_{OC} – open-circuit voltage (V)

Greek Symbols

μ – an average of the logarithm of SOC

σ – typical deviation of the logarithm of SOC

β - tilt angle (º)

ρ - reflectance of the ground

ε – gap band (eV)

Chapter 1

1. Introduction

From all technological innovations likely to impact and disruption in the power sector, the rise of electric vehicles and the evolution of the autonomous versions thereof are among the most noteworthy. The automotive industry is entering an era of unprecedented transformative change, the increasingly rapid uptake of electric cars EVs.[1] The annual doubling of EV sales has pushed the global population over to five million marks for the first time in 2018. While this represents only 0.5% of the current global population of around one billion passenger cars, an ongoing exponential rise in sales and ultimately wholesale replacement of the internal combustion engine automobile (ICEs) is being seen as increasingly inevitable. The International Energy Agency[2] projects a global population of 60 million vehicles in 2025 and more than doubling to 140 million by 2040. These transformative changes are now becoming more visible with a rising uptake of EVs as their price falls and becomes cheaper to run and maintain. Therefore, charging facilities, charging time and power supply issues will inevitably become the focus of attention [1].

Policies play a critical role in electric mobility and currently, leading countries use a variety of measures and policy supports such as fuel economy standards coupled with incentives for zero- and low-emission vehicles, economic instruments that help bridge the cost gap between electric and conventional vehicles and support for the deployment of charging infrastructure. As one of the main key enablers technology advances are delivering substantial cost cuts as well as developments in battery chemistry. Battery manufacturing is also undergoing important transitions, including major investments to expand production. On the other hand, the private sector response to public policy signals confirms the escalating momentum for electrification of transport. Utilities, charging point operators, charging hardware manufacturers and other power sector stakeholders are also boosting investment in charging infrastructure. Adjustments to current transport-related taxation schemes, gradually increasing taxes on carbon-intensive fuels can support the long-term transition to zero- emissions mobility while maintaining revenue from taxes on transportation [1].

[1] For this purpose, EVs include both plug-in hybrid electric vehicles (PHEVs) and battery electric vehicles (BEVs).
[2] Autonomous organization which works to ensure reliable, affordable and clean energy for its 30 member countries and beyond.

1.1. Objectives

The main goal of this thesis is to analyze and suggest the optimal and desirable number of fast charging posts required to be installed in a hub for electric vehicles in the three main cities of Portugal, Lisboa, Porto, and Faro. This study was accomplished in collaboration with EDP Inovação. This will be considered regarding the demand rate of the installed chargers in which city, as well as the number assumption of EVs[3] in those locals. Likewise, it will be taking into account the expected load time, state of charge, battery capacity and market share for each BEV type which will lead to a queuing model. Also, the number of EVs waiting in line in that place, the EVs arrival distribution as well as, external characteristics and related to the fast charging system besides the EVs features such as the energy demand model, the solar photovoltaic energy model, and PV battery energy storage model. These fast-charging posts, E-Hubs, would be available for private and public transport and are mainly to be constructed on highways, shopping centers, airports, urban centers, B2B[4] fleets and parking lots. E-Hubs is a more carbon-free solution, although it isn't complete carbon-free since it must be taken into account its life cycle, and production of cars, charging posts, photovoltaic panels, and batteries for the storage system. Nowadays in Portugal, most fast-charging stations are deployed in highways.

The system will, therefore, be tested in terms of connection to the grid, photovoltaic energy usage, either used on roofs or solar parking lots and/or battery storage. The last one is the main profit source concerning these systems. Thereby to optimize the hub for electric vehicles there are two relevant issues to be answered by the model. In a scenario that includes photovoltaic energy usage the optimal number of PV will, therefore, be analyzed in order to meet the demand rate and prevent energy waste. In the case, energy waste cannot be prevented it would be socially, environmental and economically preferable to use battery storage or sell it to the grid. Thus, three main scenarios will be analyzed in this model which best gather an economic and social performance in order to get the maximum NPV[5]. The three scenarios are the following:

- Scenario 1: Grid connection;
- Scenario 2: Grid connection plus solar energy usage;
- Scenario 3: Grid connection plus solar energy and battery storage.

Besides, the main goal mentioned previously it will be assessed the current status of electrical mobility and specifically the publicly fast-charging stations, their hurdles and possible future developments regarding government policies and investments and the energy production and consumption model approach. Additionally, these models and optimization algorithms will be carried out in the Python programming language. For the sake of clarity, we refer to a charging point as a device suited for charging a BEV that only charges one BEV at a time.

---

[3] For this purpose, EVs include solely battery electric vehicles (BEVs).
[4] Business carsharing enables commercial businesses to reduce or eliminate private vehicle fleets.
[5] Difference between the present value of cash inflows and the present value of cash outflows over a period of time. Analyzes profitability of a project.

1.2. Methodology and Thesis Outline

Considering the research questions outlined above this thesis is structured as follows:

- Chapter 1: a general introduction to the topic is being studied and the main goals and research questions as well as the outline of this thesis;
- Chapter 2: the background regarding the current status of electrical mobility and specifically the publicly fast charging points, their hurdles and government international, national and local policies, regulations, supports, and investments as well as possible future developments in the following years. Regarding the future developments is discussed how the energy production and consumption model approach would change;
- Chapter 3: a review of relevant works similarly to this thesis main goal with methods that have been deployed in similar tasks and analyze of possible strategies on the three different scenarios;
- Chapter 4: presents the structure of the EDP model as well as the adapted model modified in order to use the optimization algorithm. The three different cities for this study will be shown the solar resource potential and differences between each other and lastly the outline of the three possible scenarios, solely grid network, grid plus photovoltaic generation and grid plus photovoltaic generation plus a storage system. The economic aspect will, therefore, be analyzed applying an optimization method which simulates and provides the possibility to validate different scenarios;
- Chapter 5: the methodology used to structure, analyze and test the model on the three different scenarios together with EV energy demand model, solar photovoltaic energy model, PV battery energy storage model, queueing model, EVs arrival distribution in accordance to EVs state of charge (SOC), battery capacity and market share as well as the economic aspects for each technology;
- Chapter 6: the results of the analysis presented in the previous chapter are highlighted and validated by the optimization method. This leads to the best scenario choice for the charging posts to be installed in a hub for electric vehicles. Thereby results of the three main possible scenarios are discussed and laid out as their economic feasibility analyzed;
- Chapter 7: the main conclusions of the proposed questions in this chapter are returned as well as the proposed potential improvements of the model are explained and suggested as possible future work.

Chapter 2

2. Background

This section provides a clear understanding of all concepts and technologies and advances of electrical mobility and specifically the fast chargers installed in hubs for electric vehicles which are the key enablers to create the framework of this thesis. Thereby this section is divided initially into the sales and market share worldwide in order to address the need for hubs' creation as well as current achievements by electrical mobility. Thereafter the current status of the publicly accessible fast charging points worldwide as well as specifically in Portugal and related policy supports that supports their deployment. Subsequently, the chapter concludes with the presentation of possible future developments that should be implemented for the future development of electric mobility and keeping the deployment growth and thence of electric vehicle supply equipment.

2.1. Sales and Market Share

Global EV sales were close to two million in 2018 after peaked the one million mark in 2017 as represented in Figure 1 which presents only data up to 2018, representing year-on-year growth of 68% between 2017 and 2018 among Electric Vehicles Initiative (EVI) countries and Europe. China has the highest volume of EV sales worldwide, followed by Europe and the United States whilst Norway is the global leader in terms of market share. China has been legislating and incentivizing industry to substantially and rapidly electrify both private and public transport resulting in now the world's largest and fastest-growing market for EVs. Has nearly 1.1 million EVs sold in 2018 up from almost 600,000 in 2017 and accounting for 55% of the global EV market share. In 2018 Europe was the second-largest EV market with 385,000 units sold followed by the US, the third-largest with 361,000 units sold. There was an increase in EV sales of 31% from 2017 to 2018 in Europe, lower than 41% between 2016 and 2017 and below the global average. However, Europe hosts countries with the largest penetration of EV sales. Norway approached 50% in 2018 of new electric cars followed by Iceland with 17,2% and Sweden with 7,9%. As related by the European Federation for Transport and Environment (T&E):

> *"The number of electric car models on the European market will more than triple within the next three years, new analysis shows. After several years of timid growth, EU carmakers will be offering 214 electric models in 2021 – up from the 60 available at the end of 2018."* [2].

As mentioned previously Norway was also one of the countries with the highest sales volume followed by Germany, the United Kingdom, and France up to 2018. Although Denmark and Netherlands' sales declined in 2017, they retrieved strongly in 2018. In the US from 2016 to 2017 sales increased by just 24%, whereas in 2018 they rose 82%, faster than the global market rate. Some other markets saw EV sales dropping such as Canada, India, South Africa, and Mexico. Worldwide BEV[6] constituted in 2018 more than two-thirds of EV sales that have been steadily increasing since 2012 (50%) to 2018 (68%). Although Europe remained a strong market for PHEV[7] sales mastering in Finland (86%), Sweden (75%) and United Kingdom (69%) [3].

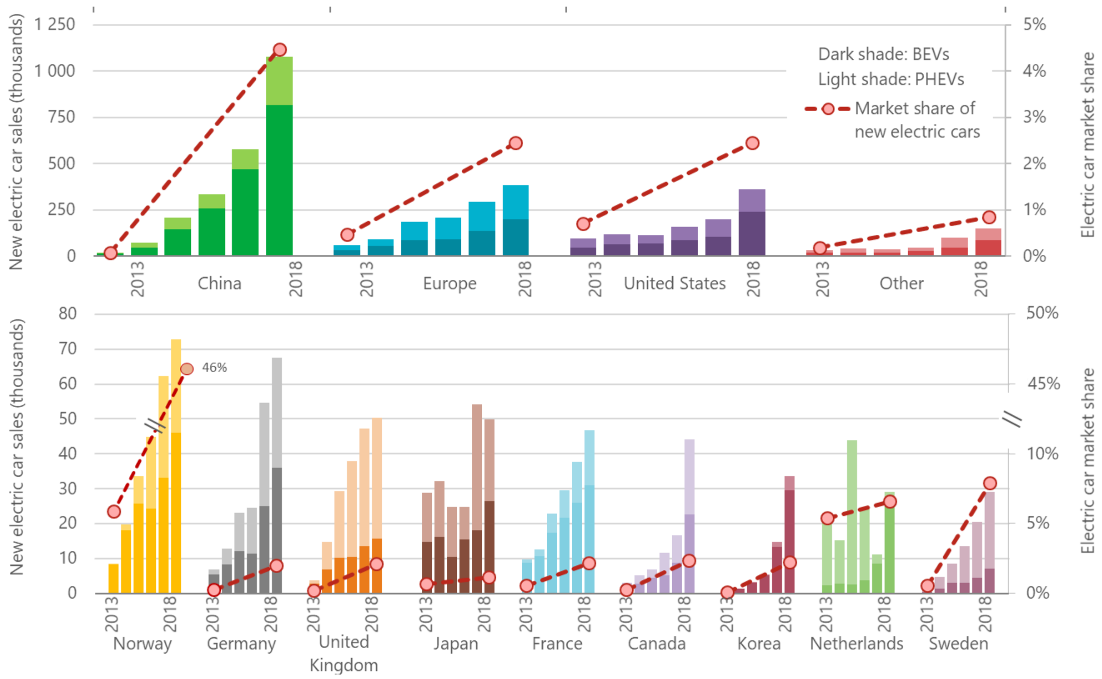


Figure 1 - Electric car sales and market share in the top-ten EVI and Europe between 2013-2018. Source: https://webstore.iea.org/download/direct/2807?fileName=Global_EV_Outlook_2019.pdf

Notes: Others include Australia, Brazil, Chile, India, Japan, Korea, Malaysia, Mexico, New Zealand, South Africa, and Thailand. Europe includes Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Liechtenstein, Lithuania, Luxembourg, Malta, Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, and United Kingdom.

Although the information presented above is representative of EV sales as a set of PHEVs (Plug-in Electric Vehicle) and BEVs (Battery Electric Vehicle), the following information in this thesis will be only concentrated regarding BEVs once they are the main users of fast-charging stations.

Figure 2 represents BEV sales in Portugal and has data from European Alternative Fuels Observatory (EAFO) and gathered until August 2019. According to Figure 2, there has been exponential growth throughout the years. From 2010 until 2016 the EVs were being launched, still trying to gain market share and groping ground until 2017 where a change happened on sales volume and consumer choice. Currently, the Portuguese EV market reaches a BEV passenger car fleet of 12,240, around 4,000 more than the previous year and 8,000 from two years ago.

---

[6] Has all its power from its battery packs and thus has no internal combustion engine.
[7] Shares the characteristics of both conventional hybrid electric vehicle and battery electric vehicle, with an electric motor, an internal combustion engine and a plug to connect to the electrical grid.

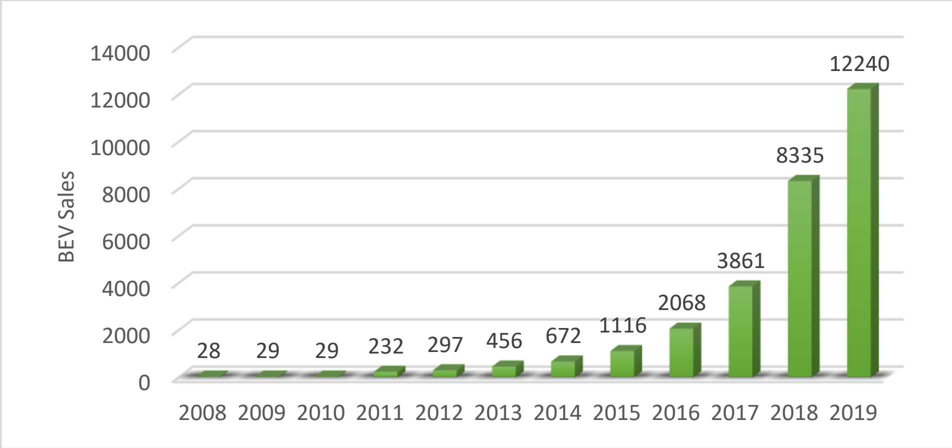


Figure 2 - Battery Electric Vehicles sales volume in Portugal between 2010-2019. Source: https://www.eafo.eu/

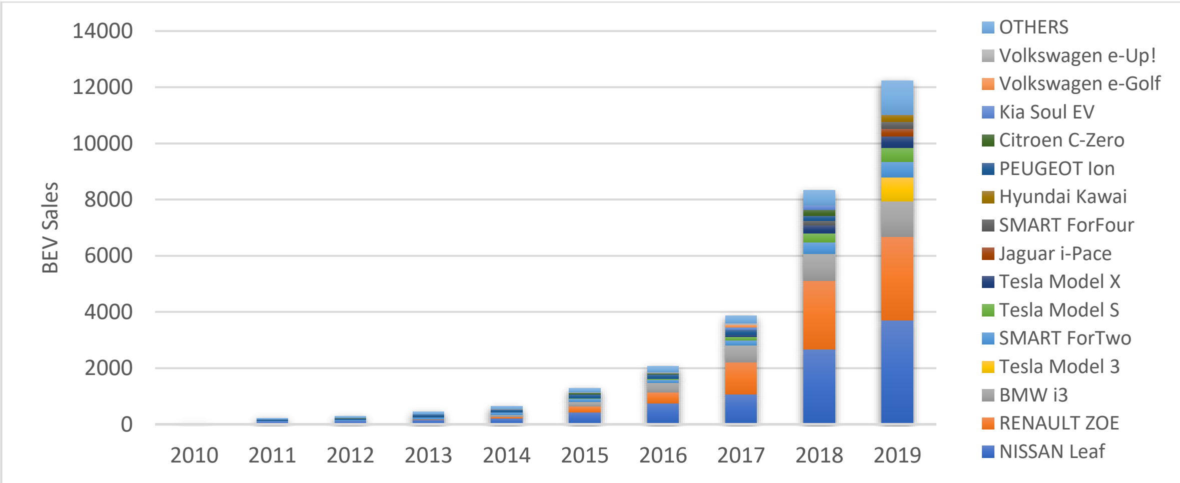


Figure 3 - Battery Electric Vehicles sales volume in Portugal between 2010-2019 by brand. Source: https://www.eafo.eu/

As important as to know the BEV fleet in Portugal is to know their variety, therefore the same data is presented but with sales' comparison of each car brand being part of the 15 best sellers in Portugal in Figure 3. According to Figure 3, the best-selling cars since 2015 have been the Nissan Leaf, Renault Zoe, and BMW i3 whereas this year there was a booming growth for Tesla Model 3, Jaguar i-Pace and Hyundai Kawai. For those who are not among the 15 best sellers in Portugal are considered as "Others" tab.

It was analyzed the evolving of EVs, thus is appealing to analyze how the fleet in Portugal is evolving detailly analyzing the registrations of new BEVs every year and the market share of BEVs' new registrations annually. As far as new registrations of BEVs annually are concerned, there was a sharp growth since 2015 and a very favorable growth for the EVs market development in 2018 as presented in Figure 4. Nevertheless, this year appears undermost because the data collection was taken out in August of 2019. Thence 2019 doesn't count as a full year as others but evidences an upgrowth as fair or foremost as 2018.

As it was mentioned previously, 2019 could be a year that evidences a superior upgrowth and it appears as it is. The market share of new registrations in 2019 in Figure 4 is 1% more accounting with the numbers until end-August, intending that it will be larger throughout the year. Even so, the number of new registrations is set below 2018, the market share is bigger, indicating the number of new BEVs in Portugal is taking advantage with respect to the ICEs sales.

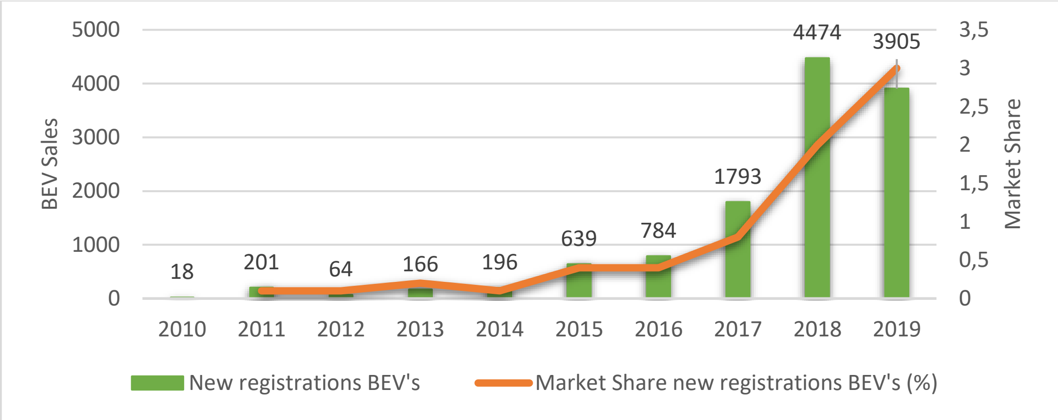


Figure 4 - Battery Electric Vehicles' new registrations and new registrations market share in Portugal between 2010-2019. Source: https://www.eafo.eu/

Although there has been a great EV uptake, Portugal is still one of the countries under the global average when compared with the top-five including EU[8], European Free Trade Association (EFTA[9]) and Turkey. (Figure 5)

A fully-fledged EV take-off will come only when BEVs are competitive in costs and have an adequate range and reasonably extensive refueling infrastructures.

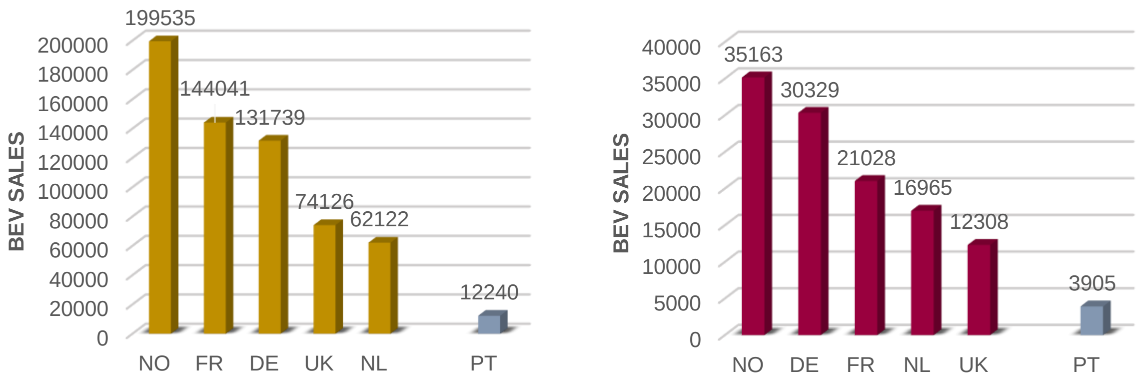


Figure 5 - Top 5 BEV fleet in 2019; Top 5 BEV new registrations in 2019. Source: https://www.eafo.eu/

Notes: NO – Norway; FR – France; DE – Germany; UK – United Kingdom; NL – Netherlands; PT – Portugal.

[8] European Union includes 28 country members as of 2019. Austria, Belgium, Bulgaria, Croatia, Republic of Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden and UK.

[9] Intergovernmental organization of Iceland, Liechtenstein, Norway and Switzerland.

2.2. Electric Vehicle Supply Equipment: Current Status

In this section, we will look at the Electric vehicle supply equipment (EVSE) and the variety of options such as normal and fast charging as well as private but mostly focusing on publicly accessible chargers. Their development and inclusion in mobility are a consequence of policy developments as well as governments' commitment to making forward EV power outlet rollouts and seen as a complement to private charging infrastructure rather than a replacement, even more for those who are allocated on long-distance journey ways. EV power outlets have been and will continue to grow roughly in line with the EV owner's growth.

The EVSE is differentiated by three main features, such as the power output range of the outlet, the socket, and connector used for charging and lastly the communication protocol between the car and charger. Table 1 highlights an updated of the most predominant fast charging standards in the three main markets of EVs detailing the types of fast chargers, i.e. sockets and connectors. Considering Table 1, there is a variety of electrical sockets and connectors that are in use in these 3 main markets/Countries/Regions. Fast chargers operate on triphasic AC (> 22 kW and ≤ 43.5 kW) but mostly on DC with a power rating beyond 22 kW and currently beneath 200 kW. The last ones will be the most focused on this thesis.

Table 1 - Overview of the EVSE types in China, Europe, and North America

COUNTRY/REGION	AC	DC	
CHINA		GB/T 20234 DC	
EUROPE	IEC 62196-2 Type 2	CCS Combo 2 (IEC 62196-3)	Tesla Supercharger and CHAdeMO (IEC 62196-3 Type 4)
NORTH AMERICA		CCS Combo 1 (SAE J1772 & IEC 62196-3)	

Furthermore, there also differences in the communication methods of the charging protocols. These protocols lean on physical connections that vary from car to car and charger to charger and there is little openness to turn out them in a compatible approach. Supposing DC fast chargers the Combined Charging System (CCS) connectors[10] are coupled with power line communication (PLC) protocols that typically make part of smart grids, i.e. communication in smart grids whilst the other three connectors, Tesla Supercharger[11], GB/T and CHAdeMO, which stands for *charge de move*, employ controller area network communication that were formerly full-blown for electric components inside cars.

In 2017 there was a global development for charging standards releasing new descriptions and official protocols to charge at up to 200 kW. There was a limited amount of deployment of these high-power

[10] Type 2 IEC 62196-2 and 62196-3 (CCS Combo 2) connectors are mandated by the European Union 2014/94 Directive.

[11] Tesla Supercharger has an adapter whom can link both Tesla and CHAdeMO plugs from 2013 onwards.

chargers, notwithstanding that there is almost inexistence of EVs on the road that can already charge at this top level. Nevertheless, as mentioned previously and according to Table 1, Tesla has been instrumental in the deployment and upgrowth of superchargers who nowadays enable Tesla cars to charge up to 150 kW, faster than any other EV available in the market. Although DC fast charging is mostly used by currently purchased cars leading off at 50 kW [3].

The number of charging stations worldwide was lately estimated, end-2018, at 5.2 million, up 44% since 2017. The charging stations are made up of private, normal chargers, and both publicly available fast and normal chargers. Normal chargers provide power less than or equal to 22 kilowatts (kW). Private chargers outnumber publicly accessible ones, thence the growth is mainly due to private charging points which account for almost the entire market share of charging structures' deployment as it is 90% of the 1.6 million installations in 2018. At end-2018 the publicly accessible installed fast chargers were numbered as 144,000 and normal chargers as 395,000. Figure 6 provides an overview of chargers' deployment from 2013 up to end-2018. As far as chargers' global installation is concerned there is an ongoing upward trend for all charger types but the growth rate of new installations of publicly accessible chargers is slowing in comparison to previous years such as 30% in 2017 and 80% in 2016 [1].

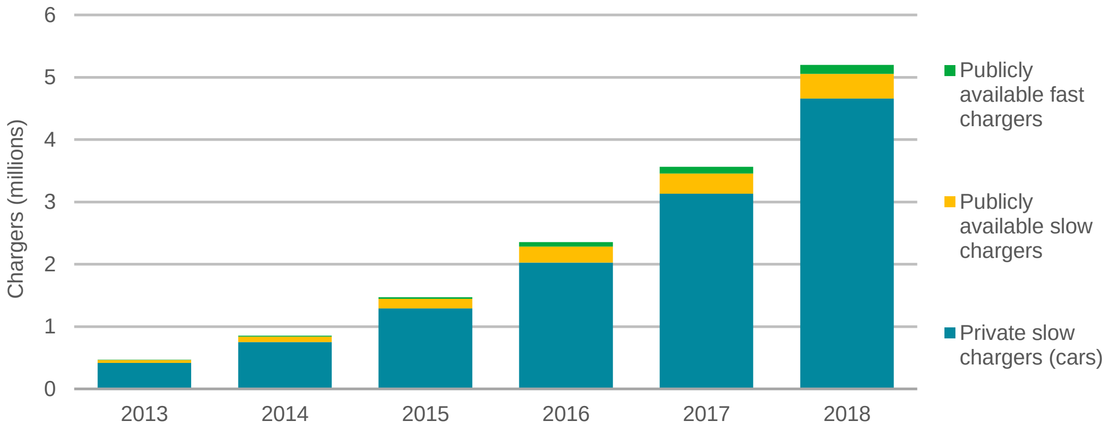


Figure 6 - Global installation of electric charging stations 2013-2018. Source: https://webstore.iea.org/download/direct/2807?fileName=Global_EV_Outlook_2019.pdf

For this figure's presentation the data taken out from charging stations assumed that for private chargers, each electric car is coupled to 1.1 private chargers (conventional wall plugs or using a dedicated connector) either at home or workplace worldwide except China and Japan. China and Japan, as densely populated urban areas, assumed 0.7-0.8 private chargers per EV [1].

In addition, as mentioned previously the publicly accessible fast-charging stations can be both operated at AC and DC. They are usually operated only at DC as EVs' demands are up 50 kW. It is possible to charge two EVs simultaneously if the charger is equipped with an AC connector and a DC connector. One good reason for this possibility is that for instance the sold cars from Smart such as Smart ForTwo and Smart ForFour can only be charged with AC connectors. However, if there are two different DC connectors instead, for instance, CCS and CHAdeMO, it usually isn't possible to charge simultaneously.

Emphasizing detailly and merely the publicly accessible charger worldwide, these reached 539,000 in 2018, 24% more than in 2017. China remains the country with the largest installed publicly accessible charging infrastructures. In Figure 7 is estimated to have approximately three-quarters of the world's publicly accessible fast chargers and a major part of the normal chargers, 41%. Around a third of the publicly accessible chargers installed were fast chargers in 2018 whereas in Europe and the US (United States) a large majority are still normal charging stations [1].

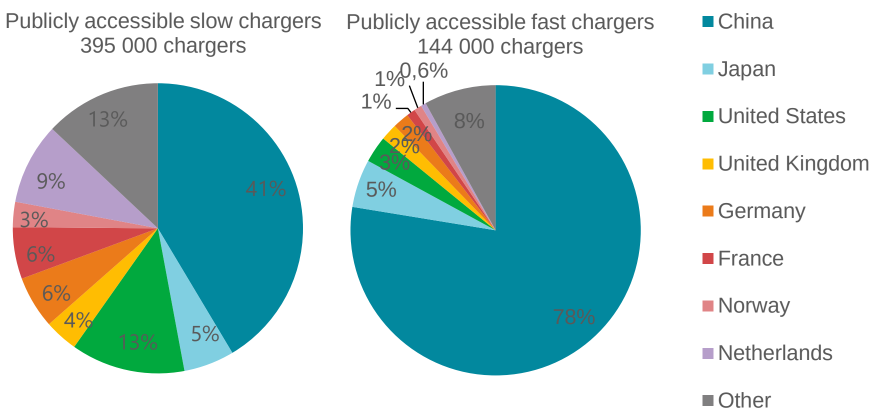


Figure 7 - Publicly accessible chargers by country in 2018. Source: https://webstore.iea.org/download/direct/2807?fileName=Global_EV_Outlook_2019.pdf

Regarding the EVSE/EV ratios, the number globally has decreased from 0.14 in 2017 to 0.11 at the end-2018. As in many countries, EVs are at an early development stage the EVSE/EV ratios across those countries aren't straightforward. Still, this ratio remains higher than the charger per 10 electric cars recommended by the European Union Alternative Fuels Infrastructure Directive. US and Norway, one of the many leading countries on EVs deployment, remains below the average with a ratio of 1 charger per 20 electric cars. Inversely the Netherlands and Denmark have a ratio of 1 charger per 4-8 electric cars [1].

Thereupon, the demand for publicly accessible charging infrastructures isn't automatically a prerequisite for EV deployment, it depends mostly on population density, access to workplace charging infrastructure, vehicle range of each country, driving patterns and public transport infrastructure [1].

As mentioned previously there are two types of EVSE, normal chargers, and fast chargers. The purpose is to study fast-charging stations in this thesis, but we count both to better understand the market in Portugal. According to Figure 8 the disparity between normal and fast public charging points is due to the launch of PHEV, Hybrid Electric Vehicles (HEV) and Extended-Range Electric Vehicle (EREV) cars before the completely pure electric (BEV) cars began to gain market share from 2014 onwards. Another reason is that fast public charging requires better technology and more initial investment to be more installed from 2016 onwards since until then the market share of EVs wasn't very significant for the outlay. Yet less than normal public charging point fast charging points are steadily increasing, 80 filling stations more than three years ago and even more still to be constructed. The figure account for all the normal and fast charging stations, although this number represents the installed charging posts, not necessarily the operational posts.

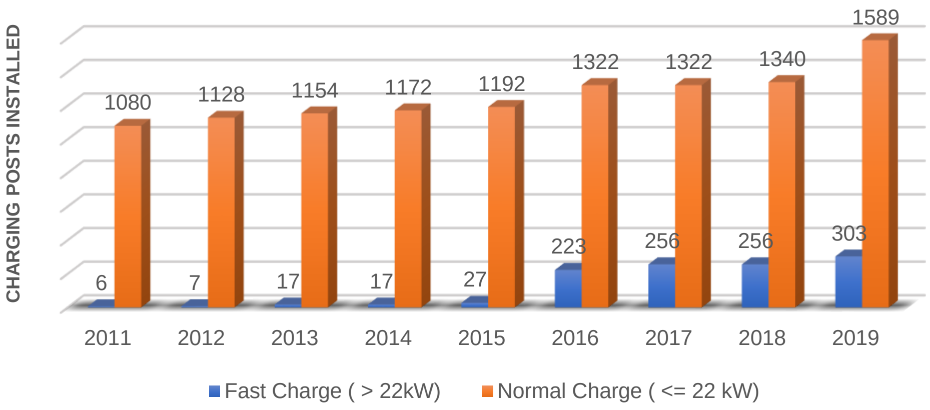


Figure 8 - Slow and fast public charging points in Portugal between 2011-2019. Source: https://www.eafo.eu/

2.3. Electric Vehicle Supply Equipment: Policy Supports

This section describes the current and likely government role in incentivizing the adoption of EVs. The uptake of EVs will not be driven simply by the extraordinary commercial opportunities they present. Sustaining a rapid uptake of EVs is still very much a government priority if the tough GHG emissions targets from the Paris agreement on climate are to be met [4].[12]

As well as publicly accessible charging infrastructures depend on the topics discussed previously, it also depends upon local, national and international policy support and decisions. These include regulations, funding for direct investment, financial support and deployment targets such as the Paris agreement of 2015[13]. [14] The previous policy supports are responsible for creating conditions in order to catalyze, boost and foster EVSE's deployment. Financial support can be financial incentives, tax relief, and direct investment. The number of countries with financial incentives has been increasing substantially and overall the government has ramped up on investments in recent years.

The deployment targets help to set up a plan, to design a horizon with a goal thereby matching EVSE developments and EV uptake. EVSE deployment targets have not been set worldwide, some countries don't have it yet, solely for EV uptake. As far as national and international measures are concerned, there are two examples for China and Europe. Chinas plans to deploy 12,000 stations to swap batteries, 4.3 million private outlets for EVSE and 500,000 publicly accessible chargers by 2020. Whereas for Europe, the European Commission requested deployment targets for 2020, 2025 and 2030 wherefore to match the required infrastructure number from the Alternative Fuels Infrastructure (AFI) Directive.

[12] EU is committed to 80%-85% by 2050.

[13] The Paris agreement has set out targets for GHG reductions within the transport sector in the form of a global EV fleet of 100 million in 2030. A European Environmental Agency (2016) report estimates that if 80% of EU cars were EVs in 2050, a 10% reduction in total emissions would occur taking into account emissions produced by the increased generation of electricity to meet EV demand.

[14] There are funding and financing supports in EU such as Horizon 2020 – "Smart, Green and Integrated Transport", European Energy Efficiency Fund, LIFE program, INTERREG Europe 2014-2020, URBACT III, the European Fund for Strategic Investments, ELENA and COSME [3].

Only 80% of EU (European Union) countries submitted targets in 2017. Only 35% of the publicly accessible charging stations required by 2020 have been deployed. Although the ratio EVSE/EV of one publicly accessible charging stations per ten cars is probable to be achieved in 2020 [3]. In Portugal, regarding the incentivization addressed, the purchase subsidies are a National subsidy for BEV's of 2,250€ and for PHEV's of 1,125€. Relatively to registration tax benefits, there is a tax reduction/exemption, such as vehicle tax exemption (ISV) and single road tax exemption (IUC) [5]. As well as parking fee discount in many cities. Likewise, the ownership tax benefits and value-added tax (VAT[15]) benefits offer a tax reduction/exemption based on CO_2 consumption [6].

According to the International Energy Agency (IEA), most electric car owners in Europe and the US have their own garage or driveway. All in all, EV owners living-in apartment blocks, condominiums or city center dwellings require EVSE so that a larger market share can be reached. Thence there is a need to create building codes and permits. Nowadays many building regulations forbid parking facilities. Yet a limited number allows charging outlets. The main barriers here are the procedures for changes such as the installation of charging outlets in existing buildings, in car parking spaces, and to ensure that the new buildings are capable to easily install EVSE. Thus, the key regulatory policies that guarantee a steadily increase and greater diffusion in private households are the development of building codes embedding requirements by including conduits for EVSE cables and grid connections to newly built parking spaces and later on, existing buildings. In 2017 a political agreement of the European Directive stated that non-residential new and renovated buildings, with more than ten parking spaces, must install at least one charging point, as well as one-out-of-five spaces, must have a conduit installed. Likewise, for residential new and refurbished buildings, with more than ten parking spaces, every parking space must be equipped with a conduit. Moreover, it is required for public parking lots and all buildings, residential and non-residential, and member states are asked to set up a minimum number of charging points for those with more than 25 parking spaces. For instance, a minimum of 6% for the parking lots and areas in new buildings must be allocated to EVs in Norway.

As well as building codes and permits EVSE are subject to power sector regulations once they are integrated into the electricity system. The regulatory structure has a strong impact and implications for the ownership structure. For instance, in Germany and the UK (United Kingdom), it isn't allowed for distribution companies to operate charging infrastructures. Depending on the legislation EV charging stations can be considered a retailer or a distributor of electricity and that amongst the regulatory environment can facilitate or hinder investments by electricity sectors or private companies. Sometimes the regulatory environment limits the possibilities for utilities to invest or own EVSE since they receive regulated revenues from network operations which grants benefits when competing with companies that don't have a regulated income stream in the market for charging infrastructures. If these restrictions were eased, EVSE expansion would be easier allowing utilities to invest in their development.

[15] VAT is a consumption tax placed on a product whenever value is added at each stage of the supply chain, from production to the point of sale. The amount of VAT that the user pays is on the cost of the product, less any of the costs of materials used in the product that have already been taxed.

Cities are using a variety of measures to promote the development of charging infrastructure. Highlighted in Figure 9, there are some examples of recent measures of local policies that have a clear impact on the development of urban EVSE networks and focus of attention on major initiatives that have been adopted and implemented for promoting EVSE deployment in major cities.

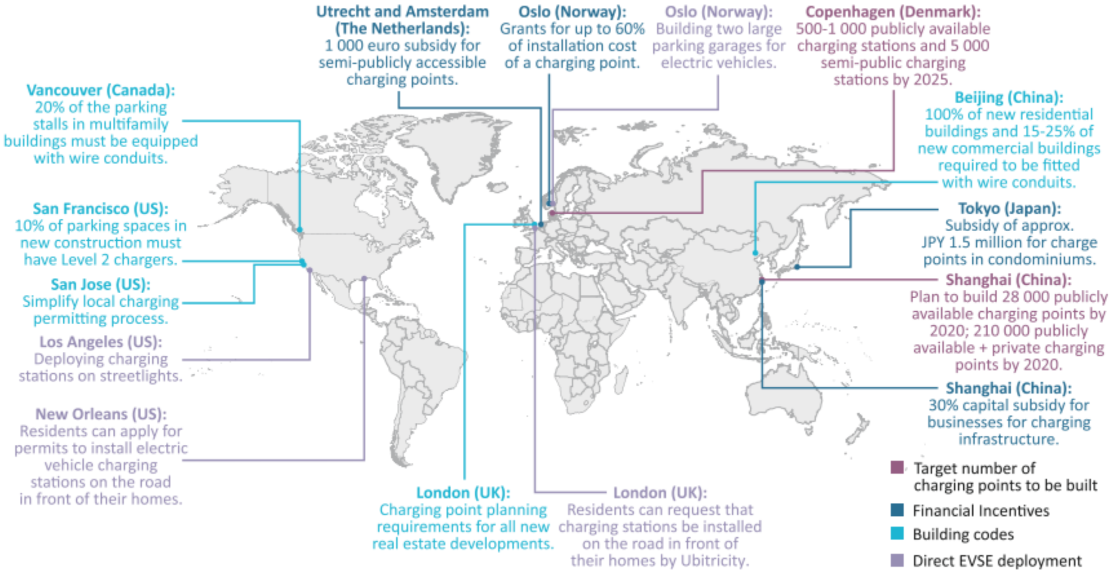


Figure 9 - Examples of recent policy measures promoting charging infrastructure deployment in major cities. Source: https://activatecp.com/wp-content/uploads/2018/06/global_ev_outlook_2018.pdf

According to Figure 9, there is a variety of policy measures used currently to incentivize EVSE development in big cities. They are separated into four types:

- Targeting the number of charging points to be built;
- Financial incentives for EVSE;
- Building codes change in order to promote easier installation;
- Installation of charging points.

Some of the policy measures in Europe which don't include target measures are like in Utrecht and Amsterdam (The Netherlands) where there is a 1,000€ subsidy for semi-publicly accessible charging points, in Oslo (Norway) there are grants for up to 60% of installation cost of a charging point and there are being built two large parking garages for EVs, and in London (UK) there is a charging point planning requirement for all new real estate developments and residents can request charging stations to be installed on the road in front of their homes by Ubitricity[16] [3]. In Lisbon there is free parking for EVs, as well as, the local utility company gives a one-year discount in electricity for BEV (Battery Electric Vehicles) buyers. According to EAFO, the incentives used in European Union in all countries can be done in many ways: purchase subsidies, registration on tax benefits, ownership tax benefits, company tax benefits, VAT benefits, other benefits, production, and infrastructure. Table 2, withholds information about all EU+EFTA+Turkey countries and shows few countries with infrastructure supports as well as

[16] London's charging infrastructure company.

investments. Portugal aren't included on the countries with support, although leading countries on publicly accessible fast-charging stations such as the United Kingdom and Norway relating the importance and relation amongst policy supports and deployment of EVSE [6].

In addition to government targets, private sector stakeholders such as car manufacturers, oil companies and utility companies are engaged and planning to deploy fast-charging stations along highways demonstrating an increasing variety of players entering the infrastructure market. Their aim is to bridge the gap of limited publicly accessible infrastructure for long-distance trips to be a barrier for EV adoption. For instance, in Portugal, there is a network composed of charging stations for electric vehicles mostly located in publicly accessible spaces, namely MOBI.E, with 768 charging posts of which 58 are fast charging posts [7], which has operators from a variety of enterprises such as EMACOM, Prio Energias, EV POWER, CME, Galp Power, Galpgeste, EDP Comercial, Kilometer Low Cost, Propel and Mobilectric for fast charging [8]. Figure 10 presents us with the number of fast public charging points per 100 km of the highway. One notices that as the booming growth in 2016 of fast public charging points happened (Figure 8), the number of fast-charging stations per 100 km of highway occurred likewise. Leaped in such a way that in 2015 there was only 1 fast charger per 100 km of highway and in 2016 there were already 8 fast chargers per 100 km of highway.

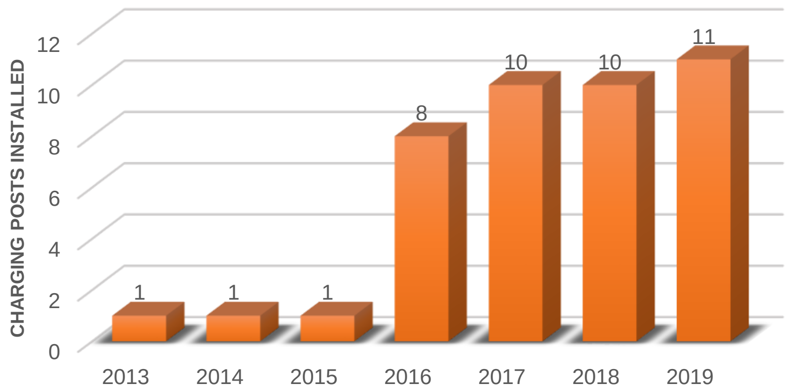


Figure 10 - Fast public charging stations per 100 km of highway in Portugal between 2013-2019. Source: https://www.eafo.eu/

Table 2 - Incentives adopted and implemented through every EU country. Source: https://www.eafo.eu/

COUNTRY	Purchase subsidies	Registration on tax benefits	Ownership tax benefits	Company tax benefits	Vat benefits	Other benefits	Production	Infrastructure
Austria	✓	✓	✓	✓	✓		✓	
Belgium	✓	✓	✓	✓			✓	
Bulgaria			✓				✓	
Croatia		✓						
Cyprus		✓	✓					
Czech Republic		✓	✓					
Denmark	✓	✓					✓	✓
Estonia							✓	
Finland		✓	✓					
France	✓	✓	✓	✓			✓	
Germany	✓		✓	✓			✓	
Greece		✓	✓			✓		
Hungary		✓	✓	✓			✓	
Iceland		✓	✓		✓	✓	✓	✓
Ireland	✓	✓	✓					✓
Italy			✓					✓
Latvia		✓	✓				✓	
Liechtenstein	✓							
Lithuania		✓					✓	✓
Luxembourg	✓		✓	✓				
Malta	✓	✓	✓	✓			✓	
Netherlands		✓	✓	✓		✓	✓	
Norway		✓	✓	✓	✓	✓	✓	✓
Poland								
Portugal	✓	✓	✓	✓	✓		✓	
Romania	✓	✓	✓					
Slovakia	✓	✓					✓	
Spain	✓	✓	✓	✓			✓	✓
Sweden	✓	✓	✓	✓	✓			✓
Switzerland		✓	✓			✓		
Turkey					✓			
United Kingdom	✓	✓	✓	✓			✓	✓

2.4. Electric Mobility: Future Developments

In concert with the uptake of EVs, the prospect is being created of battery-powered vehicles (BEVs) becoming an integral part of electricity grids in terms of both representing sources of demand and supply and thereby creating a new class of prosumers [1].

The fast-smart charging can go a long way to facilitate a smooth transition to an EV dominated transport system, although policy, regulatory and financial investment will be required in order to realize it. Thus, not only will the balance of peak and off-peak charging need to be closely managed but the investment to roll out adequate high voltage fast-charging stations on a national scale will need to be carefully scheduled [4].

Policies and market frameworks need to ensure that electric mobility can play an active role in increasing the flexibility of power systems. This feature has positive implications for the increasing contribution of variable renewable energy in a power generation mix and can also address grid stability issues. The following features are therefore that electricity markets should facilitate the provision of ancillary services such as grid balancing that are suitable for EV participation and allow for the participation of small loads through aggregators[17]. They shouldn't face high transaction[18] costs in order to pool a large number of small loads. Likewise, EVs can minimize the impact on load profiles of power systems by managing their charging patterns to coincide with low demand periods. Also, EV batteries can store energy that may be used later on for other purposes than powering the vehicle due to opportunities accessible by vehicle-to-grid (V2G) or vehicle-to-home approaches [1].

While there may be space for V2G to become an alternative to increasing grid peak capacity, the accelerated depreciation of car batteries when used in this way needs to be taken into account. The sheer range of new battery developments and the evident potential to effect major increases in storage and decreases in cost indicates the potential for EV uptake to be part of a radical spread of distributed power generation and storage. Although it is expected that electric vehicle owners only charge their cars in fast-charging stations when in need for fast charging such as in freeways and when in a rush, since the fast charging depreciates the battery lifetime, therefore the concept V2G for users might not occur as much as it is expected in the future because it impacts the battery lifetime. On the other hand, if EV battery prices continue to fall as predicted so will the home storage batteries. A natural progression as costs of batteries and solar PV continue to decline and their efficiencies rise to appeal to PV/battery combinations to move off-grid [4].

[17] New type of energy service provider which increases or moderate a consumer group's electricity consumption regarding grid total electricity demand.
[18] Including fees and regulatory, administrative or contractual hurdles.

Chapter 3

3. Literature Review

In this section, the most relevant previous works from the literature review will be contextualized. These were selected based on sharing critical insights for this work's main goal. It will be examined the current state of the different scenarios used mentioned previously as well as investigating the methods that have been deployed in similar tasks and analyze possible strategy options.

Recently published literature provides a wide range of definitions and detailed discussions regarding the models developed for the design of EV charging stations. For instance, one of them developed a model to calculate the size of an EV charging station resorting to renewable energies but it considered that the demand is constant and that there was no connection to the grid. Therefore, the charging station is only supplied by wind and solar energy and battery storage systems [9], an off-grid charging station. Another published paper presented the optimal design of a charging station in order to minimize its lifecycle cost considering renewable energies, grid connection, and storage systems. The charging demand was estimated considering real driving data. They consider a load profile that did not take into account when each car arrived at the stations and subsequently when the charging operation of each vehicle began and finished. Rather, they consider an average value for each hour [10]. In some designs, the energy demand models were more complex by considering real-world traffic data [11]. The energy management models from the previous literature are based on the prioritization of the EVs' charging and use of battery storage systems to store the energy provided from wind and solar energy when there are no EVs in the charging stations [9]. A similar form of management is used by [10] in which when there is an energy surplus, it feeds a thermal load.

This work is based on some of the previous ideas. The EV fast-charging station is designed to be supplied solely by solar energy and not wind energy, by a storage system and by the grid network. The load profile does not take into account when each car arrives, but rather the average value for each hour. For the energy management model, it is considered whether it is a peak hour or not as a criterion to supply the charging station from the storage system or not.

Regarding the objectives when designing an EV charging station, these can be to minimize the energy cost for EV users [12], to minimize the overall energy cost of the system [13], to maximize profits to EV owners while satisfying the system [14] or to maximize the profits from the EV charging station[15].

For this work, the main objective will be to maximize the profits from the EV fast-charging station according to its net present value.

Some of the reviewed works do not consider the charging dynamic, i.e. the arrival time and the state of charge of each electric vehicle. However, these particularities were considered in a different work [15] that also considered the procurement and sale of energy in the electricity market and adopted a genetic algorithm to deal with the complexity of the design problem which finds the optimal solution that maximizes the profit measured by its net present value (NPV). The EV power demand is represented by an Erlang B queuing model and the charging station is supplied resorting to renewable sources, both wind and solar energy, to the grid network and to batteries.

In addition, this same paper [15] was very relevant since it has a more holistic view and approach that is congruent with the objective of this thesis since this work also uses a genetic algorithm as a mean of finding the optimal solution which maximizes the NPV and considers the charging dynamics such as the state of charge. However, the queuing model considered is represented by an M/M/s queuing model, which will be explained later. In this study, the EV station is fed from a mix of renewable energy and by the grid. The results were for this case, 5 charging posts, an NPV of 990.445€, and a payback period of 4 years.

Chapter 4

4. Model Framework

This chapter provides the structure of the EDP model as well as the adapted model modified in order to perform an optimization algorithm instead of a simulation. Explanations about three different possible scenarios are presented such as scenario one which uses only grid network, scenario two which uses the grid network and photovoltaic energy generation and scenario three which uses the grid network, the photovoltaic energy generation, and a storage system. Also, the three different cities from Portugal under analysis are presented regarding their solar resource as well as explanations regarding their differences between each other according to GHI (Global Horizontal Irradiation) average annual availability and GHI relative annual variability. Finally, the economic aspect, specifically the objective function of the algorithm, the net present value, is analyzed applying the optimization method;

4.1. Model schemes

As stated in the main goals of this thesis, the developed models and optimization algorithm have been applied and tested in order to analyze and suggest the optimal and desirable number of fast charging posts in a hub for electric vehicles. There are more variables that were analyzed and used in the optimization algorithm, although the number of charging posts depending on the chosen scenario is the main goal to find. Firstly, a scheme was drawn for the model development which connects all variables, variable models and distributions carried out for the optimization algorithm. Thereby below are presented the scheme, however, there are two models for the same purpose. As this thesis is carried out together with EDP Inovação and they had already developed and used a similar model beforehand for EDP purposes, I obtained EDP's overview model and adapted it. The model I developed was made from scratch by me and presents us with a new problem resolution, a different way of variables usage and a different method to achieve the optimal and desirable solution. The EDP model is presented in Appendix A, and the model developed by me is presented in Figure 11, where the results are presented in Chapter 5.

Table 3 - Main differences between EDP model and the adapted model

EDP MODEL	ADAPTED MODEL
Simulation Tool	Optimization Method – Genetic Algorithm

As far as EDP's model is concerned and the main difference is the method to achieve the optimal and desirable solution, i.e. EDP's model uses a simulation tool whereas the adapted model uses an optimization method resorting to the genetic algorithm as well as the variables used as inputs and outputs (Table 3). Appendix A presents the layout of the model from EDP which displays four models, EVs data and the simulation tool used as well as consequently the business plan chosen regarding the variables chosen in the simulation tool. The four models are the queuing model, solar model, storage model, and grid model. Each one of them has input and output variables. Input variables are highlighted with red color and output variables with a blue color. The solar model and storage model are interconnected to the grid model because one must balance out the solar and storage model with the grid model, if these do not suppress EV needs, i.e. energy demand. The solar model is directly connected to the storage model as the energy stored comes from photovoltaic solar energy production. The queuing model receives data from three different sources such as EVs data, the data from the charging station and driving data. The EVs data access the features from main EV versions circulating on the roads. The charging stations box accesses data of the number of charging post which will be utilized and their power and charger type. Lastly, the driving data box admits driving data, for instance, EV state of charge (SOC). Thereby, all models are used in the simulation tool which returns the related data of peak power, energy demand, cars served/lost and service time per car according to all variables mentioned above. Consequently, the economic component is assessed and evaluated regarding the net present value (NPV) and the internal rate of return (IRR) values. The input variables to take into account are CAPEX[19], OPEX[20], energy tariffs and the revenue model.

In every simulation, varying the input variables gives diverse solutions, the optimal solution is the one which maximizes NPV and has a positive IRR, i.e. an IRR higher than the cost of capital.

As mentioned before the EDP model was optimized and adapted in order to fulfill different requirements, uses different variables as well as a different method to achieve the optimal and desirable solution, the optimization resorting to the genetic algorithm, refer to the scheme in Figure 11. Firstly, the charging posts for a hub for electric vehicles need EV customers. If the demand is greater than the supply these customers will create a queue, i.e. the waiting line. These waiting lines depend on the car's number in the queue as well as the number charging points installed in the hub. Therefore, an EV arrival distribution can be created depending on those variables. The following important step is to acknowledge what type of customers they are, i.e. the EV market which requisite this service as well as their charging state. Hence, the input variables of the state of charge for each car have to be recognized. Likewise, each car battery capacity and the market share in Portugal are used to obtain the consumption profile of EV charger usage which will then be verified in order to choose a scenario either with PV, with PV and a PV battery or just the grid connection fulfilling the energy demand.

[19] Funds a business uses to acquire physical goods or services that will expand the company's ability to make a profit.
[20] Result of the ongoing costs a company has to keep running.

As far as solar and storage models are concerned it is imperative to know their CAPEX and OPEX, as well as the number of batteries for the storage model and the local irradiance for the solar model, depending on the chosen city for evaluation to decide on which scenario should be chosen. These data will sort out a production profile detailing how much energy was produced/consumed from EV owners by each technology, grid, battery, and solar PV. Lastly, the optimal scenario is chosen according to all previous variables as well as the respective NPV. Additionally, there is an optimization method to process the following data which resorts to a genetic algorithm instead of a simulation tool. Thence, it won’t be required to simulate as many times as the simulation tool from EDP needs, it will be optimized instead with all input variables range picking the solution which maximizes the NPV and consequently provides us also with the production profile allowing to perceive what would be the scenario chosen, from the previously explained in the Introduction chapter. Similarly, it will be possible to recognize what is the ideal number of charging posts, solar photovoltaic panels, and batteries required to accomplish that technical and economic optimal and desirable solution. As far as the frameworks are concerned the adapted model seems way simpler, although is just presented in a simpler way. However, all input and output variables will be detailed in the following sections.

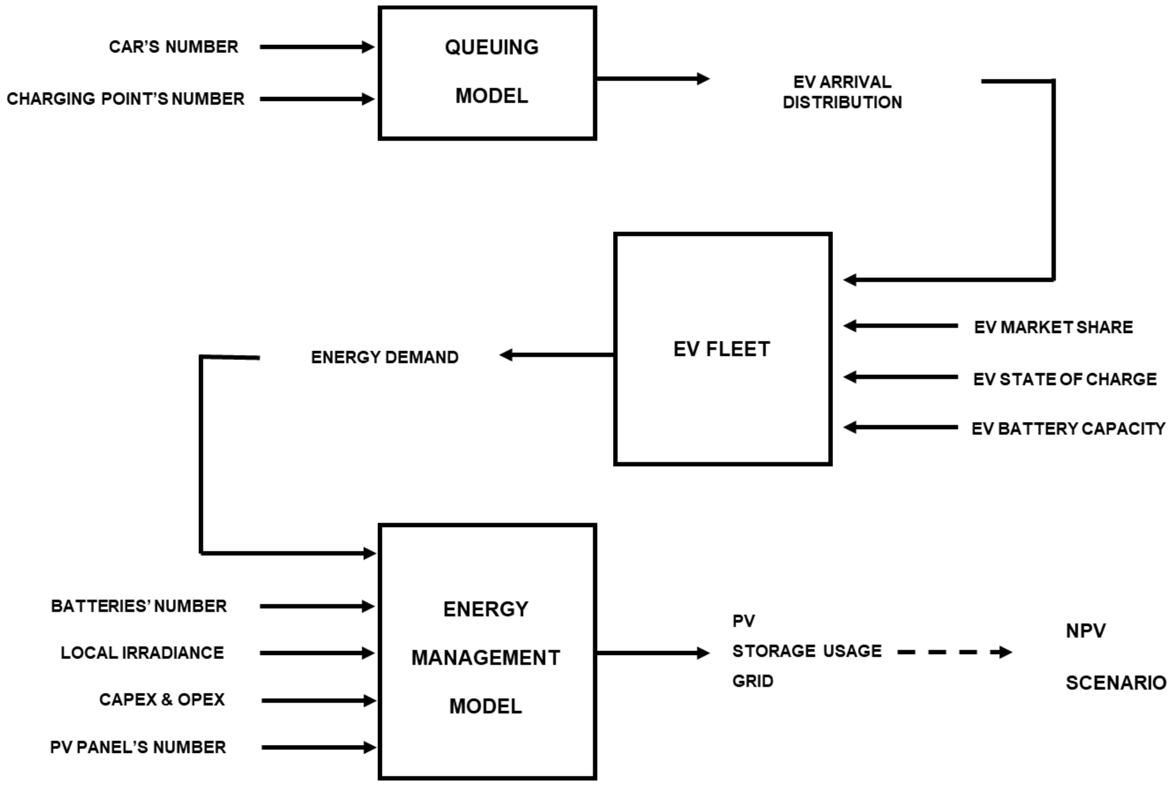


Figure 11 - Optimized and adapted Model

4.2. Three Scenarios Revision

As stated in the main research questions of this thesis there are three main different scenarios presented for the development of the model mentioned and explained before which provides us with three different layout structures. The technologies behind it and making part of these frameworks are:

- Connection to the grid;
- Roof or solar parking lots with photovoltaic panels;
- Batteries for solar energy storage.

The main purpose of the development and analysis is in Figure 12, which is scenario one with a grid connection. In this case, is taking into account the energy tariffs resorting to EDP tariffs of buying energy from the grid by using the grid connection. The hurdles of this scenario at first is to:

I. Acknowledge if it is enough to supply the EV demand with grid connection;
II. If so, would it be cheaper for the hub owners to harvest solar energy by means of maintaining and purchasing photovoltaic panels or not?

Figure 12 - Scenario 1

From here, it is established scenario two with grid connection and solar energy production represented in Figure 13 which raises another issue, the optimal number of photovoltaic panels in order to meet the demand rate and prevent energy waste. In this case is considered the energy tariffs resorting to EDP tariffs of:

a. Buying energy from the grid when using the grid connection;
b. As well as the tariffs of selling energy to the grid from solar energy production as added revenue for the model which attenuates the expenses;
c. Likewise, the costs of buying, maintaining and running photovoltaic modules and its respective structures.

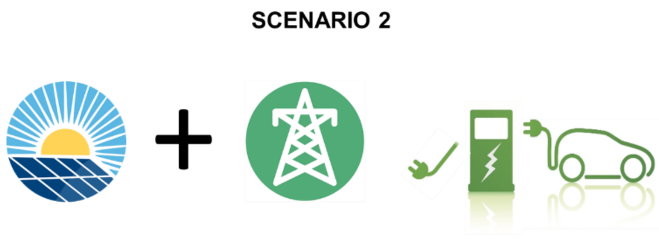


Figure 13 - Scenario 2

The hurdles of scenario two are to acknowledge if, in the case of energy waste from PV production, would it be preferable and cheaper to use battery storage or sell it to the grid. In case it is cheaper for the hub owners to store the energy produced by photovoltaic panels, it culminates in scenario three with grid connection, solar energy production and battery storage from photovoltaic panels which is presented in Figure 14. This raises up another issue, what is the optimal capacity of the storage system in order to meet the demand rate and prevent energy waste. In this case is considered the energy tariffs resorting to EDP tariffs of:

a. Buying energy from the grid when using the grid connection;
b. As well as the tariffs of selling energy to the grid from battery storage surplus as revenue for the model which attenuates the expenses;
c. Likewise, the costs of buying, maintaining and running photovoltaic modules, battery storage, and its respective structures.

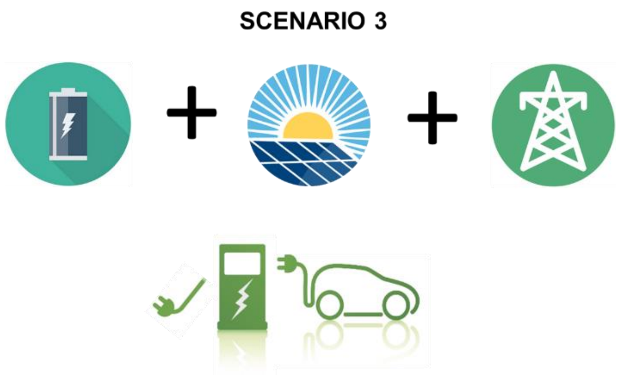


Figure 14 - Scenario 3

The hurdle of this scenario is the surplus which also cannot be stored, because of full batteries, would be sold to the grid or used to supply directly EV customers.

For all scenarios, there is a common revenue which is unalterable besides the scenario, the charging revenues. These revenues are solely the result of EV customers' payment for energy consumption usage in the charging station. For this purpose, the energy tariffs for EV customers are based on the EDP price tables.

To sum up, it is mandatory to perform the analysis on how big the cost difference between those 3 different installations of the model would be in order to set up the scenario which ultimately fulfills the requirements and maximizes the NPV regarding CAPEX, OPEX, and revenues from each scenario. Table 4 presents the differences between each scenario.

Table 4 - Differences between scenario 1,2 and 3 regarding their issues, energy tariffs, hurdles and revenues

	SCENARIO 1	SCENARIO 2	SCENARIO 3
	Grid connection	Grid connection + PV production	Grid connection + PV production + Battery storage
Issues	----	The optimal number of PV panels;	The optimal capacity of the battery;
Expenses	Energy bought from the grid	Energy bought from the grid; Cost of buying, maintaining and running PV modules.	Energy bought from the grid; Cost of buying, maintaining and running PV modules and battery storage.
Hurdles	Enough to supply EV demand by using grid connection; Even so, would it be cheaper to produce energy from PV, maintain and purchase PV panels;	When energy waste from PV, use battery storage or sell to the grid. What would be the cheapest option;	Surplus who's not stored would be used to supply directly EV customers or sold to the grid;
Revenue	EV customers' payment for energy charging posts usage;	Energy sold to the grid from PV; EV customers' payment for energy charging posts usage;	Energy sold to the grid from PV and battery storage surplus; EV customers' payment for energy charging posts usage;

4.3. Chosen Cities of Portugal

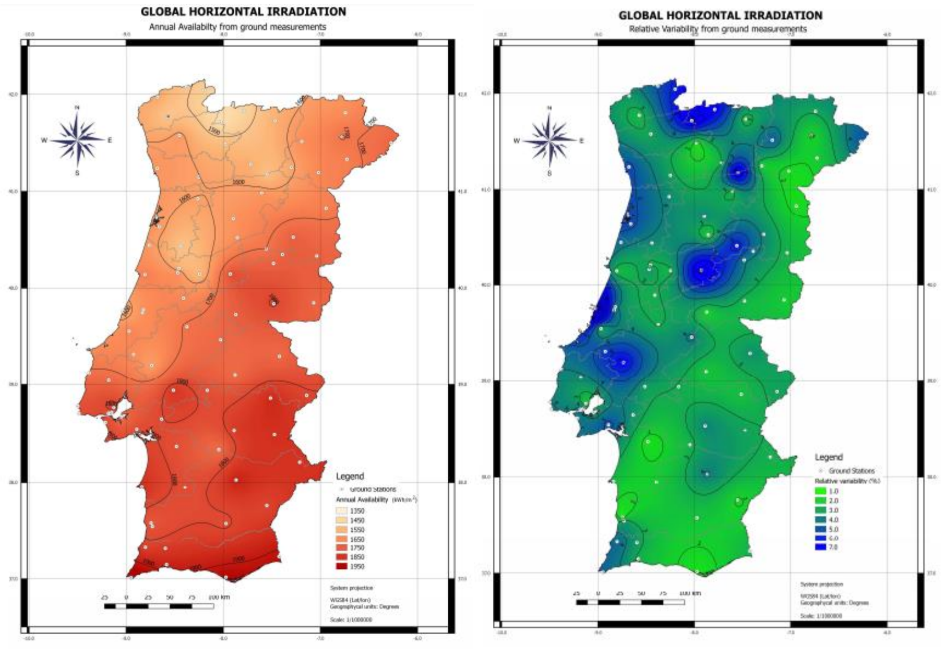
Whenever applied to a scenario resorting to solar energy production (Scenario 2 and Scenario 3), it is fundamental to assess its solar resource. This is essential for the different phases of solar energy projects, such as preliminary design engineering and financing. Likewise, this solar resource assessment is important to evaluate in the different places where it is required as solar energy project results and costs vary across Portugal. Figure 15 presents the chosen cities for solar production analysis. Faro, Lisboa, and Porto were chosen in order to evaluate three different environments across Portugal and are the principal cities of the North, Centre and South regions.

According to the paper "Annual Average Value of Solar Radiation and its Variability in Portugal", in Portugal, there are ground measured solar radiation data series and average values reported, dating back to the fifties, sixties, and seventies of the 20th century. These data were obtained with different instruments and calibration procedures and the estimations were obtained through statistical analysis of long-term data series of solar radiation measurements. This paper presents a thorough analysis performed to assess solar radiation in Portugal providing also information about its annual variability in

Figure 15 - Map of Portugal with chosen cities: Faro, Lisboa, and Porto.

sixty-six meteorological stations. The results obtained are presented in terms of annual average values and are presented in a map format showing the GHI availability and its variability in Continental Portugal in Figure 16(a) [16]. It shows up that GHI availability is higher in the southern region of Portugal, thanks to a high number of sunny hours consequently from favorable atmospheric conditions. Faro is included in this region and it has an annual GHI availability of 1950 kW.h/m^2. Furthermore, the GHI availability is increasing from North to South due to the latitude effect and the higher average cloudiness in the North region. Likewise, from West to East especially in the North and Center regions most probably because of frequently formation of fogs in the seaside. As important as the availability is, it is the variability represented in Figure 16(b). As far as GHI variability is concerned, the smaller it is the more reliable are the predictions of GHI estimations as shown by the figure for the Alentejo and Algarve regions of Portugal. According to both GHI availability and variability figures, the zones where GHI relative variability is higher the GHI availability is lower, as well as Faro is the most suitable city for solar energy project deployment. Figure 17 presents the GHI average monthly availability values as a dark blue line and GHI relative variability as the light blue area for all three cities: Faro, Lisboa, and Porto. As shown, Porto is the city with the lowest GHI availability values whereas Lisboa and Faro present similar values (Lisboa slightly lower) however Lisboa has a greater relative variability throughout the year as evidenced previously in Figure 16(b).

For the chosen cities, regarding the publicly accessible fast-charging stations currently available and on the operation, we used the MOBI.E website to get the accurate number of those currently installed. In Figure 18 the three cities are represented. The first image representing Faro has only one publicly accessible fast-charging station currently operating, the second image representing Porto has four fast-charging stations and lastly, Lisboa represents the city with the most stations installed with five publicly accessible fast-charging stations. However, these are not a very high number of installed charging stations for the main cities from the South to the North of Portugal. Additionally, the publicly accessible fast-charging stations are mostly found on freeways in MOBI.E, representing a large percentage compared to fast charging stations installed in large and medium cities [8].



(a) (b)

Figure 16 - GHI Average Annual Availability (kW.h/m2) (a) and GHI Relative Annual Variability (%) (b) in Continental Portugal. Source: http://www.ipes.pt

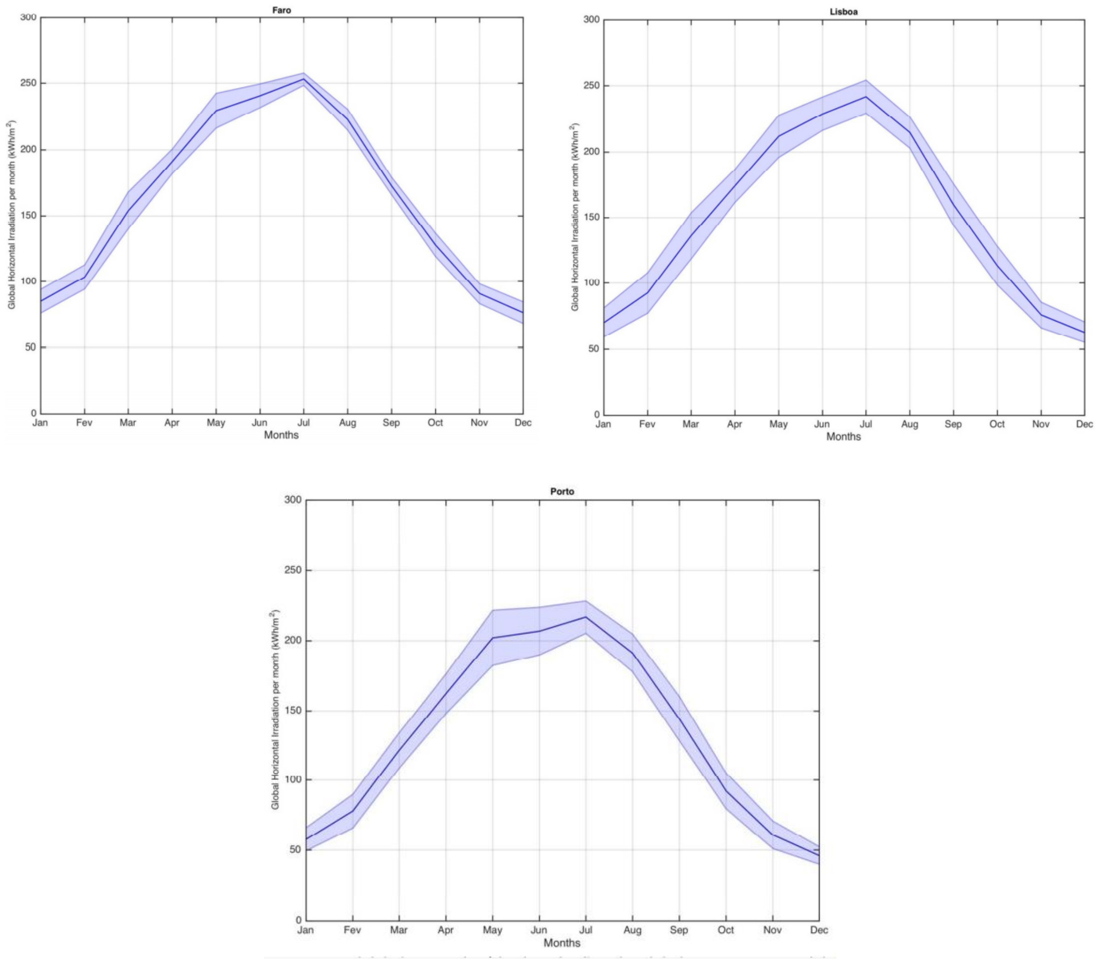


Figure 17 - GHI average monthly availability (kW.h/m2) and relative variability in Faro, Lisboa, and Porto. Source: http://www.ipes.pt

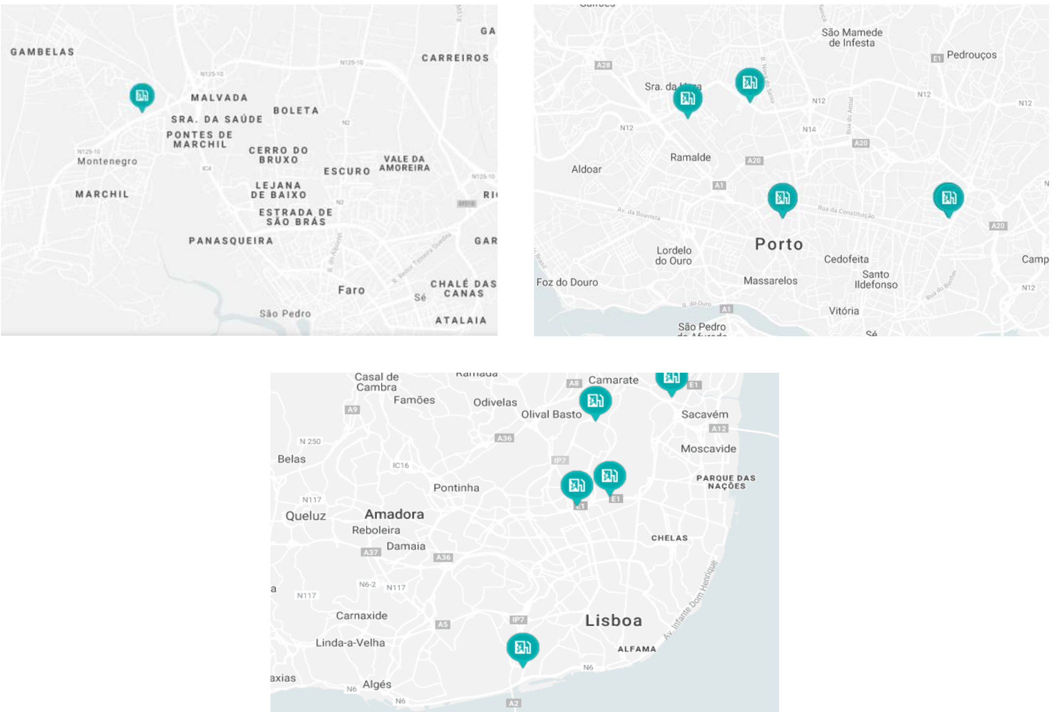


Figure 18 - Publicly accessible fast-charging stations currently available in Faro, Porto, and Lisboa. Source: www.mobie.pt/map

A representation of how is possible to use the fast charging points in Portugal by using the MOBI.E follows. As mentioned previously, it shows the number of publicly accessible fast-charging stations available all over the country. When accessing one of the available fast-charging points it is possible to recognize if the fast charging point is free to use or occupied. Whether it can be used at the moment or not it also provides some relevant information regarding the operator, the charger type and its location which in the case of Figure 19 is Mobiletric network, fast, and Avenida Marechal Craveiro Lopes, respectively. As well as how many and what type of electrical outlets. In this case, the electrical outlet is a CHAdeMO with 50 kW power.

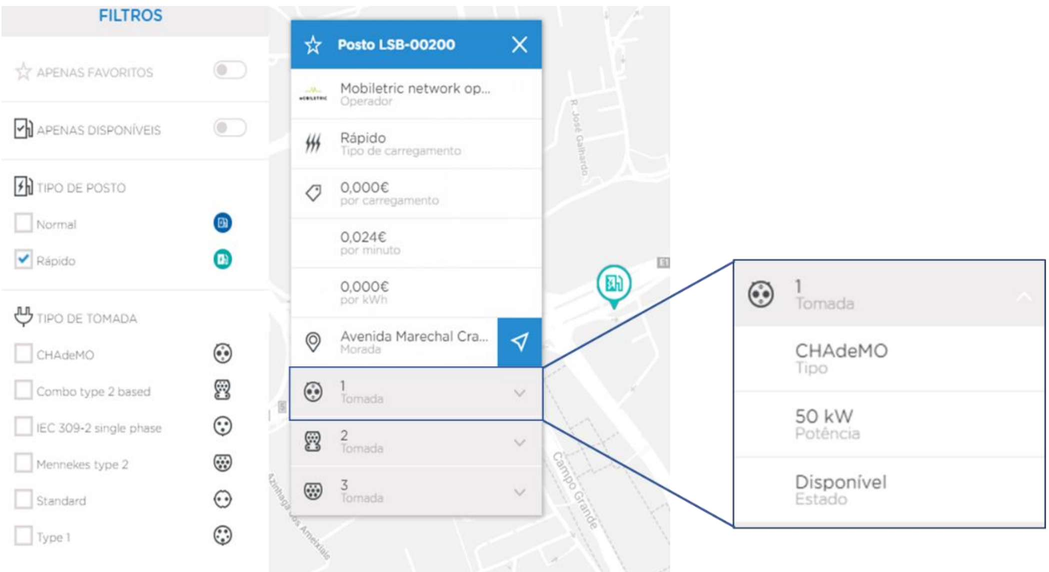


Figure 19 - MOBI.E access for the publicly accessible fast-charging stations in Lisboa. Source: www.mobie.pt/map

4.4. Optimization Method: Genetic Algorithm

An optimization method is compound by a few phases which are following described:

1. Defining the problem and gather possible and relevant data;
2. Formulating a mathematical model, i.e. a problem;
3. Developing a computer algorithm;
4. Testing the model previously created and refine it if necessary;
5. Preparing model application;
6. Implementing.

In the first phase, the objectives should be defined and be as specific as possible as well as consistent. In this case, the defined objectives are as follows, maximizing NPV, minimizing CAPEX and OPEX, minimizing the number of charging stations regarding the maximum possible NPV returned and maximize the use of solar energy generation and battery storage as so minimize the usage of grid connection. Therefore, the global approach decided to meet all these goals is to maximize the Net Present Value, which implies directly affecting others. The data gathered in this phase is used as input variables for the mathematical model.

By formulating the mathematical model, the decision variables, the objective function, and the constraints are defined as well. When developing the algorithm, the goal is to find an optimal solution, which in this case as mentioned is maximizing the profit measured by NPV. By testing and validating, the model assures a high correlation between predictions and real-world data. When preparing to apply the model the inputs are obtained from databases or information systems.

One of the main methods used for optimization is metaheuristic. As for our optimization, we deal with a very large number of variables, metaheuristics methods are the most specific to be used for this purpose. A metaheuristic is a method to find a good feasible solution close to the optimal which deals with very large problems and it is an iterative algorithm. Because sometimes optimization procedures converge to local optimum whereas there is more than a local optimum, metaheuristic is a solution method that orchestrates the interaction between local improvement procedures and a process to escape from local optima in a robust way, so it can find other optimum solutions. The advantage of these methods is they deal well with very large complicated problems and the drawback is that there is no guarantee to find the optimal solution. One of the most common metaheuristic methods is the genetic algorithm (GA) [17]. The difference between traditional algorithms and GA is that GA isn't static but dynamic instead, as they can evolve over time. They optimize a process in which there is a set of current solutions called population. As there are several solutions, one way to indicate that a solution is better than other it is its associated fitness value calculated by a fitness function. This will reflect on how good each solution is. Lastly, in case there isn't an acceptable solution in the current population, according to the fitness function, it will generate new better solutions. As a result, individual solutions will undergo a number of variations to generate new solutions.

The genetic algorithm is a random-based algorithm, since random changes are applied to the current solutions to generate new ones. Better specifying GA is based on Darwin's theory of evolution, therefore it is a slow and gradual process which works by making slight and slow changes. It makes these to its intermediate solutions slowly until getting the best solution [18]. Thus, the genetic algorithm is based on natural selection principles:

- Fitness function;
- Chromosome structure;
- Crossover and mutation rates.

As presented in Figure 20 genetic algorithm uses a population of solutions, as mentioned previously, instead of searching one solution at a time where multiple solutions are evaluated in parallel. This population is a collection of solutions to the optimization problem and is formed by individuals. An individual is a single solution represented by a chromosome. The chromosome is a candidate solution encoded as a string of characters or as a binary operator.

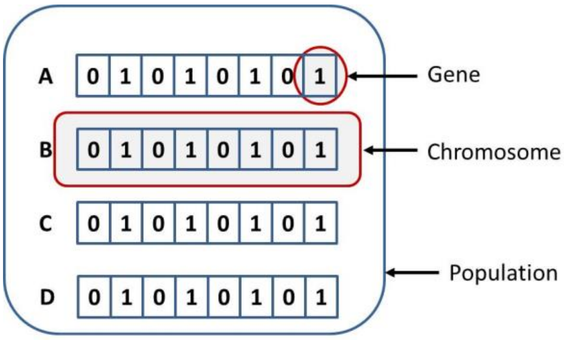


Figure 20 - Representation of population, chromosome, and gene in genetic algorithms. Source: https://www.kindsonthegenius.com/2018/12/14/basics-of-genetic-algorithm-ga-explained-in-simple-terms/

For instance, a chromosome (Figure 21) as an example could be made up of the following input variables (genes):

- Number of chargers installed (NoC);
- Rated power of EV fast-charging supplier (Rpower)(kW.h);
- The surface installed of PV (Sinst)(m^2);
- The nominal energy capacity of the installed storage system (NCStorage)(kW.h).

NoC	Rpower	Sinst	NCStorage

Figure 21 - Example of a chromosome composition

Likewise, a gene is part of a chromosome usually representing a variable characterizing part of the solution, such as the number of chargers installed in this example. Also, each individual has a fitness value associated. The population is updated iteratively, and each iteration is called a generation. The objective function is called fitness function which is used to select the best individuals.

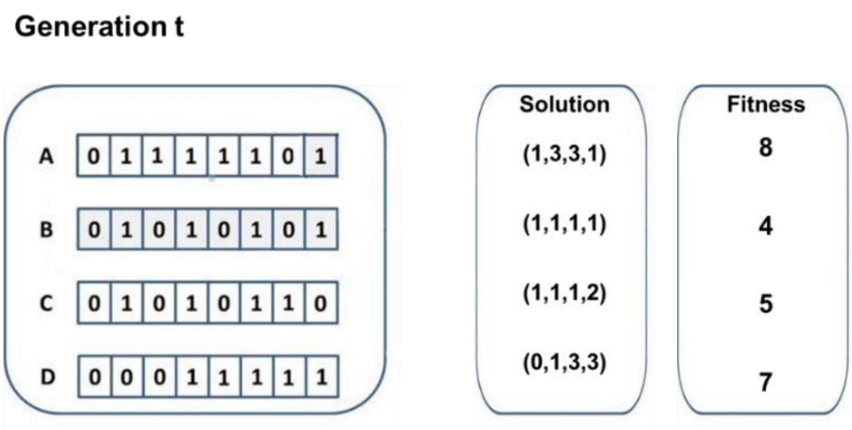


Figure 22 - Representation of genetic algorithm generation

The result of the fitness function is the fitness value which represents the solution quality. The higher the individual fitness value the higher the quality of the solution. In Figure 22 it is graphically possible to better understand the designations of generation, individual, solution and fitness function. Figure 23 presents how the genetic algorithm works, as explained briefly before:

1. Firstly, starts with an initial randomly defined population by selecting the proper number of individuals within it.
2. Afterward, it starts the iterative algorithm which will select some members of the population to become parents, who were evaluated by the fitness function for each individual and have the best score/ fitness value from the initial population where the higher quality individual has a higher probability of being selected. The best individuals are chosen based on a threshold;
3. Hereupon, the crossover operation which consists of crossing the genetic material of parents in a crossover operation is completed. By crossing, genetic material from every two parents selected with the higher quality will generate two children (offspring) which will be therefore a new population with the best individuals based on a threshold. By just mating high-quality individuals, it is expected to get a better-quality offspring than its parents. And so, avoiding generating more bad individuals by disqualifying them.
4. The next variation operator is the mutation. It selects some genes and changes its value. This is possible to occur but isn't common as it is applied to a small number of chromosomes. As an example, it could be generated for instance: generating a random number between 0 and 1. If this number is less than 0,001, then the mutation is applied to the chromosome.
5. The new population will be then evaluated again from the fitness function, for every generation, and so on as described before until the best chromosome is found. Therefore, throughout the genetic algorithm process, i.e. generations by keeping selecting and mating high-quality individuals, there will be higher chances to keep good properties of the individuals and leave out the bad ones and the solutions will end up with the desired optimal or acceptable solution [17].

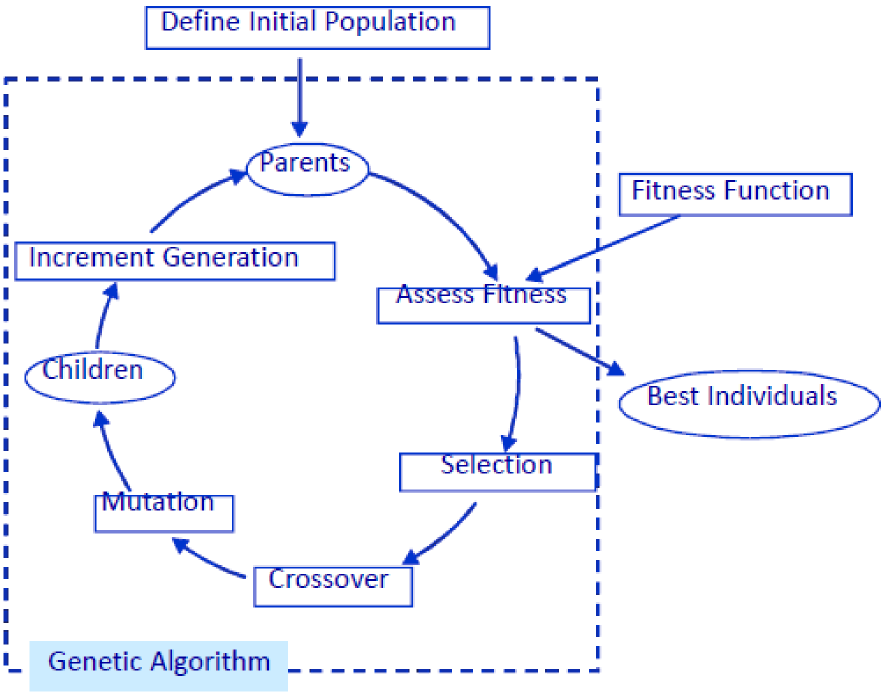


Figure 23 - Representation of genetic algorithm operation: Source: Genetic Algorithm optimization classes [17].

4.4.1. Chromosomes and its constraints

The chromosome for this thesis with the variables to be found is presented in Figure 25 and is composed of the following genes of the adapted model, as presented in Figure 24:

- Number of charging points;
- Number of photovoltaic modules;
- The number of batteries.

Ncp	Npv	Nsto

Figure 24 - Chromosome of the adapted model

As represented in the chromosome above, the genes that will be evaluated and used in the genetic algorithm are presented in Figure 25. The number of charging points is an input for the queuing model once it influences the EV customers waiting time, i.e. the higher the number of fast charging points the lower the waiting time. By having more charging points, the waiting time is lower although the related costs are higher. Therefore, it is one of the variables which will be used and evaluated in the genetic algorithm, the reason why is included in the chromosome of this problem, in order to find the optimal number of charging points needed for the problem. As input variables for the energy management model, there is also the batteries' number and the number of PV panels. In case it is chosen as a chromosome with a certain number of batteries, the best scenario was chosen to meet the objective function is scenario 3. Otherwise, it won't be used and scenario 2 or 1 would be the best solution. Likewise, in case it is chosen as a chromosome with a certain number of PV panels, the best scenario chosen to meet the objective function is scenario 2 or 3. Otherwise, it won't be used and scenario 1 would be the best solution. Also, in case there is a certain number of batteries chosen, it will be necessary to find out what would be the optimal number of photovoltaic modules to meet the objective function as the previous case.

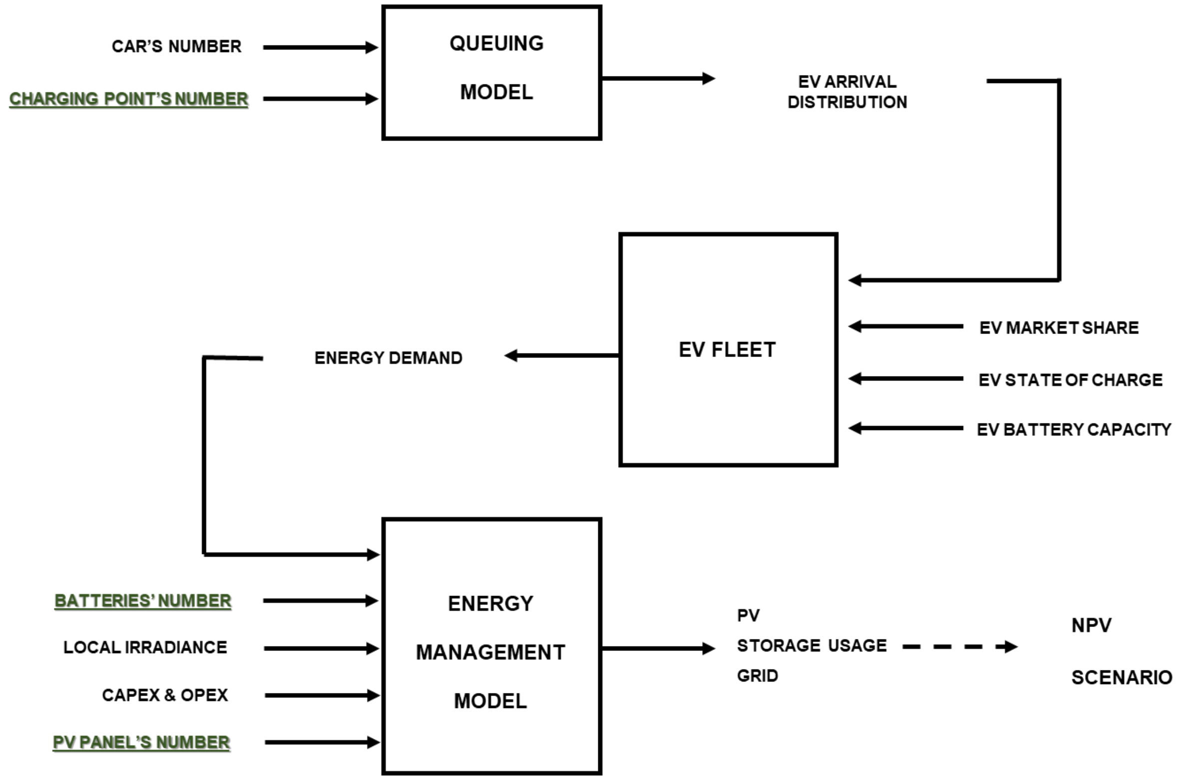


Figure 25 - Optimized and adapted Model with optimization method highlighted

The variables presented in the chromosome in order to be included in the genetic algorithm need to be constrained by thresholds. These genes are constrained by the limits presented in Table 5. Beforehand, some variables were also set up as constant such as the charging point power and the maximum time limit for charging each EV customer. For this thesis is assumed that a single charging point has a power of 50 kW, according to the statistical data detaily provided in Chapter 5.1.2, because for a good percentage of EV sold cars in Portugal the maximum possible charger porter for DC is 50 kW. Therefore, it wouldn't be possible for those EVs to charge in stations with higher capacities. Likewise, the maximum limit time for charging an EV is 25 minutes.

For instance, this case will use a number of charging points ranging from one to 20, because one fast-charging point is the minimum number possible to use, otherwise, there wouldn't be any installed. We limited the maximum number of fast charging points to 20, taking into account the lifetime of the project, 20 years, and the evolution of the arrival distribution per year explained in Chapter 5.2.2. The number of charging points for the model varies randomly by 1 fast charging point.

For the number of batteries, it was decided to include a range between zero and 20. The minimum is zero as there is a chance that the optimal solution doesn't include a storage system. As the maximum time limit for charging one EV is 25 minutes is assumed that the maximum number of EV customers charging 25 minutes during an hour is two. Therefrom, during an hour only 50 minutes would be used for charging EVs, while the other 10 minutes are for connecting and disconnecting cables and so on. As the power of the fast charging point is 50 kW, as mentioned previously, we assume that the battery could charge EVs for around 1 hour non-stop. Therefore 50 kW.h of maximum capacity would be needed. Although for a scenario with 20 fast-charging points, the maximum capacity would be 20 times more, 1000 kW.h. The battery can't be fully discharged during this operation hour as it has a minimum state of charge that can't be reached. Therefore, it is taken into account that from this hour, it would have to operate less than that hour, which can meet the free time mentioned before for connecting and disconnecting cables. The battery capacity for the model varies by 50 kW.h, i.e. each battery capacity has 50 kW.h, therefore by using 1000 kW.h means it is being used a maximum of 20 batteries.

Table 5 - Limits of the gene variables

	RANGE	VARIATION
NUMBER OF CHARGING POINTS	1 - 20	1
NUMBER OF BATTERIES	0 - 20	1
NUMBER OF PV PANELS	0 - 5000	1

For the number of photovoltaic panels, it is assumed that the solar panel used as a maximum peak power production of 250 W. As the power of 20 fast-charging stations is 1000 kW, we assume that solar production can go up to 1000 kW.h to fulfill the station requirements. However, it is assumed that part of this energy is used as a surplus for the storage system. Thereby, it is assumed the solar production can go up to 1250 kW.h. Therefore, this energy production is reached by having 5000 PV panels of 250 Wp. The number of PV panels for the model varies by 1 photovoltaic module.

The variables from the chromosome are real type genes as they take into account real values.

4.4.2. Objective Function

The fitness function is the same as the objective function. The objective function of this problem is related to the profitability of the scenarios as mentioned before. The optimal solution that presents the maximum possible NPV. For this GA problem when evaluating an individual, their fitness function reporting their quality is related to the NPV. If an individual is high-quality it will, therefore, have a high NPV value and vice versa. The objective function is:

$$NPV = \sum_{t=1}^{n} \frac{NCF_t}{(1+i)^t} - I \qquad (4.1)$$

Table 6 - Nomenclature of the economic variables

NPV	net present value (€)	**Esg_h**	the energy supplied to grid at hour h (kW.h)
NCF_t	net cash flow at year t (€)	**Csg_h**	remuneration price of selling to the grid (€)
I	initial investment (€)	**Ecg_h**	energy consumed from the grid at hour h (kW.h)
i	interest rate	**Ccg_h**	energy price from the grid at hour t (€)
$INFLOW_h$	cash inflow (income) at hour h (€)	**Ccp**	cost of charging point (€)
$OUTFLOW_h$	cash outflow (expenses) at hour h (€)	**Ncp**	number of charging points installed
$Csto_t$	replace and maintenance of the storage system at year t (€)	**Cpv**	cost of purchasing PV panels (€)
Cpv_t	replace and maintenance of PV panels at year t (€)	**Npv**	number of PV panels installed
Eev_h	the energy supplied to EV customers at hour h (kW.h)	**Csto**	cost of the storage system (€)
Cev_h	energy price station at hour h (€)	**Nsto**	number of batteries

The variables from each equation are presented in Table 6. The initial outlay for the fitness function corresponds to the cost of installing each energy system element, i.e. solar photovoltaic modules installation, battery storage installation and fast charging stations installation and construction. The income for the function will be the energy supplied to customers who recharge their vehicles as well as the surplus energy sold to the grid. Likewise, the expenses are the energy purchased from the grid, the maintenance of the EV station, as well as the solar photovoltaic modules and batteries replacement. According to (4.1) the Net Present Value is subject to net cash flow at each year t (4.2) which is the difference between present values of cash inflows (4.3) and present values of cash outflows (4.4), including the cost of replacement and maintenance of the batteries as well as the cost of the maintenance of the PV panels and the initial investment (4.5) over a period of time, which in this case is 20 years. The PV panels have around 25 years of lifetime, but one must think and account for failures. Additionally, inverters and other electrical components have a smaller lifetime period, as well as the storage system which usually has a lifetime of 20 years by replacing once. However, we assumed that the system lifetime is 20 years because we are doing a conservative analysis, and this is the minimum range time to evaluate a project and to perform investment analysis. This model evaluates the charging station’s behavior for 8760 h per year.

$$NCF_t = \sum_{h=1}^{8760}[\,INFLOW_h - OUTFLOW_h] - Csto_t \times N_{sto} - Cpv_t \times N_{pv} - Ccp_t \times N_{cp} \qquad (4.2)$$

$$INFLOW_h = Eev_h \times Cev_h + Esg_h \times Csg_h \qquad (4.3)$$

$$OUTFLOW_h = Ecg_h \times Ccg_h \qquad (4.4)$$

$$I = C_{cp} \times N_{cp} + C_{pv} \times N_{pv} + C_{sto} \times N_{sto} \qquad (4.5)$$

4.4.3. Constraints

The optimization problem is also subject to several constraints, for instance during the charging process, during exchange energy flows between the grid, PV panels, batteries, and fast charging station as well as limiting, for instance, the maximum time for EVs' charging, as mentioned previously, like 25 minutes. These constraints are presented below and the variables from each equation are presented in Table 7.

For the energy balance, one must account for the photovoltaic panels' energy generation, the energy consumed from the grid and the energy injected in the grid by the PV panels and storage system. Therefore, the PV energy generation, the energy discharged from the battery and the energy consumed from the grid must be equal to the energy supplied to EVs, the energy-charged to the battery and the supplied energy to the grid network at each hour h:

$$Espv_h + Ecg_h + Edsto_h = Eev_h + Esg_h + Ecsto_h \qquad (4.6)$$

The energy stored in the batteries at each hour h is the energy stored at the hour (h - 1) plus the energy-charged to the storage system minus the energy discharged from the storage system:

$$Esoc_h = Esoc_{h-1} + Ecsto_h - Edsto_h \qquad (4.7)$$

The discharged and charged energy of the storage system is that the energy discharged from the storage system must be less or equal than energy stored in the battery at the previous hour and the energy-charged to the storage system must be less or equal than the energy capacity of the installed storage system minus the energy stored in the battery at the previous hour:

$$Edsto_h \leq Esoc_{h-1} \qquad (4.8)$$

$$Ecsto_h \leq Esto_c - Esoc_{h-1} \qquad (4.9)$$

The stored energy in the storage system is the energy stored in the battery and must be less or equal than the energy capacity of the installed storage system as well as the energy stored in the battery must be greater or equal than the minimum energy capacity of the storage system according to the minimum state of charge of the battery:

$$Esoc_h \leq Esto_c \qquad (4.10)$$

$$Esoc_h \geq SOC_{min} \times Esto_c \qquad (4.11)$$

The maximum energy demanded by EV customers at every hour h must be greater or equal than the energy supplied to EV customers by the fast charging station at every hour h since isn't possible to supply more energy than what is demanded:

$$MAXev_h \geq Eev_h \qquad (4.12)$$

The maximum time that an EV customer is in the queue waiting for its turn:

$$Tw \leq Tw_{max} \qquad (4.13)$$

The maximum time that an EV customer is charging its car in the charging station:

$$Tc \leq Tc_{max} \qquad (4.14)$$

Table 7 - Nomenclature of the technical variables

$Espv_h$	the energy supplied by PV at hour h (kW.h)	**SOC_{min}**	minimum state of charge of the battery (p.u)
Ecg_h	energy consumed from the grid at hour h (kW.h)	**Psg_h**	**POWER** supplied to grid at hour h (kW)
$Edsto_h$	energy discharged from the storage system at hour h (kW.h)	**Pcg_h**	power consumed from the grid at hour h (kW)
Eev_h	the energy supplied to EV customers at hour h (kW.h)	**Pg_{max}**	power limit in the grid connection point (kW)
Esg_h	the energy supplied to grid at hour h (kW.h)	**$MAXev_h$**	maximum energy demanded by EV customers at hour h (kW.h)
$Ecsto_h$	energy charged to the storage system at hour h (kW.h)	**Tw**	waiting time for each EV (min)
$Esoc_h$	the energy level in the battery at hour h (kW.h)	**Tw_{max}**	maximum waiting time (min)
$Esoc_{h-1}$	the energy level in the battery at hour h-1 (kW.h)	**Tc**	charging time for each EV (min)
$Esto_c$	the energy capacity of the battery (kW.h)	**Tc_{max}**	maximum charging time (min)

Chapter 5

5. Model Development

This chapter provides the methodology used to structure and test the model on the three different scenarios. Explanations on how the different models were developed, implemented and their performance according to this thesis main goal. As well as explanations of the models such as EV energy demand model, energy management model, solar photovoltaic energy model, PV battery energy storage model, queueing model, BEVs arrival distribution and BEVs state of charge (SOC), battery capacity and market share. All simulations and optimization algorithms for economic and technical performance analysis, as well as models' implementation, were carried using the Python programming language and available packages which allowed the calculation of the different models mentioned previously.

5.1. EV Data

The EV data presented in this chapter cluster several variables such as the EV market share in Portugal by presenting the top 10. Additionally, it is assessed their battery capacities as well as their autonomies, i.e. distance range, and the maximum fast charger power. There isn't available data for the state of charge as it is an independent variable, therefore it is presented and assumed lognormal distribution. Finally, explanations of how AC/DC charging power for electric vehicles work are introduced.

5.1.1. Market Share in Portugal

As one of the settings for EV data inputs for the model is the EV market share in Portugal. In order to analyze the market share and according to EAFO in Table 8 is outlined the number of EV sales for every model every year and detailed the best sellers. For each year is only accounted the ten best-sellers of that same year or less than, once we aren't counting with EV car models which have lowered sales or got out from EV market, i.e. ten is the maximum number of best sellers for a year. Whenever a type of car isn't a best seller, precisely for that year, it is considered as "Others". Conferring to the table below, since the early years of EV deployment the models Nissan Leaf and Smart ForTwo have led the EV market share in Portugal followed by BMW i3 and Renault ZOE whereas Tesla started gaining market share since 2014 having succeeded and managed not only to sell one but several models (Figure 26).

Table 8 - EV model cars best sellers 2010 – August 2019. Source: www.eafo.eu

CAR MODEL	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Volkswagen e-Up					10	32	40	60		
Volkswagen e-Golf								79		
Kia Soul EV								95	174	
Citroen C-Zero		6	11	11	11	38	40		204	
Peugeot I-on		50	56	98	99	157	163	171	173	
Hyundai Kawai										252
Smart ForFour									173	259
Jaguar i-Pace										265
Tesla Model X								78	286	406
Tesla Model S					5	19	40	121	320	490
Smart ForTwo	5	19	36	67	84	91	92	182	402	560
Tesla Model 3										853
BMW i3				6	65	173	350	605	968	1259
Renault ZOE				22	56	209	379	1130	2435	2982
Nissan Leaf	10	108	123	161	221	430	758	1076	2669	3701
Others	3	36	57	83	94	135	206	264	531	1213

Figure 26 - Nissan Leaf, Smart ForTwo, BMW i3, Renault ZOE, Tesla Model 3. Source: ev-database.org

The market share of Portugal will, therefore, be a tool and variable to study the program. Better to understand the market and the needs for EV infrastructure construction and development. Thence, below in Figure 27, there is a chart with the EV market share in Portugal including only the 10 best sellers this year, until August 2019, where the “Other” tab considers the car types which are not part of the 10 best sellers in 2019. These data will be imported and used in the python program as a list with each EV model, together with the SOC and battery capacity of each car arriving in the fast charging station.

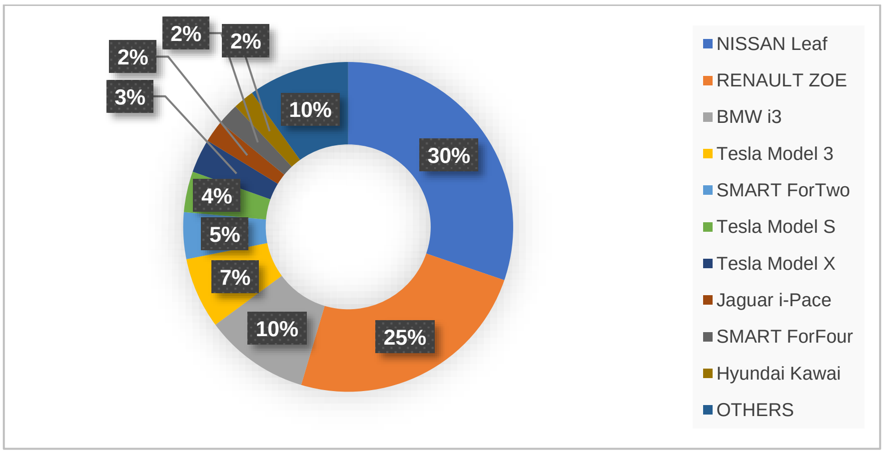


Figure 27 - EV market share in Portugal in August 2019. Source: www.eafo.eu

Conferring to Figure 27, highlighted the Nissan Leaf (30%) and Renault Zoe (25%) are the choice of most buyers followed by BMW i3 with 10% market share and Tesla Model 3 with 7%. The remaining are Smart ForTwo, Tesla Model S and Tesla Model X, Jaguar i-Pace, Smart ForFour, and Hyundai Kawai which increased the market share this year becoming one of the 10 best sellers according to Table 8. The other car models in the Portuguese market have only a market share of 10%. For the program purpose, we will follow the values of a discrete distribution which are more detailed in Table 9.

Table 9 - EV detailed values of market share in Portugal in August 2019. Source: www.eafo.eu

TIPO	MARKET SHARE	
	Relative Frequency	Cumulative Frequency
Nissan Leaf	30,24%	30,24%
Renault Zoe	24,36%	54,6%
BMW i3	10,29%	64,89%
Tesla Model 3	6,97%	71,86%
Smart ForTwo	4,58%	76,44%
Tesla Model S	4,00%	80,44%
Tesla Model X	3,32%	83,76%
Jaguar i-Pace	2,17%	85,93%
Smart ForFour	2,12%	88,05%
Hyundai Kawai	2,06%	90,11%
Others	9,89%	100%

In the simulation process, a random number set up from a randomly uniform function is given from zero to 100 and compared with the accumulated probability, i.e. the cumulative frequency, to obtain the type of vehicle that arrives at the charging station as presented in Figure 28. In Figure 29 is presented the number of cars by type for the same simulation for one day. The figures present an example of simulation for one day, 24 hours, where the maximum EVs arrival was 69 while using 900 PV panels, four batteries and four charging points for Lisboa.

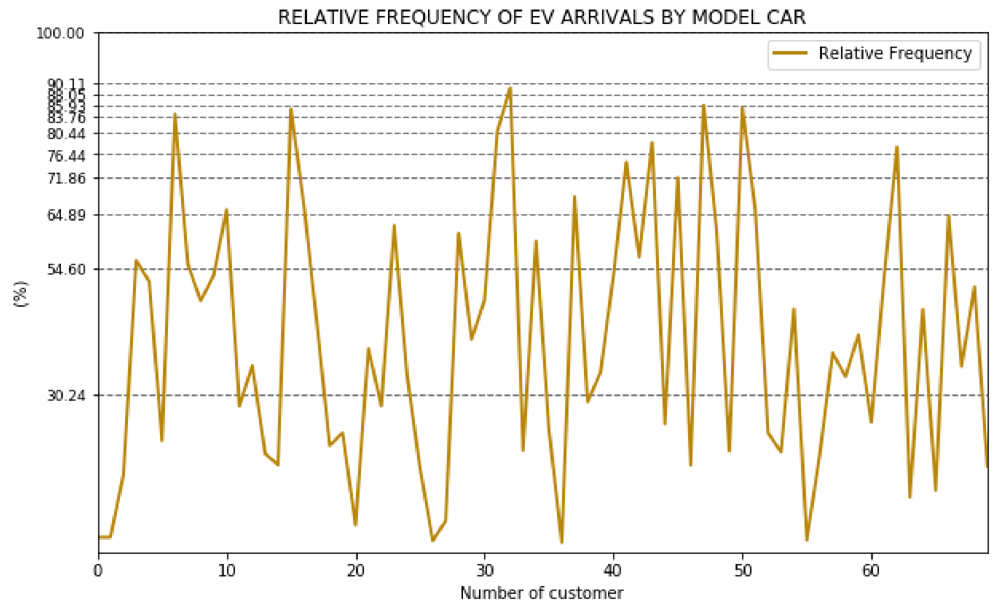


Figure 28 - Relative frequency of EV arrivals by type for one day example

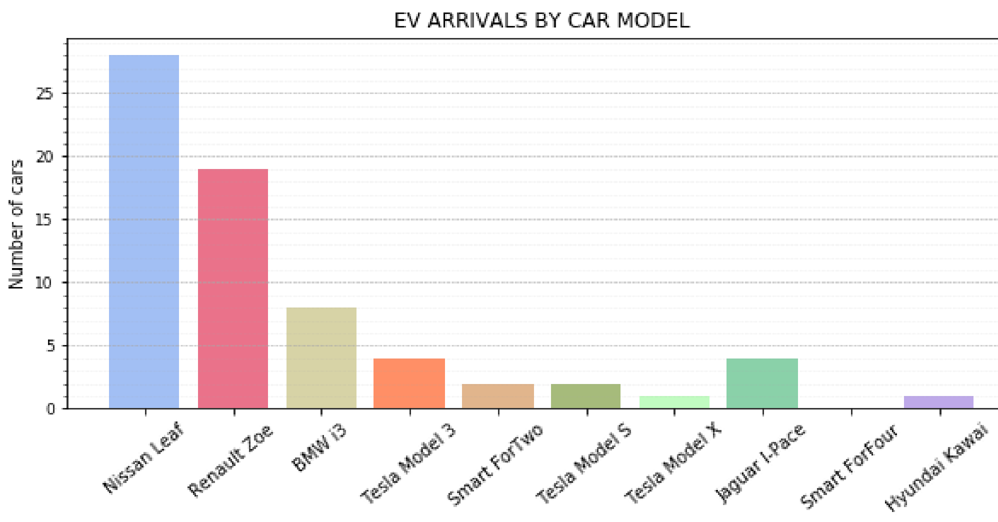


Figure 29 - Number of cars by model for one day example

5.1.2. Battery Capacity

More details and features are presented in Table 10 with the collected data of the 10 BEV best sellers this year in Portugal, until August 2019. The data were collected to better understand the market that is being developed and attend their needs as electric demand purposes. The data from all cars were taken from *ev-database.org* which gathers all data from BEVs whether they are already on roads, being launched or will be launched. There is also data from cars that are still prototypes.

Table 10 presents and emphasizes for each car model the battery capacity, the autonomy according to Worldwide Harmonized Light Vehicles Test Procedure (WLTP) ratings, the maximum fast charger power and port type (protocol) as well as the normal (slow) charger power. I chose also the latest versions of the following cars' model as the electrical mobility are an emerging market, i.e., for instance, the best seller Renault Zoe nowadays can be purchased with 55 kW.h battery capacity whereas when was launched it was only 22 kW.h.

Table 10 - EV 10 best sellers features' in Portugal in August 2019. Source: ev-database.org

MODEL		BC (kW.h)	A WLTP (km)	CP & Port DC (kW)		CP AC (kW)
1	**Nissan Leaf**	40	270	CHAdeMO	50	6,6
2	**Renault Zoe**	55	390	CCS	50	22
3	**BMW i3**	42,2	310	CCS	50	11
4	**Tesla Model 3**	75	530	CCS/ Supercharger	150	11
5	**Smart ForTwo**	17,6	145			22
6	**Tesla Model S**	75	450	Supercharger	100	16,5
7	**Tesla Model X**	100	485	Supercharger	200	16,5
8	**Jaguar i-Pace**	90	470	CCS	104	7,4
9	**Smart ForFour**	17,6	160			22
10	**Hyundai Kawai**	42	289	CCS	50	7,2
		55,44	**349,90**		**94,25**	**14,22**

Notes: BC – Battery Capacity; CP – Charge Power; A – Autonomy;

Briefly, the end of the table presents the average values for each tab. The needs for EV infrastructures construction and EV battery capacity and range evolution in Portugal nowadays are:

- Cars with around 55 kW.h of battery capacity;
- 350 km of autonomy WLTP;
- Fast Charge power around 94 kW;
- Normal (slow) Charge power around 14 kW.

To meet the EV demand car models currently, the fast charger power should be around 94 kW, however, the maximum nowadays is 50 kW unless it's used a Tesla supercharger of 100/150/200 kW. In spite of such huge power from Tesla superchargers, they are only used for Tesla models, thence for this thesis purpose is considered a maximum charge power of 50 kW in EV charging stations to charge the EV car models in this study intended in the EV arrival distribution. Likewise, the market share also the battery capacity for the program purpose is imported and used in the python program as a list with each EV model battery capacity following the values of a discrete distribution detailed in Table 11. By knowing which type of vehicle will arrive at the charging station it is automatically related value from the table below by using a dictionary in the python program.

Table 11 - EV detailed values of battery capacity in Portugal in August 2019. Source: www.eafo.eu

TIPO	BATTERY CAPACITY (KW.H)
NISSAN LEAF	40
RENAULT ZOE	55
BMW I3	42,2
TESLA MODEL 3	75
SMART FORTWO	17,6
TESLA MODEL S	75
TESLA MODEL X	100
JAGUAR I-PACE	90
SMART FORFOUR	17,6
HYUNDAI KAWAI	42

5.1.3. State of Charge

The charging demand of an EV is determined by the initial battery SOC and its charging characteristics. The state of charge (SOC) of an EV battery depends and is defined by the average (μ) and typical deviation (σ) of the logarithm of the SOC variable [15]. Therefore, it can be modeled by the lognormal distribution. This distribution has the particularity, in relation to others, which takes into account only positive SOC as in the real world there are not negative numbers for this variable. In other distributions, such as normal distribution and uniform distribution, there is a possibility of returning negative values, for this reason, they weren't considered. An example of lognormal PDF is presented in Figure 30 and follows the equation, for which the μ and σ are 3.66 and 0.25 that was returned from an assumed 40% mean value for SOC[21] of arriving rate of electric vehicles and a standard deviation of 10% by means of [20]:

$$SOC = \frac{1}{SOC_{initial} \times \sigma \times \sqrt{2\pi}} . e^{\frac{-(\ln(SOC_{initial}) - \mu)^2}{2\sigma^2}} \qquad (5.1)$$

[21] Once there isn't much literature review regarding the mean and standard deviation values of SOC upon arrival at the charging stations.

Where:

- $SOC_{initial}$ - initial SOC of the battery (p.u);
- σ – typical deviation of the logarithm of SOC;
- μ – an average of the logarithm of SOC.

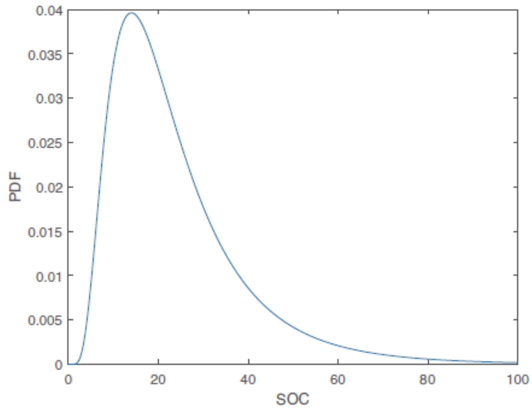


Figure 30 - Lognormal PDF distribution

The mean value is assumed to be 40% once the EV owners' won't charge their vehicles when it's almost charged, for instance at 60%/70% and won't charger also when are almost out of battery at 20% for instance, i.e. the EV owners start being willing to charge their vehicles when the battery is at half or more of the vehicle's autonomy but not too low in order to be out of battery. A random number from 0 to 1 is simulated for the SOC of each car arriving at the station according to the lognormal distribution and is presented as an example of a simulation for one day, 24 hours, in Figure 31. The figure presents the same example of simulation with maximum EVs arrival of 69 using 900 PV panels, 4 batteries and 4 charging points for Lisboa.

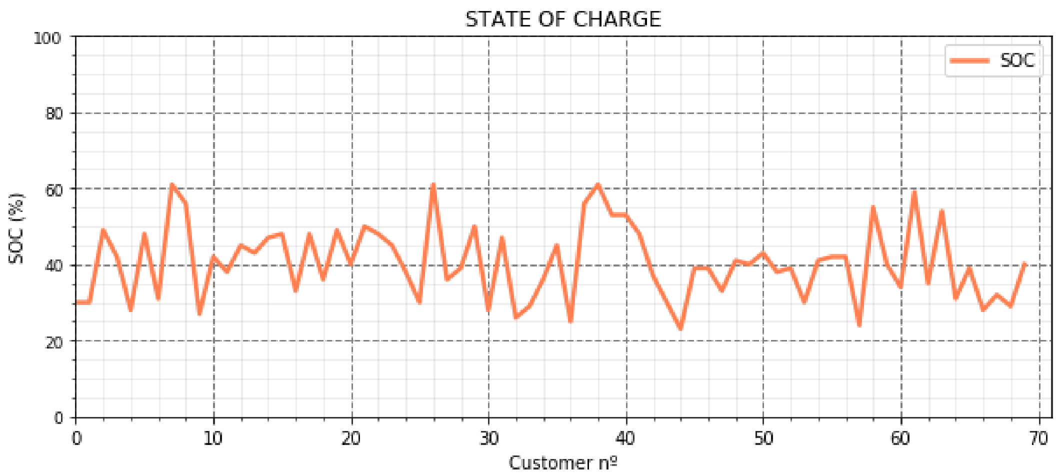


Figure 31 - SOC for every EV arrival for one day example

5.1.4. AC/DC Charging Power

Another variable of each car model is the AC/DC charging power presented in Table 10. As mentioned previously in Chapter 2.2 there are car models that can't be charged in fast charge power mode (DC), solely AC. To avoid confusion, it was also explained in Chapter 2.2 that although AC current type stands for normal charging there is also triphasic AC current type that provides fast charging capability and operates over 22 kW and below or equal to 43,5 kW. Thus, fast charging can be done by AC triphasic current type, type 2 cable connectors, or DC current type. Figure 32 shows the two possible charging types and according to the figure in the first example, the cars which cannot be charged by DC, thence triphasic AC current type and AC connection cables are used. AC power is supplied from the charging station to the on-board charger which supplies DC power to the battery by means of the electric vehicle's own rectifier. On the other hand, in the second example, the charger is off the board the vehicle and supplies DC power directly to the battery whereas the transformer is directly in the charging station. The figure below its representative but fast charging facilities have both charging types in one charging point, therefore it can be either two DC fast charging or one DC fast charging and one AC fast charging. Although triphasic AC current type of power has a range between 22 kW and 43,5 kW, each car has its own maximum AC charge power. As presented in Table 10, Charge Power AC column, each car has a different value. Therefore, the range between 22 kW and 43,5 kW depends on the charging facility installed whereby even if the charging facility is operating at 43 kW, and the maximum AC charge power of a car is 22 kW, the charging power will always be the maximum AC charge power available in the car. Likewise, was presented in Table 10 is presented that Smart ForTwo and Smart ForFour cannot be charged in DC, only AC, maximum charge power of 22 kW.

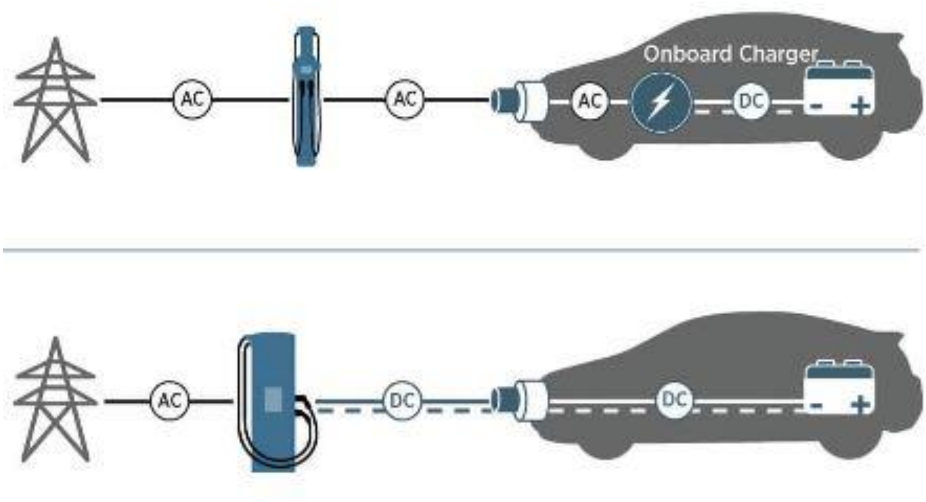


Figure 32 - AC/DC fast charging in EV charging stations. Source: https://www.chargepoint.com/blog/when-and-how-use-dc-fast-charging/

5.2. Fast Charging Station Models

One of the most important characteristics of an EV charging system and which depends upon the deployment of electric vehicles is not only the charging infrastructure but also the charging process. It depends directly on variables related to infrastructures such as the arrival time distribution of EV to the charging stations and while charging their batteries, the service time. Likewise, it depends indirectly on the state of charge of each car user, which will then modify the service time distribution. The charging process determination develops the energy consumption profile as well and in order to improve it, one must study the queuing model which depends upon the EVs arrival time and the service time, as mentioned previously.

5.2.1. Queuing Model

The queuing process happens when EVs need to wait a certain time to get charged by the charging points. The purpose of the queuing system is to transfer these EVs and consist of customers (EV owners) and servers (charging infrastructures) and the facilities where the customers can queue. As mentioned previously, the customers may arrive at a certain time and a certain queuing discipline such as for instance, the basic first come first served. Likewise, the servers that provide services to the customers may have a certain service time as well and a certain configuration such as serial or parallel servers. These queuing facilities sometimes according to each problem restrictions and goals may involve certain design with a limited capacity which that might cause customers rejection when reached its limit. In addition, based on the waiting line's existence the queuing systems are categorized into two different types, the bulk queue which is a system where the customers don't form a waiting line, they are spread and randomly ordered instead. Likewise, there is also the waiting line queue system, the one we will follow in order to reproduce our queuing model, where the customers form a waiting line just as its name implies [21].

The queuing theory attempts to estimate queuing behavior based on assumptions and assumes as mentioned previously, inputs of arrival distribution and service time distribution for an unknown number of servers. From these queuing theories is possible for instance to compute the number of servers needed by the following measurements: estimation of the waiting time or delay, the queue length or the probability that the server is idle. Queuing model assumes different types of distribution such as Exponential, Poisson or Erlang distribution, as mentioned previously from the working papers studied in the literature review chapter. It is therefore important to analyze and check which of the following EV arrival distribution it is similar to. Subject to the queuing theory is imperative to understand and study how possible is to optimize the queuing system, by minimizing the waiting line and/or reduce the delay while keeping the optimum cost for both customers and server owners [22]. To make an optimization one must take into account the arrival rate of customers, the service rate, the service cost to operate the queuing servers and the customer waiting time. The aspect with more importance of queuing optimization is the comparison between the customer value and the server cost value. Therefore, it is necessary to find a balance between the demand and the supply.

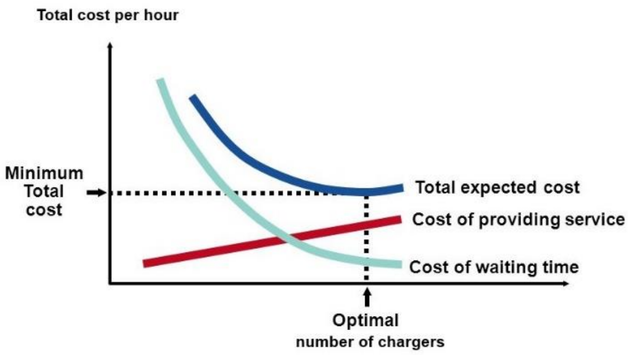


Figure 33 - Queuing system optimization example. Source: https://slideplayer.com/slide/4771447/

An example of the optimization of a queuing system is followed in Figure 33, the larger the number of parallel servers, the waiting time and queue length reduces drastically. Although, adding servers means additional cost to serve the customers. Therefore, there is an optimal number of chargers that balance the number of chargers, i.e. the additional costs related, and the waiting time and queue lengths [23].

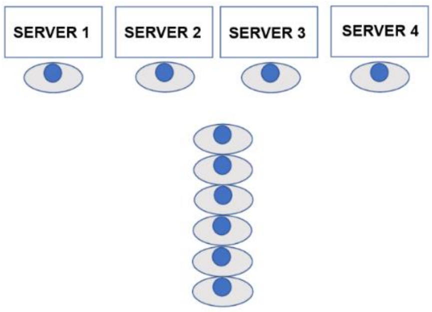


Figure 34 - M/M/s queuing system representation. Source: https://www.researchgate.net/figure/M-M-s-queuing-system_fig4_327770162

The queuing model of this thesis will follow the M/M/s queuing system as represented in Figure 34. The M/M/s is a queuing system where there are a number of ‘s’ parallel servers with only one queue. Likewise, for this queuing system, the EVs arrival distribution follows the Poisson distribution.

5.2.2. EVs Arrival Distribution

The arrival distribution represents the EV customers’ arrival into the queuing system. They usually arrive randomly, and the arrivals are independent of each other, i.e. it is unknown whether an EV will arrive and if the next EV will arrive one minute later or one hour later. Therefore, can be modeled by the Poisson distribution. This distribution arises from the situation in which there is a large number of opportunities for the event under scrutiny to occur but a small chance that it will occur on any one trial. An example of Poisson PDF with x arrivals in a specific time period, for which the λ=3, follows the formula:

$$P(X = x) = \frac{\lambda^x * e^{-\lambda}}{x!} \qquad (5.2)$$

Where:

- λ is the mean of x arrivals;
- e = 2,71828 (Euler's constant).

In the simulation process, a random number following the Poisson distribution is taken to obtain the number of EV arrivals for each hour for an example of simulation for one day, 24 hours, from the python program where the maximum EVs arrival was 76. The EVs arrival distribution is presented in Figure 35 with a mean of EVs arrival of three. The figure presents the same example of simulation using 900 PV panels, four batteries and four charging points for Lisboa. The time resolution is hourly and there isn't a car loading transition between hours, i.e. every electric vehicle is charged during the hour it arrives or it isn't charged (leaves).

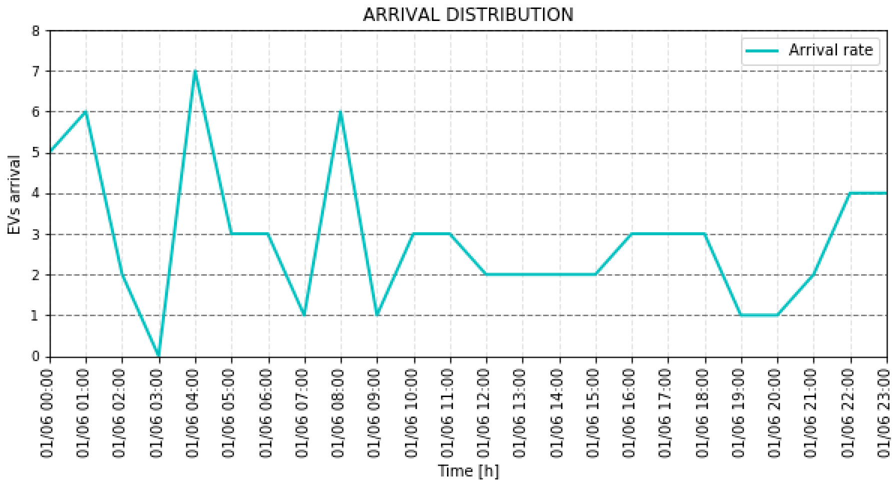


Figure 35 - EVs arrival distribution for one day example

Throughout the years, the lifetime of the project – 20 years, the mean of EV arrivals, λ, is increased by one, i.e. in the present year is assumed an arrival distribution with a mean of three arrivals per hour and the next year is assumed an arrival distribution with a mean of four arrivals per hour, and so on, until the last year, which will have an arrival distribution with a mean of 23 arrivals per hour. As the evolution of the various electric vehicles development markets, represented in this thesis, Faro, Lisboa and Porto, the growth from year to year could be changed for every city, since the growth is bigger in Lisboa and less for Faro, therefore Lisboa could have a growth of 3 EVs average arrivals per hour, and Porto a growth of 2 EVs average arrivals per hour.

5.2.3. Waiting Time

It is assumed that the maximum waiting time in the waiting line is 40 minutes. Therefore, we consider that in case all chargers are busy, the customer will wait up to 40 minutes to recharge its car. After this period, the EV customers will leave the EV fast-charging station and will not charge its vehicle. Thereby Tw_{max} = 40 (min). Additionally, the model assumes for each hour that, whatever the number of

EV arrivals, these will arrive in the beginning of the hour, i.e. if two EVs arrive at midnight is assumed both arrive at midnight sharp.

5.2.4. Service Time

The service time, i.e. the time while the EVs are charging in the fast-charging stations, depends upon the EVs' state of charge, market share and battery capacities. It is assumed that the maximum charging time in the EV fast-charging station is 25 minutes, stated and according to EDP objectives and business model. Whether it is completely charged or not, after 25 minutes it has to leave the fast charging station to give priority to other EV customers. Thereby Tc_{max} = 25 (min).

Additionally, the charging time is given by the following formula:

$$Tc = \frac{Bcapacity_k \times \left(\frac{SOC_{full} - SOC_{initial_k}}{100}\right)}{P_{charger}} \qquad (5.3)$$

Where:

- Tc – charging time (min);
- $Bcapacity_k$ – battery capacity of each k EV model car;
- SOC_{full} – SOC when is battery-full: 100 (%);
- $SOC_{initial_k}$ – initial SOC of each k EV arriving at charging station;
- $P_{charger}$ – fast charger power: 50 (kW).

In case of EV arriving at the fast charging station with an initial SOC that would need a charging time beyond 25 minutes, according to its battery capacity characteristic, it would not charge until it is fully charged. Therefore, the EV customer will come out of the fast-charging station with an upper level of SOC, although it isn't SOC_{full} but SOC_{final_k} instead.

5.3. Energy Models

As far as the fast charging station models are concerned, then it provides the arrival distribution for the model where the number of EV arrivals for each hour is obtained as well as the charging time needed for each car arriving at the fast-charging station, wherein the maximum charging time possible is 25 minutes. By gathering these data, we create the consumption profile whose model in this section is the EV energy demand. In order to return the consumption of EV customers using those EV fast-charging stations, a solar energy production profile is created, which is prioritized as the first energy source to be used. The production profile model in this section is the solar photovoltaic model. By having these two energy profiles one must balance the energy throughout energy exchange flows, therefore the energy management model is created so it can manage the exchange flows between the fast charging points from the station and solar panels, storage system, grid network, and EV customers. Similarly, attention is paid to the storage system model and grid network model.

5.3.1. EV Energy Demand Model

Previously mentioned, the consumption profile is traced from the energy demanded by EV customers as well as the energy provided by the EV fast-charging stations. These consumption profiles describe the consumption behavior of each customer arriving at the charging station and their details are available in time intervals of every hour during the whole year. In order to get the consumption profile, it is strictly necessary to use the data from market share, the battery capacities, the state of charge and the arrival distribution from previous sections. Firstly, the arrival distribution for every hour is set up. These data are randomly generated by means of a Poisson PDF in order to get the number of EV arrivals for every hour. Afterward, a random uniform function returns values from 0 to 100%, defining what type of car is arriving for each arrival, i.e. Nissan Leaf, Renault Zoe, BMW i3, Tesla Model 3, Smart ForTwo, Tesla Model S, Tesla Model X, Jaguar I-Pace, Smart ForFour or Hyundai Kawai, according to the cumulative probability of the market share given in Chapter 5.1.1. Subsequently, for every EV model, it is associated with a battery capacity according to the battery capacities of each model presented in Chapter 5.1.2 which is therefore associated with every EV arrival. In parallel, the state of charge of every EV arrival is set up. These data are randomly generated by means of a lognormal PDF in order to get the state of charge of every EV arriving at the station.

As far as the energy demand is concerned it is calculated according to every EV arrival with a different SOC and battery capacity, i.e. for every EV arrival it is associated with the battery capacity of the model arriving and its SOC at the moment. The energy required by the EV customer and provided by the EV fast-charging station is given by the following formula:

$$Eev_k = Bcapacity_k \times \left(\frac{SOC_{full} - SOC_{initial_k}}{100}\right) \qquad (5.4)$$

Where:

- Eev_k - energy supplied to every k EV (kW.h);
- $Bcapacity_k$ - battery capacity of each k model car (kW.h);
- SOC_{full} – full state of charge of EVs battery (%);
- $SOC_{initial_k}$ – initial SOC of each k EV arriving (%).

The energy required by each EV customer gives the energy required for every hour. These data consequently created the energy consumption profile for the whole year presented in Figure 36. The figure presents the same example of simulation using 900 PV panels, four batteries and four charging points for Lisboa.

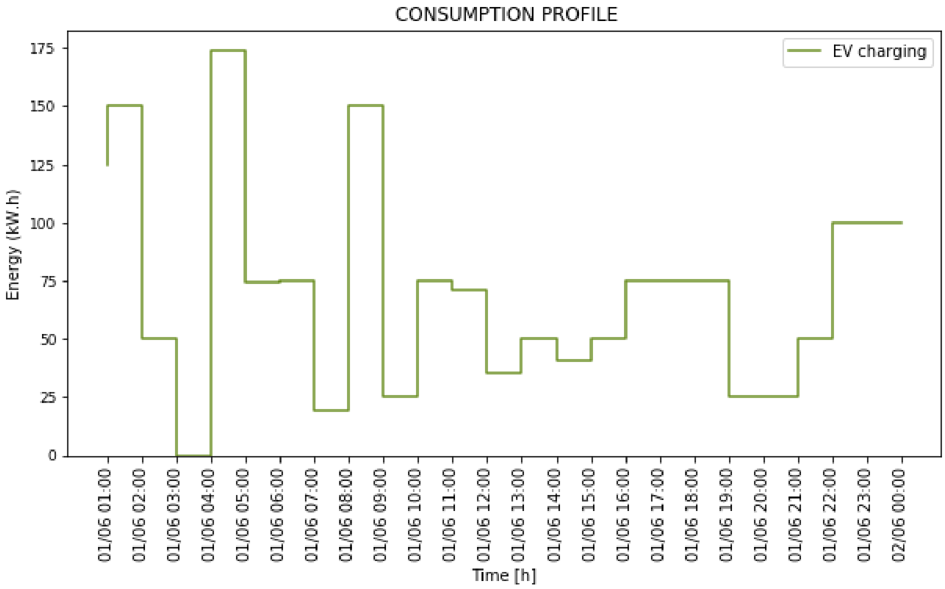


Figure 36 - Load profile from EV fast charging

5.3.2. Solar Photovoltaic Model

In order to meet the energy demand, is created a production profile from the solar photovoltaic system. The solar photovoltaic system generates electric power by using solar cells. In order to calculate the output power of a solar cell, one must implement a model to compute irradiance on its surface through one of the existing solar radiation models and afterward implement the solar cell model to compute the power output.

Usually, photovoltaic modules aren't installed horizontally but with an angle instead to increase the irradiance intercepted at the module so that reduces reflection. Mostly available irradiance data are measured or estimated for normal incidence or for horizontal surfaces. The amount of insolation on a terrestrial surface at a given location for a given time depends on the orientation and slope of the surface. For this reason, there is a need to convert these irradiance data to the irradiance on tilted surfaces. Both cases are presented as an example in Figure 37.

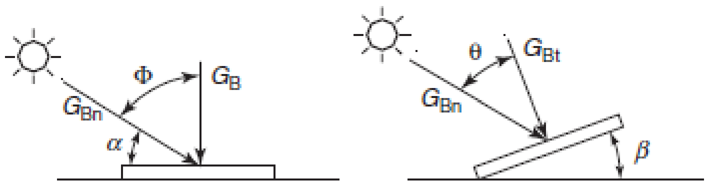


Figure 37 - Beam irradiance on horizontal and tilted surfaces. Source: [24]

A flat surface in a tilted surface absorbs beam irradiance (G_{Bt}), diffuse irradiance (G_{Dt}) and ground-reflected solar irradiance (G_{Gt}) which is given in the following formulas:

$$G_t = G_{Bt} + G_{Dt} + G_{Gt} \qquad (5.5)$$

In the formula above G_t is the total incident solar irradiance on a tilted surface. The beam irradiance refers to the quantity directly received without any reflection or refraction from the sun. The diffuse irradiance, also known as sky irradiance or solar sky irradiance, is a fraction of the total solar irradiance which has its direction changed by atmospheric scattering, it is highly variable and depends on cloudiness and atmospheric clearness. The ground-reflected solar irradiance is the ratio of irradiance received from the sun under the form of light after it has been reflected from the surroundings.

Many models give the solar irradiance on a tilted surface. The isotropic sky model is the simplest model that assumes that all diffuse irradiance is uniformly distributed over the skydome and that reflection on the ground is diffuse. The used model for this thesis is the Hay-Davies, which assumes that the diffuse irradiance from the sky is composed of isotropic and circumsolar component and the horizon brightening is not taken into account the ground-reflected solar irradiance is dealt with as in the isotropic model. The transmittance through the atmosphere for beam irradiance is defined as the anisotropy index, A. This index is used to quantify the portion of the diffuse irradiance treated as circumsolar with the remaining portion of diffuse irradiance assumed isotropic. The total irradiance is given by:

$$G_t = (G_B + G_D A)R_B + G_D(1 - A)\left[\frac{1+\cos(\beta)}{2}\right] + (G_B + G_D)\rho\left[\frac{1-\cos(\beta)}{2}\right] \quad (5.6)$$

$$A = \frac{G_{Bn}}{G_{on}} \quad (5.7)$$

Finally, in order to implement the solar cell model, the three parameters and one diode model were chosen to compute the power output. When the sun rays reach the surface of the solar cell, the energy of the photons produces free charge carriers. A single solar cell under illuminated conditions can be represented as in Figure 38 [24].

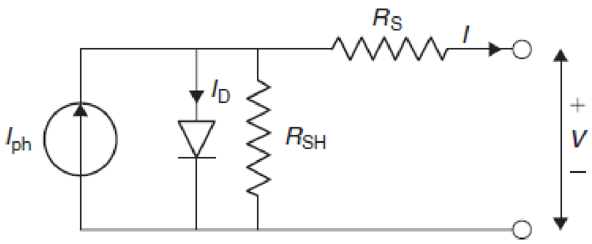


Figure 38 - Single solar cell model. Source: [24]

The following equations [25] can be used in order to determine the I (V) characteristics of a solar cell, according to the three parameters and one diode model where for all the equations but Equation 5.16 – 5.18, is used the maximum power point voltage and current as well as the short circuit current and open-circuit voltage from the manufacturer data given as reference values in Table 12:

$$I = I_{SC} - I_0\left[exp\left(\frac{V}{mV_T}\right) - 1\right] \quad (5.8)$$

$$I_0^r = \frac{I_{SC}^r}{e^{\frac{V_{OC}^r}{m\,V_T^r}} - 1} \quad (5.9)$$

$$m = \frac{V_{MP}^r - V_{OC}^r}{V_T^r \times \ln\left(1 - \frac{I_{MP}^r}{I_{SC}^r}\right)} \qquad (5.10)$$

It is possible to calculate the data at different irradiances and temperature. The temperature of the cell depends upon these values of irradiance and temperature and the following variables as well:

$$T = \frac{G_t(NOCT - 20)}{800} + T_{amb} \qquad (5.11)$$

$$I_{SC} = \frac{G_t}{G_t^r} \times I_{SC}^r \qquad (5.12)$$

$$I_0 = I_0^r \left(\frac{T}{T^r}\right)^3 \times e^{\frac{\varepsilon}{m'}\left(\frac{1}{V_T^r} - \frac{1}{V_T}\right)} \qquad (5.13)$$

$$m' = \frac{m}{N} \qquad (5.14)$$

$$V_T^r = \frac{kT}{q} \qquad (5.15)$$

In order to get the maximum power current and voltage the following formulas are computed:

$$e^{\frac{V_{MP}}{m\,V^T}} = \frac{\left(\frac{I_{SC}}{I_0} + 1\right)}{\left(1 + \frac{V_{MP}}{m\,V_T}\right)} \qquad (5.16)$$

$$I_{MP} = I_{SC} - I_0\left(e^{\frac{V_{MP}}{m\,V^T}} - 1\right) \qquad (5.17)$$

Once the maximum power point voltage is found, is calculated the maximum power current. The maximum power produced in these conditions is given by multiplying the maximum power point current and voltage:

$$P_{MP} = V_{MP} \times I_{MP} \qquad (5.18)$$

Where:

- G_t – total incident solar irradiance on the tilted surface (W/m^2);
- G_{Bt} – beam irradiance on the tilted surface (W/m^2);
- G_{Dt} – diffuse irradiance on the tilted surface (W/m^2);
- G_{Gt} – reflected irradiance on the tilted surface (W/m^2);
- G_B – beam irradiance (W/m^2);
- G_D – diffuse irradiance (W/m^2);
- A – anisotropy index;
- R_B – the ratio between tilted and horizontal beam irradiance;
- β - tilt angle (º);
- ρ - reflectance of the ground;

- G_{Bn} – beam irradiance on the horizontal surface (W/m^2);
- G_{on} – extraterrestrial irradiance (W/m^2);
- I – current (A);
- I_{SC} – short circuit current (A);
- I_0 – reverse saturation current (A);
- V – voltage imposed across the cell (V);
- m – diode's ideality factor;
- V^T – thermal voltage (V);
- V_{OC} – open-circuit voltage (V);
- V_{MP} - maximum power point voltage (V);
- I_{MP} – maximum power point current (A);
- P_{MP} – maximum power point power (W);
- T – cell temperature (K);
- T_{amb} – ambient temperature (K);
- NOCT – Normal operating cell temperature (ºC);
- N – number of panels;
- k - Boltzmann's gas constant = 1.381 × 10^{-23} (J/K);
- q - electronic charge = 1.602 × 10^{-19} (J/V);
- ε - gap band = 1.12 eV for silicon.

Table 12 - Manufacturer datasheet of the chosen panel

	MANUFACTURER DATA SHEET
V_{MP}	28,35 (V)
I_{MP}	7,69 (A)
V_{OC}	36,38 (V)
I_{SC}	8,38 (A)

In order to get the power of the module was used a python library, in the program pvlib [26], which collects data from the irradiance in the horizontal surface for any place, in this case for Lisboa, Porto, and Faro. Considering this, it is necessary to know for each city what is its latitude, longitude, and altitude which is presented in Table 13.

Table 13 - Latitude, longitude and altitude data from Porto, Lisboa and Faro [27]

	LISBOA	PORTO	FARO
LATITUDE (º)	38,73	41,16	37,03
LONGITUDE (º)	- 9,14	- 8,63	- 7,93
ALTITUDE (M)	57	115	80

The yearly energy production from only one photovoltaic module for each city was, as presented in Figure 39 is:

- Faro: 467 kWh
- Lisboa: 456 kWh
- Porto: 459 kWh

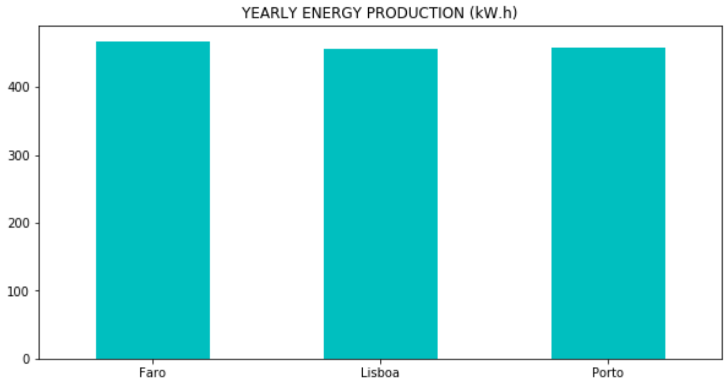


Figure 39 - Yearly energy production for Porto, Lisboa, and Faro from one photovoltaic module

The yearly energy production difference between cities is not considerable. Even though, Faro is the city with higher production according to GHI average annual availability mentioned previously in Chapter 4.3. In order to have a mean of comparison with this data, the yearly energy production was compared to the PVGIS data [28] which was 459 kWh, 429 kWh, 390 kWh, for Faro, Lisboa, and Porto, respectively, as presented in Figure 41, Figure 41 and Figure 42. The values obtained by the program are subtly underestimated because the pvlib uses a different data source for historical radiation (PVGIS uses Meteonorm while pvlib uses NREL). However, the values aren't too away from those returned from PV-GIS, except Porto which has a difference of 70 kWh.

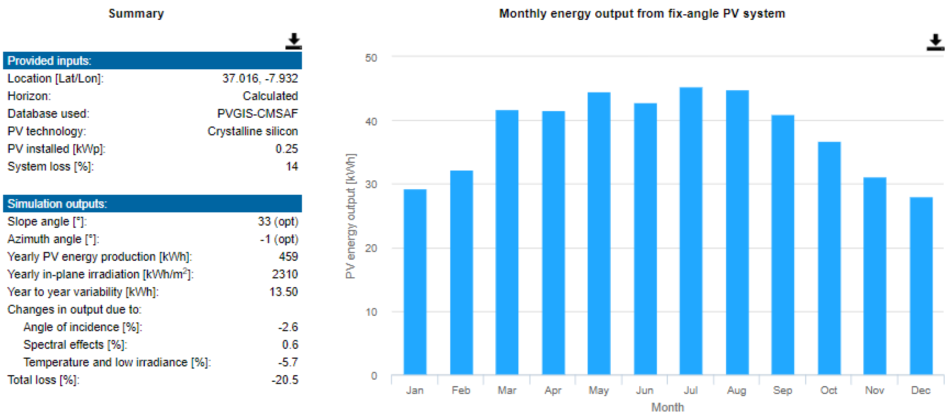


Figure 40 - Yearly energy production from PV-GIS for Faro from one photovoltaic module [28]

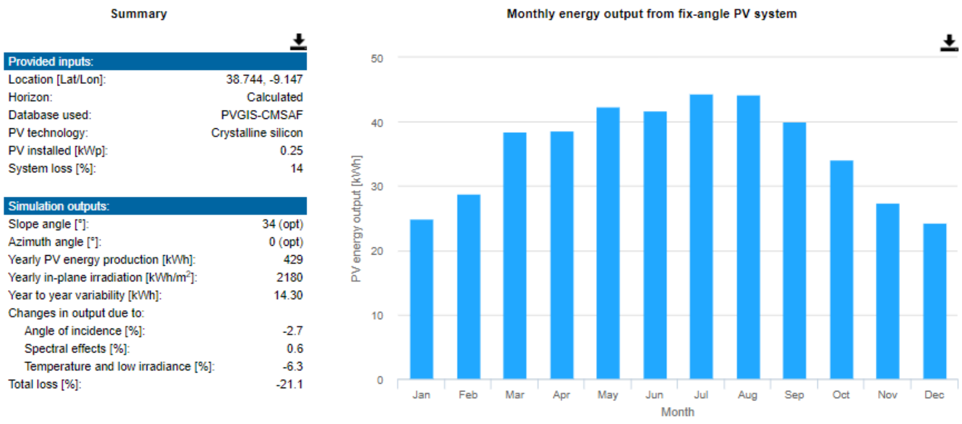


Figure 41 - Yearly energy production from PV-GIS for Lisboa from one photovoltaic module [28]

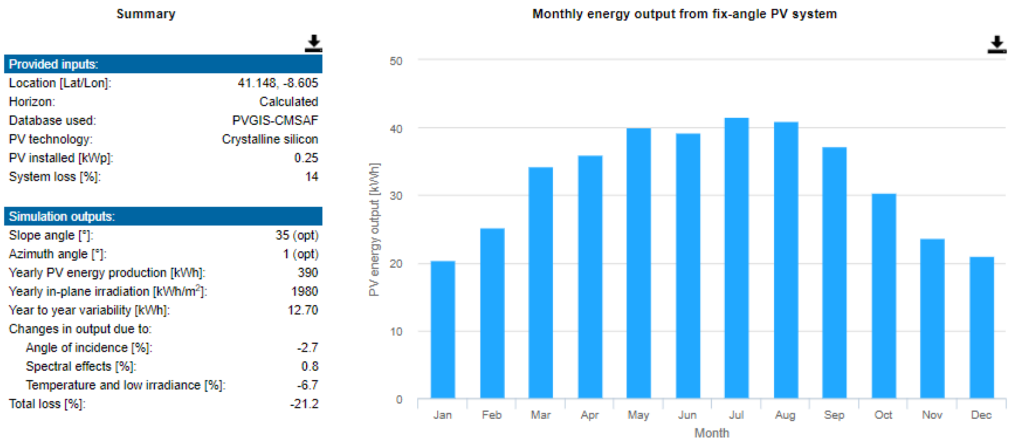


Figure 42 - Yearly energy production from PV-GIS for Porto from one photovoltaic module [28]

Figure 43 presents the energy consumption and PV production profile for one day with 900 installed PV panels for Lisboa. The energy produced by the PV panels installed is returned for every hour. The figure presents the same example of simulation using 900 PV panels, four batteries and four charging points for Lisboa. The energy production from PV panels is continuous throughout the day, although it is represented in the figure as a constant value for each hour, to be easily compared with the consumption values.

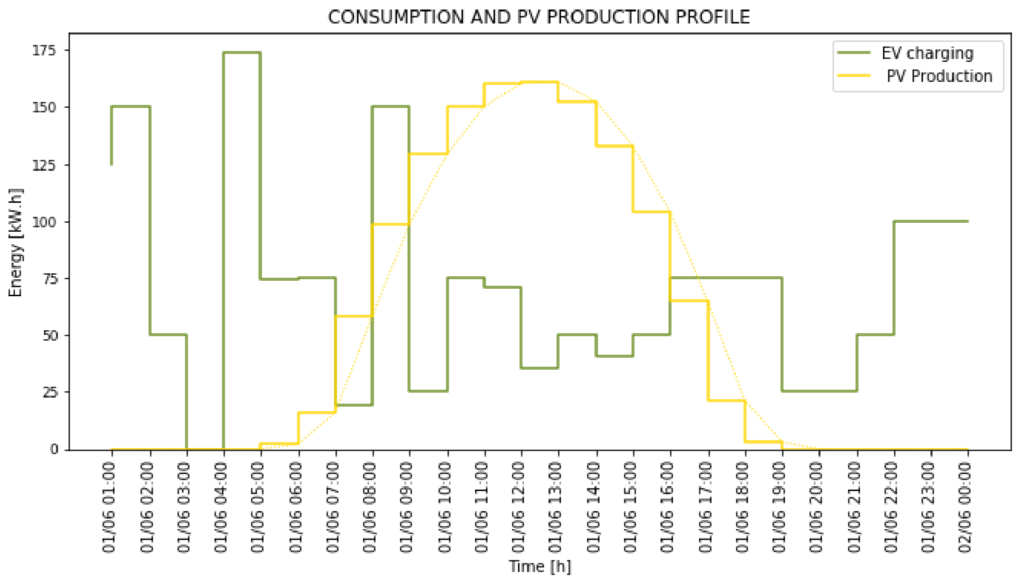


Figure 43 - Energy consumption and PV production profile for Lisboa

5.3.3. Storage System Model

Whenever a storage system is used one must take into account the discharge and charge cycles for technical and investment analysis purposes. Usually, the number of charging and discharging cycles are around 5.000 – 10.000 cycles, therefore when analyzing for one charge/discharge cycle per day, its lifespan is around 8 – 10 years. When accounting for the lifetime of the system modeled in the program of this thesis, 20 years, it would be necessary for the replacement of the battery system once. As mentioned previously in Chapter 4.4.3, the storage system must follow the following requirements and should take into account that:

- The energy stored at each hour must be the difference between the energy-charged and the energy discharged at that same hour;
- The energy discharged from the storage system cannot be higher than the energy stored in the previous hour as well as the energy-charged cannot be higher than the difference between the storage energy capacity and the energy stored in the previous hour;
- The energy stored cannot be higher than the storage energy capacity and it can't be lower than the minimum storage energy capacity, as it may damage the battery and its lifespan will be lower. Therefore, taking into account that the minimum state of charge for those batteries are 10% of its capacity [29], they cannot be discharged after reaching this minimum. In this case, five kW.h, taking into account that each battery has 50 kW.h, as mentioned in Chapter 4.4.1.

Figure 44 presents the schematic diagram of the system, the fast charging station connected to the utility grid, PV system, and storage system. As can be seen, the PV array produces electricity, which can be directed from the controller to either to the battery storage, to the EVs (used immediately) or sold to the grid. Whenever there is not enough solar power, the battery can supply power to the load if it has enough capacity otherwise if there is not enough capacity the electric vehicles can also be charged by the power bought back from the grid network.

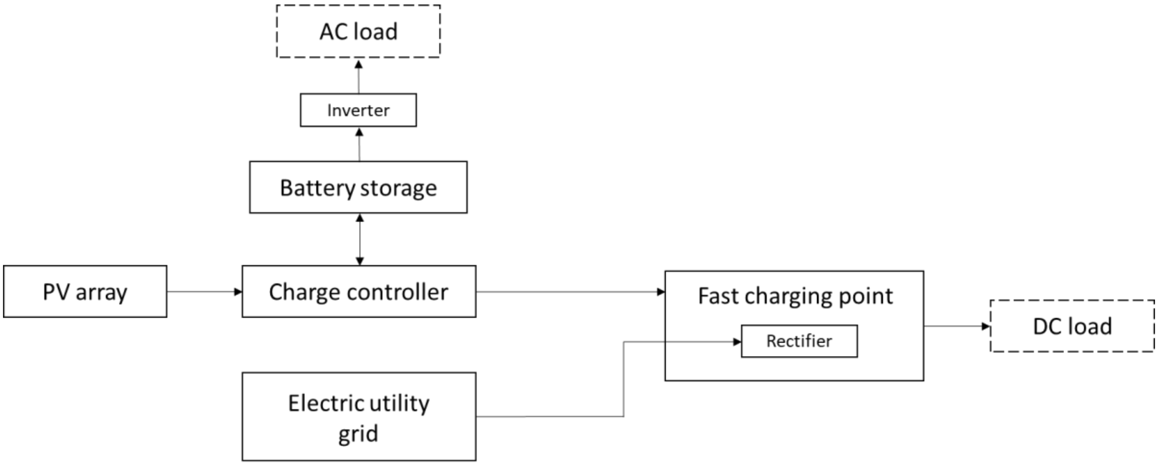


Figure 44 - Schematic diagram of a fast-charging station connected to the utility grid, PV system, and storage system

5.3.4. Energy Management Model

By having a consumption and production (scenario two and three) profile one must think about how to balance and manage the energy exchange flows among the EV fast-charging station and EV customers, photovoltaic panels, grid network, and storage system. These energy flows must take into account the restrictions mentioned in Chapter 4.4.3. In order to assess the energy management of the system, the following steps should be followed. This is the example whenever the chosen scenario has a storage system that accounts for more technologies regarding the energy exchange flows. The examples for scenario two and one are further detailed.

I. The solar photovoltaic generation to feed the EV chargers it is prioritized, as colored in green in Figure 45. In other words, if there is energy produced by the photovoltaic panels, the energy provided to the EV fast-charging stations will be acquired by means of photovoltaic energy;

II. When the energy available is greater than the EV demand as colored in yellow in Figure 45, the surplus energy is stored. In other words, if the energy produced by means of photovoltaic panels is greater than the consumption, the surplus is stored in the storage system giving rise to the blue colored area in the figure. If the maximum battery capacity of the storage system is reached, the surplus energy stored from the previous case is sold to the grid;

III. When there is a deficiency of energy to feed EV chargers, i.e. energy available is lower than the EV demand, the energy is firstly provided by the storage system as colored in blue in the figure and afterward by the grid as last resort.

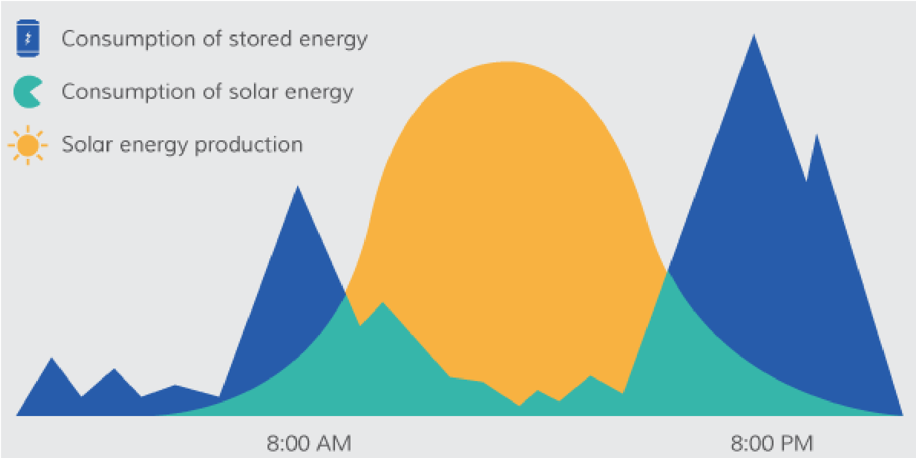


Figure 45 - Energy management of the adapted model. Source: https://www.sumo.com.au/solar/

Whenever there is not energy storage (scenario two), the energy is provided to EV customers by means of photovoltaic production in case its production being is higher than the consumption. If the energy available is greater than the EVs demand, the surplus energy is sold to the grid. When there is a deficiency of energy to feed the EV chargers, the energy is provided by the grid. In the case of having neither a storage system neither photovoltaic panels (scenario 1), the EV customers are fed solely by the grid network.

The flow chart in Figure 46 presents the logic behind the energy management model used. As far as the energy management model is concerned, its input variable is the hour to be evaluated. Every hour of the day, it evaluates the energy management model. As during peak hours, the energy purchased from the grid is more expensive, the model evaluates whether it is a peak hour or not in order to use the energy stored in the storage system in case there is enough to use during that hour. Therefore, the first evaluation is to analyze the type of hour. If it is not a peak hour, full hour/ empty hour/ super empty hour then, verifies if there is PV energy. If so, charges EVs from PV energy, and if there is an energy surplus, it charges the storage system. In case, the storage system is full, it sells the energy to the grid network. If there are not enough PV energy charges from the grid network. The difference from the peak hours is that, when there is not enough PV energy, instead of charging from the grid, charges from the storage system. In the case, there is no battery and PV energy, as last resort, it uses the grid network.

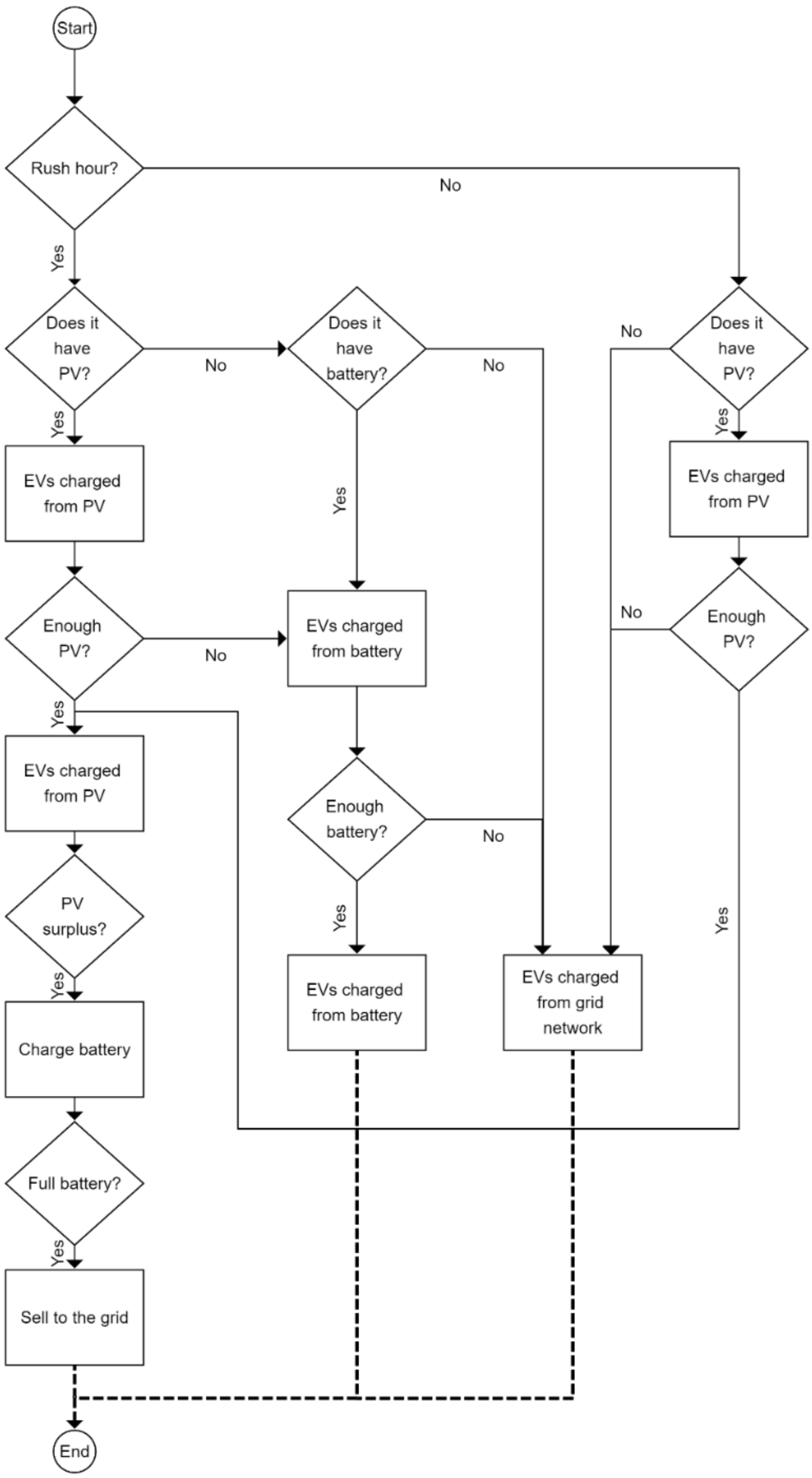


Figure 46 - Energy management model flowchart

Figure 47 presents the same example of simulation using 900 PV panels, four batteries and four charging points for Lisboa with the energy management model.

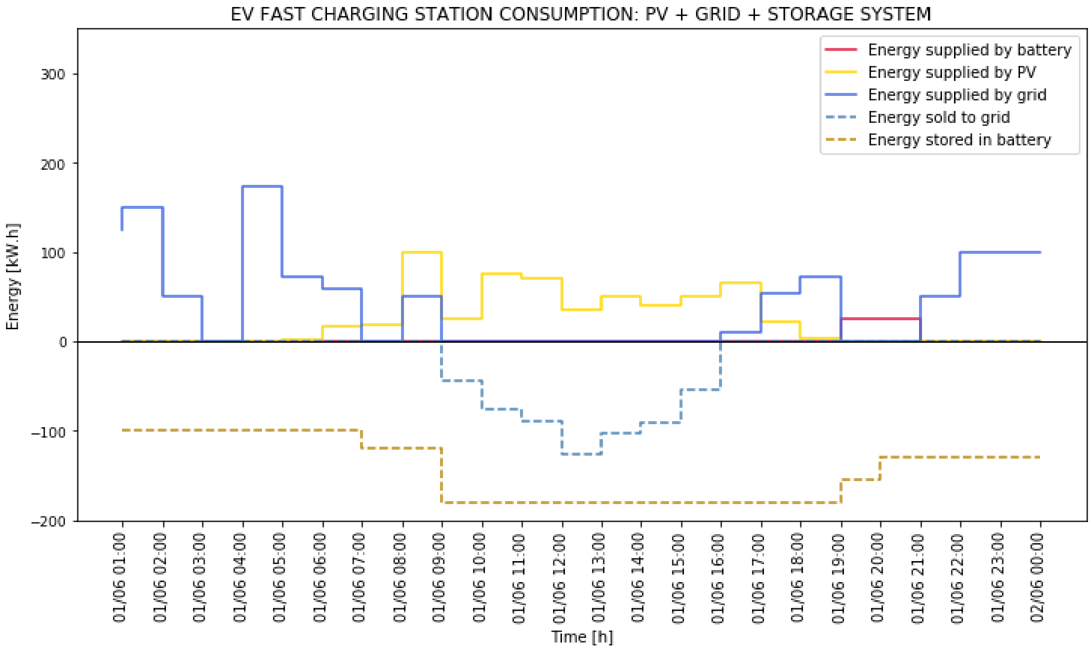


Figure 47 - EV fast-charging station consumption with the energy management model

This figure presents the energy supplied by the battery, outlined in red, the energy supplied by the PV, outlined in yellow, the energy supplied by the grid, outlined in blue which are in the upper part of the graph, demonstrating the three different technologies used throughout the day to supply the EV fast-charging station. In the bottom part, it presents the energy sold to the grid, dashed in blue, and the energy stored in the battery, dashed in brown. These are presented as negative values in order to improve readability. It is assumed that the battery is half-charged at the start of the day. As it is possible to verify, the energy is stored throughout the day while it is not peak hour, up to its maximum capacity and the surplus is sold to the grid. When reaches the peak hours, the battery is discharged, and the energy consumed by the EVs is only provided by the battery while enough charge is available and until the cutoff value. During the daytime, the energy provided to EVs is mostly done by PV and during nighttime by the grid network, once there is not PV and as is not peak hour, the system cannot use the storage system to provide energy.

5.4. Energy prices

Below it is presented the energy prices charged in the model in relation to energy sold to the grid from the photovoltaic energy production and storage system, as well as to the energy purchased from the grid when using the grid network and lastly the energy sold to EV customers for the EV whose charging in the EV fast-charging station.

5.4.1. Energy Purchased from Grid

The energy pricing of the E-Hub fast-charging station takes into account the medium voltage schedule [30] and the EDP medium voltage energy tariffs [31] when using the national grid network to charge the electric vehicles. The medium voltage schedule is presented in Figure 48 and Table 14. The medium voltage energy tariffs charged for the medium voltage schedules are presented in Table 15 assuming that the fast charging station is a facility for long use. The medium voltage schedule is assumed in the model as only the winter schedule and for the active energy price in the energy tariffs, the mean value between summer and winter prices for each kind of hour. The energy tariffs take into account the power charges and active energy prices presented in Table 15. As it is possible to verify, what increases superbly the amount paid for grid network usage is the power charges. This value may make the storage system use a more affordable price scenario during nighttime and the PV system use a more affordable price scenario during the daytime even though there is an investment for these systems. The related variable to the energy purchased from the grid for each hour t is, Ccg_h.

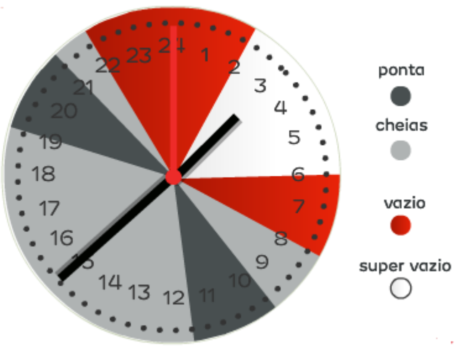


Figure 48 - Medium voltage schedule. Source: https://www.edpsu.pt/pt/tarifasehorarios/horarios/Pages/HorariosMT.aspx

Table 14 - Medium voltage schedule [30]

	MEDIUM VOLTAGE SCHEDULE
PEAK HOURS	9h30 – 11h30; 19h – 21h
FULL HOURS	8h – 9h30; 11h30 – 19h; 21h – 22h
EMPTY HOURS	22h – 2h; 6h-8h
SUPER EMPTY HOURS	2h – 6h

Table 15 - Medium voltage energy tariffs [31]

MEDIUM VOLTAGE ENERGY TARIFFS	ACTIVE ENERGY PRICE (€/ KW.H)	POWER CHARGES (€/ KW.DIA)
PEAK HOURS	0,1395	0,3316
FULL HOURS	0,1113	
EMPTY HOURS	0,0784	
SUPER EMPTY HOURS	0,0697	

5.4.2. Energy Sold to Grid

The remuneration price of the amount of electricity supplied to the national grid network by the EV fast-charging station covered by the provisions of the following article [32] is calculated according to the following expression:

$$Csg_h = Esg_h \times OMIE \times 0.9 \qquad (5.19)$$

Where:

- Csg_h - remuneration price of selling to the grid (€);
- Esg_h - energy supplied to grid at hour h (kW.h);
- OMIE = 0,05729 (€/kW.h) given by [33] for 2018 – the resulting value of the simple arithmetic average of the closing prices of the Iberian Energy Market Operator (OMIE) for Portugal;

5.4.3. Energy Sold to EVs

The revenue concerning the EV fast charge of electric vehicles using the E-Hub of this model is based on the revenue model of EDP [7]. When using the charging station, the paid price for charging the electric vehicle is composed of the charging energy, the station usage as well as the fees and taxes. The model only takes into account the charging energy and the station usage as fees and taxes (VAT) are not revenue for the project since they are directed as a debt to the state. In Figure 49 is present the revenue tariff. The related variable to the energy price station at hour h is, Cev_h.

Figure 49 - EV fast-charging revenue model from EDP

5.5. Economic assessment

Below are presented the formulas to calculate the net present value in order to choose the best scenario and the assumed values of CAPEX and OPEX of the storage system, the PV system, and the fast charging points. Also, presented are the formulas of the internal rate of return and payback period. They are not input variables for the genetic algorithm iterations, although they are relevant, and it will be presented for economic analysis.

5.5.1. Net Present Value

The net present value is the value of all future cash flows (positive and negative) over the entire life of an investment discounted to the present. NPV is used extensively across finance to determine the value of a business. NPV analysis is used to help to determine how much a project is worth and it considers all revenues, expenses and capital costs associated with an investment. It also considers the timing of each cash flow that can result in a large impact on the present value of the investment. The NPV is given by the following formulas as presented previously in Chapter 4.4.2.

$$NPV = \sum_{t=1}^{n} \frac{NCF_t}{(1+i)^t} - I \qquad (5.20)$$

$$NCF_t = \sum_{h=1}^{8760} [\, INFLOW_h - OUTFLOW_h] - Csto_t \times N_{sto} - Cpv_t \times N_{pv} - Ccp_t \times N_{cp} \qquad (5.21)$$

$$INFLOW_h = Eev_h \times Cev_h + Esg_h \times Csg_h \qquad (5.22)$$

$$OUTFLOW_h = Ecg_h \times Ccg_h \qquad (5.23)$$

$$I = C_{cp} \times N_{cp} + C_{pv} \times N_{pv} + C_{sto} \times N_{sto} \qquad (5.24)$$

Where:

- n = 20 years[22];
- i = 0,06 – discount rate[23];
- Eev_h - energy supplied to EVs at hour h (kW.h);
- Esg_h - energy supplied to grid at hour h (kW.h);
- Ecg_h - energy consumed from the grid at hour h (kW.h);
- $Csto_t$ – maintenance of the storage system at year t (€);
- Cpv_t - maintenance of the PV panels at year t (€);
- Cev_h - energy price station at hour h (€);
- Csg_h - remuneration price of selling to the grid (€);
- Ccg_h - energy price of the grid at hour t (€);
- Ccp – the cost of charging point (€);
- Cpv – the cost of PV panel (€);
- Csto – the cost of the storage system (€);
- Ncp - number of charging points installed;
- Npv - number of PV panels installed;
- Nsto - number of batteries installed;
- I – initial investment (€).

[22] as explained in Chapter 4.4.2

[23] given according to used values from EDP [42], 3,3% - 6,4%, I assumed 6% inside the range

5.1.1. Internal Rate of Return

The internal rate of return (IRR) is a metric used to estimate the profitability of potential investments. It is the discount rate that makes the net present value from a particular project equal to zero, i.e. a project that returns at least its investment. It is important to look at the IRR to look at the future growth of a project. The higher is the IRR of a project, the more desirable is to undertake it. The formula relies on the same as NPV formula, presented below:

$$0 = NPV = \sum_{t=1}^{n} \frac{NCF_t}{(1+IRR)^t} - I \qquad (5.25)$$

5.5.3. Payback Period

The payback period is the time where the initial outlay of investment is expected to be recovered through the cash inflows generated by the investment. The payback period is an indicator of the risk inherent of a project. It takes the initial cash inflows into account and ignores the cash flows after the point where the initial investment is recovered. The projects with high cash inflows, in the beginning, are generally ranked with higher values when taking into account only the payback period. Whereas, the projects having larger cash inflows in the later periods are generally ranked lower, even though there can be more profitable. In order to calculate the payback period of an investment one must calculate the cumulative cash flow for each year. The formula to calculate is expressed below:

$$Payback\ period = t + \frac{C_t}{C_{t+1}} \qquad (5.26)$$

Where:

- t – last year with negative cumulative cash flow;
- C_t – cumulative cash flow at year t (absolute value);
- C_{t+1} – cumulative cash flow at year t+1.

5.5.4. CAPEX

The costs that make part of CAPEX for this project are the initial investment cost of charging points, PV panels, and storage systems. The charging points type taken into account for this thesis is fast charging QC45 type with a DC output with power up to 50 kW and dual-port [34]. Its purchase value is around 29.000€ [35]. As the charging point for this thesis is considered as device suited for charging only one EV at a time, and as the QC45 model suits up to 2 charging places at the same time, we consider in the model that its purchase price is half of the price mentioned before, 14.500€. As well as the purchasing costs one must consider the installation costs which account for 15% of its purchasing cost, 2.175€. Therefore, the correspondent CAPEX of one charging point is Ccp = 16.675€.

The CAPEX value of PV panels is given by [36] where the investment cost is interpolated with the proposed values for medium voltage installations from the retail sector from the paper giving the following function:

$$Cpv = 102 \times PV_{capacity} - 75 \qquad (5.27)$$

Where:

- Cpv – the cost of PV panel (€);
- $PV_{capacity}$ - total PV installed capacity (kW).

The CAPEX value of the storage is given by the following formula [29] taking into account that for the lifetime project the storage system is replaced once, therefore the investment cost is multiplied by two:

$$Csto = 2 \times (Bcapacity_{sto} \times SC_{battery} + P_{NOM} \times SC_{equipment}) \qquad (5.28)$$

Where:

- $Csto$ – the cost of the storage system (€);
- $Bcapacity_{sto}$ – storage system capacity (kW.h);
- $SC_{battery}$ – specific cost of the storage system = 296 kW.h (€/kW.h);
- P_{NOM} – storage system rated power (kW);
- $SC_{equipment}$ – specific cost for the equipment that complements the battery installation = 108 (€/kW).

5.5.5. OPEX

The costs making part of OPEX for this project are the operational costs for running fast charging points, the PV system, and the storage system. The OPEX value for the fast charging points is given by the following formula, according to [31] where it defines the price for the contracted power of 0,0508 €/kW per day and accounting with 1% of the investment, which is used for maintenance and other general technical problems:

$$Ccp_t = Pcharger \times 0{,}0508 \times 365 + 0{,}01 \times Ccp \qquad (5.29)$$

Where:

- Ccp_t - maintenance of the charging point at year t (€);
- $P_{charger}$ - fast charger power (kW) = 50 kW;
- Ccp – the cost of charging point (€).

The OPEX value for PV panels is given by the following formula, according to [37] where it defines the initial cost for larger systems as 0.5% as a reasonable expectation of PV system O&M costs:

$$Cpv_t = 0{,}005 \times Cpv \qquad (5.30)$$

Where:

- Cpv_t - maintenance of PV panels at year t (€);
- Cpv – the cost of the PV panel (€).

The OPEX value for the storage system is given by the following formula, according to [29] where it defines, 3% of the initial system cost per year as a reasonable expectation of the storage O&M costs:

$$Csto_t = 0{,}03 \times Csto \qquad (5.31)$$

Where:

- $Csto_t$ - maintenance of the storage system at year t (€);
- Csto – the cost of the storage system (€).

Chapter 6

6. Results and Discussion

The main goal of this thesis is to find the optimal design of the fast-charging infrastructure, using a genetic algorithm optimization method, by maximizing the NPV of the project throughout 20 years. Pursuant to this main goal, an energy management model is developed to estimate what is the energy consumed per EV from the grid network, from the photovoltaic modules installed and from the storage system as well as the energy sold to the grid and the energy stored in the storage system, taking into account the energy prices by purchasing energy from the grid, selling to the grid and selling to the EV customers.

The energy management model will thereby affect the NPV evaluated by the genetic algorithm each year, once it affects the OPEX values. As far as the genetic algorithm configuration is concerned, its optimization variables have to be tested and analyzed in order to obtain the ideal set of parameters for the algorithm, before testing the three cities. Therefore, this chapter presents and analyses the different optimization variables for the genetic algorithm such, as population size, number of generations, the convergence value for NPV, the mutation values as well as the selection of parents' parameters. Finally, it presents the ideal configuration for every city and for different arrival distributions models. The genetic algorithm was performed resorting to a modified version of the one available in [38].

6.1. Parameter optimization

In order to analyze the different optimization variables of the genetic algorithm, two main different analysis is performed. The main difference is the convergence value of the NPV in order to stop the genetic algorithm while finding the optimal configuration of chargers' number, number of installed PV and number of installed batteries.

The first analysis takes into account a convergence value of the NPV throughout the genetic algorithm of 1%, i.e. the genetic algorithm stops when the NPV value of the following generation has a difference smaller than 1%. For the second analysis, the convergence value of 0.1% is considered for the NPV. For both analyses, the generation of the initial population is completed according to the generation of random values for both the number of chargers, the number of PV and the number of batteries. Therefore, the initial population according to its size can have any combination of values for the three variables between 1-20 for the number of chargers, 0-20 for the number of batteries and 0-5000 for the number of PV. In addition, the percentage of parents in the selection pool is set to 40% of the population for the crossover operation and 5% of that total population for the mutation operation. The crossover operation is made in between gene 1 and gene 2, i.e. the number of chargers and the number of batteries respectively. The two main analysis are for:

- NPV – convergence value 1%;
- NPV – convergence value of 0,1%.

Furthermore, this analysis is completed only for Lisboa, since it is a parameter hit analysis to find the optimal optimization variables.

6.1.1. NPV – convergence criteria of 1%

For the analysis of an NPV convergence value of 1%, the following population size and number of generations combinations presented in Table 16 were evaluated and assumed. Each combination was performed three times to evaluate the parameters and verify whether the genetic algorithm for that combination converges or not.

Table 16 - Population size/ number of generations combinations

POPULATION SIZE	20	50	100	200	300	400
NUMBER OF GENERATIONS	500	200	100	50	20	10

In this analysis, and as mentioned previously only 5% of the population value is considered for the mutation operation. In accordance, for these analyses, the mutation used is a random value between -1 and 1 and summed up to the number of chargers. Likewise, the mutation variation is done in the same way for the number of batteries. The mutation used for the number of PV panels installed is a random value between -10 and 10 and summed up to the number of PV. Table 17 presents the values for every combination performed three times. The values presented in the 'Ideal configuration' column are presented in the pattern: [number of chargers; number of batteries; number of PV].

Firstly, it is possible to conclude from Table 17 that whether the maximum number of generations possible for the simulation is 10 or 500, the number of generations performed is mostly between 6-7. This occurs due to the convergence criteria applied between generations. When the value is 1%, the optimal solution is always found running a small number of generations. Therefore, this number should be lowered in order to run more generations and eventually find a better solution. Do note that the NPV, except for the population of 20, varies less than 2%, while the computational time increases considerably. The NPV difference presented for every solution is within $\pm$4% for this convergence value of the NPV.

From Table 17, it is possible to verify for combinations with lower population sizes, 20 and 50, the three simulations always returned the same value. For the population sizes of 100, 200 and 300 these returned twice the same values and the population size of 400 never returned the same values. This demonstrates that the larger the population size, the greater the probability of not returning the same solution and more difficult to find the optimal solution since there will be more mutations in the solution space. This can be solved by decreasing the convergence criteria value between NPVs from subsequent generations. Thereby, the populations with bigger sizes have more time to find the optimal solution.

Table 17 - Analysis for every population size/ generations number combination for NPV convergence value of 1%

		NPV (€)	IRR	Payback period (years)	Ideal configuration	Generations performed
Population size – 20 Generation limit - 500	1º trial	5 912 128	0,404	3,14	[13 13 4103]	6
	2º trial	5 912 128	0,404	3,14	[13 13 4103]	6
	3º trial	5 912 128	0,404	3,14	[13 13 4103]	6
Population size – 50 Generation limit - 200	1º trial	6 239 316	0,441	2,83	[12 12 4932]	7
	2º trial	6 239 316	0,441	2,83	[12 12 4932]	7
	3º trial	6 239 316	0,441	2,83	[12 12 4932]	7
Population size – 100 Generation limit - 100	1º trial	6 181 481	0,627	1,94	[16 3 4769]	8
	2º trial	6 181 481	0,627	1,94	[16 3 4769]	8
	3º trial	6 173 946	0,555	2,2	[14 6 4523]	7
Population size – 200 Generation limit - 50	1º trial	6 285 299	0,769	1,52	[12 2 4975]	7
	2º trial	6 163 034	0,83	1,39	[12 1 4622]	7
	3º trial	6 163 034	0,83	1,39	[12 1 4622]	7
Population size – 300 Generation limit - 20	1º trial	6 245 017	0,436	2,86	[15 11 4995]	7
	2º trial	6 245 017	0,436	2,86	[15 11 4995]	7
	3º trial	6 272 522	0,669	1,79	[14 3 4918]	8
Population size – 400 Generation limit - 10	1º trial	6 275 650	0,59	2,07	[12 6 4821]	7
	2º trial	6 197 355	0,602	2,04	[11 6 4619]	6
	3º trial	6 225 885	0,489	2,53	[11 10 4824]	7

Comparing the population size of 20 with the rest, the resulting NPV value is the lowest. Therefore, for this value of convergence and mutation characteristics, the population size of 20 is not an optimal optimization variable. As one of the disadvantages of the genetic algorithm, and with many other optimization algorithms, is that there is no guarantee that the solution is the optimal solution of the whole solution space.

Likewise, from Table 17 it is possible to validate that the IRR and payback period variations are significantly related to the number of batteries installed. The greater the number of batteries installed, the lower the IRR and the higher the payback period, since these are very expensive. For this reason, charging posts and PV panels dictate the economic viability of the business model.

As the values of the NPV are quite analogous for every population size except the population size of 20 with a convergence value of the NPV of 1%. These will be detailly analyzed with a lower convergence criterion for the NPV in the following section.

6.1.2. NPV – convergence criteria of 0,1%

As mentioned in the previous section, the number of the value of convergence for the difference between NPVs from every generation should be lower. Therefore, for the following analyses, the convergence criteria consider the value of 0,1% for the NPV. By using this value, it is possible to run more iterations and find a more accurate solution with a better NPV value compared to the previous criteria. In the previous analysis, the mutation used for the number of PV panels installed was a random value between -10 and 10 which was summed up to the number of PV. In this case, the mutation will be a random number within the range -200 and 200 since the number of PV installed in the previous solutions do not vary significantly. Thereby, with these values, the algorithm can vary the number of PVs if one of the chosen for the mutation with a wide range so that improved PV values can emerge faster. Table 18presents the values for every combination performed three times.

Table 18 - Analysis for every population size/ generations number combination for NPV convergence value of 0.1%

		NPV (€)	IRR	Payback period (years)	Ideal configuration	Generations performed
Population size – 50 Generation limit - 200	1º trial	6 194 456	0,605	2,02	[13 5 4544]	8
	2º trial	6 261 161	0,459	2,7	[12 11 4927]	9
	3º trial	6 104 796	0,463	2,69	[13 10 4385]	9
Population size – 100 Generation limit - 100	1º trial	6 270 279	0,548	2,22	[15 6 4916]	9
	2º trial	6 181 481	0,627	1,94	[16 3 4769]	8
	3º trial	6 181 481	0,627	1,94	[16 3 4769]	8
Population size – 200 Generation limit - 50	1º trial	6 315 087	0,592	2,06	[12 6 4955]	16
	2º trial	6 315 087	0,592	2,06	[12 6 4955]	16
	3º trial	6 315 087	0,592	2,06	[12 6 4955]	16
Population size – 300 Generation limit - 20	1º trial	6 294 522	0,715	1,66	[12 3 4947]	11
	2º trial	6 315 046	0,629	1,93	[12 5 4949]	10
	3º trial	6 306 927	0,611	1,99	[13 5 4925]	10
Population size – 400 Generation limit - 10	1º trial	6 309 067	0,692	1,72	[13 3 5000]	10
	2º trial	6 316 301	0,559	2,19	[12 7 4972]	10
	3º trial	6 296 389	0,533	2,29	[14 7 4950]	10

Firstly, it is possible to conclude from Table 18 that whether the maximum number of generations possible for the simulation is 10 or 200, the number of generations performed doesn’t vary much and is always between 8-16. In general, the returned values from NPV with this convergence criteria are higher than the ones resulting from the previous analysis. This evidences that the lower the convergence criteria for the difference between NPVs, the more accurate is the process of obtaining the maximum NPV value.

The highest values for NPV were returned from the population size of 400 and 200, 6.316.301€ and 6.315.087€. However, the population size of 200 demonstrated more convergence since the three returned values of NPV from the three generations were the same. Likewise, the difference between the highest NPV value of the population size of 400 and 200 is only 1,214€ which is a negligible value for this kind of project. Therefore, the population size of 200 will be used to perform the following simulations for Porto and Faro.

According to the population size chosen, the ideal configuration for Lisboa considers 12 charging points installed in the charging station, six batteries and 4955 PV panels installed.

Below are presented in Figure 50 and Figure 51, with the energy consumption of the EV fast-charging station for Lisboa in the last year of the project lifetime, i.e. 20th year. Figure 50 presents the energy consumption for the same configuration of the example performed and analyzed throughout this work with 900 PVs installed, four batteries and four charging points installed. As it is possible to verify, compared with Figure 47 from Chapter 5.3.4 of the first year of the same simulation, the energy supplied by the grid increased a lot since the arrival distribution also increased a lot. In the last year of the project, the arrival distribution upon the EV fast-charging station has a mean of 23 EV arrivals per hour. Thereby, energy consumption in general increases significantly. During the daytime, the energy supplied is provided mostly by the PV and consequently, there is not any energy sold to the grid since there is no energy surplus. Likewise, it is possible to verify that during peak hours the energy is always supplied by the storage system. The battery storage capacity is also completely used until the end of the day because of the high demand.

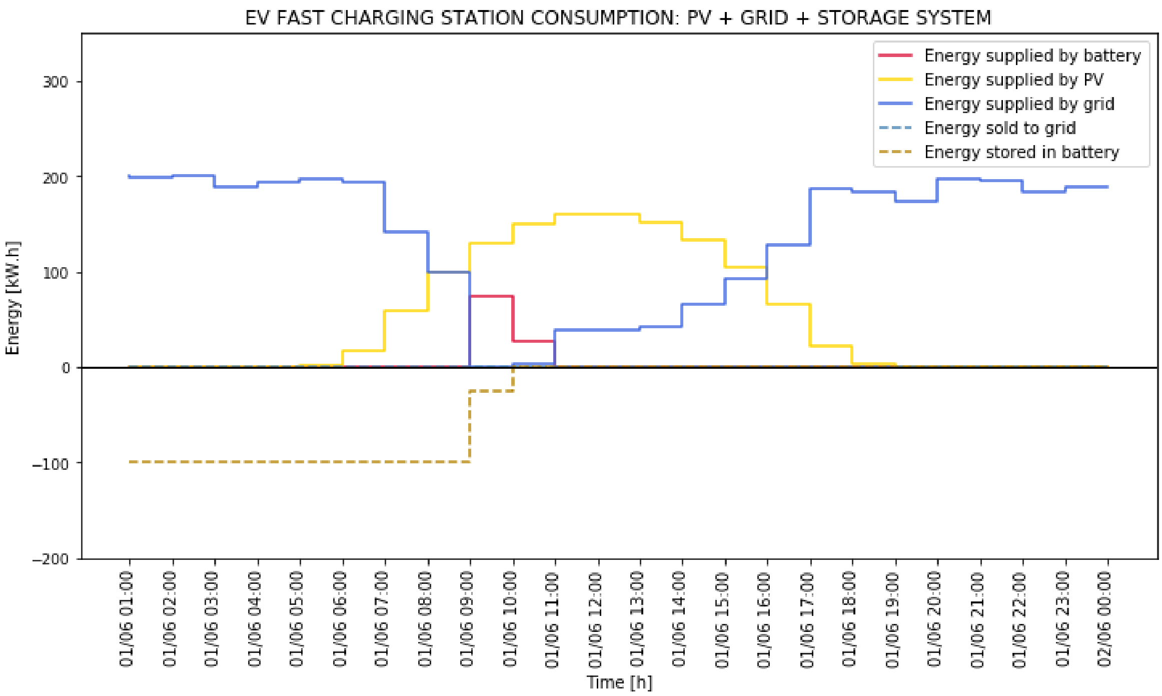


Figure 50 – EV fast-charging station consumption at year t=20 for configuration of 900 PV, 4 batteries and 4 charging points for Lisboa

In the figure below, it is possible to see for the same year, 20th year, the energy consumption of the EV fast-charging station this time with the ideal configuration. As it is possible to verify, the energy demand increased substantially since the number of charging points increased from 4 to 12. In addition, the energy supplied by PV and energy sold to the grid also increased substantially since the number of PV panels installed increased from 900 to 4955. Similarly, and as the number of batteries installed increased from 4 to 6, the energy stored in the battery storage system increased.

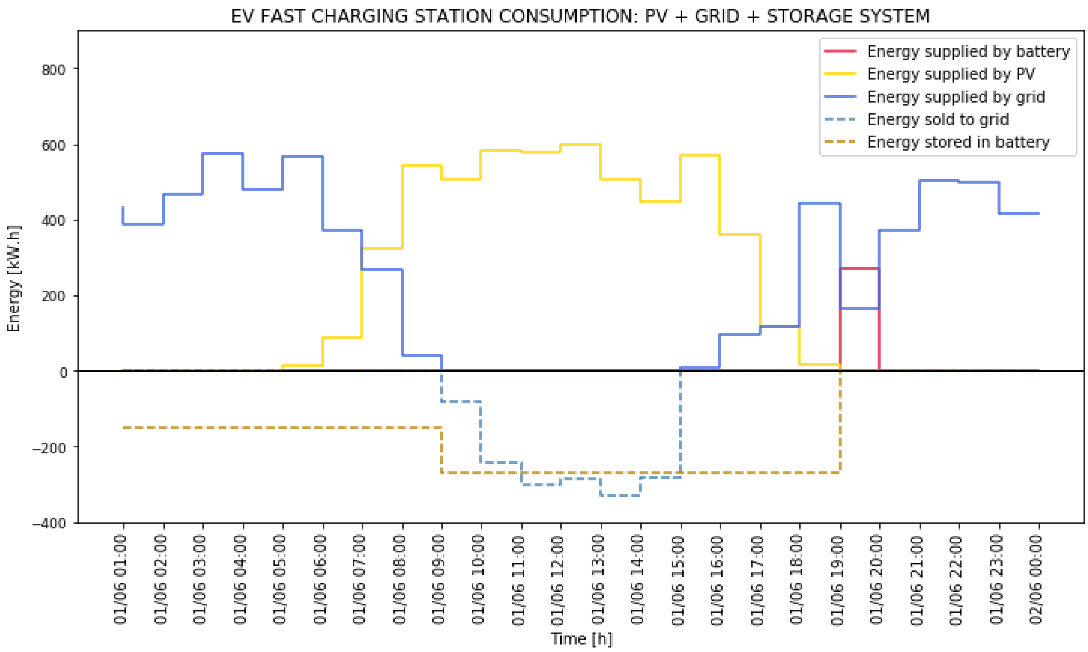


Figure 51 - EV fast-charging station consumption at year t=20 for ideal configuration for Lisboa

6.2. Analysis of the three different cities

From the ideal population size previously analyzed, the simulation for the remaining cities, Porto and Faro, are now evaluated and performed, in order to analyze the highest NPV returned. Furthermore, these are considered also with a constant arrival distribution.

6.2.1. Poisson arrival distribution

Below are presented the values for Lisboa, Faro, and Porto, where the values for Lisboa were previously presented.

Table 19 - Economic analysis for the three different cities for Poisson arrival distribution

	NPV (€)	IRR	Payback period (years)	Ideal configuration
LISBOA	6 315 087	0,592	2,06	[12 6 4955]
PORTO	6 349 288	0,637	1,9	[14 4 5000]
FARO	6 342 947	0,562	2,17	[12 7 5000]

The variable varying among the three cities is solely the GHI, which is higher for Faro, whereas the values for Lisboa and Porto are very similar. Therefore, the returned NPV values are not directly only correlated with the GHI values from every city, once the higher values of NPV are from Porto and Faro. These results depend mainly on the GHI of the days considered in the simulation to represent the full year.

In addition, generally, the higher the PV production, the more energy is sold to the grid. However, in the case of Faro, the highest number of batteries installed decreases substantially the NPV and IRR. Although Faro has a higher yearly energy production from PV which balances the difference between NPVs. It is possible to verify that, generally, a high number of PVs installed are associated with a high NPV result. This is due to its low investment value and the substantial reduction in grid network dependency, which is very expensive and increases the cash outflows.

From Table 19 it is also possible to conclude that, the higher the number of charging points and the lower the number of batteries, the highest is the NPV from an EV fast-charging station. By having more charging points, there are more EV customers charging throughout the year, increasing the revenue from the energy sold to EV customers from the charging station. Likewise, by having a smaller number of batteries, the CAPEX of the batteries decreases substantially, decreasing the investment made in the beginning.

From Table 19 it is possible to verify that Porto was the city with the highest NPV returned of 6.349.288€, with an IRR of 0,637 and a payback period of 1,9 years. Thereby, the investment is returned in almost 2 years, and the business model has economic profitability of almost 64%. Faro has the second-highest NPV returned of 6.342.947€, although it has lower values for the IRR and higher value for the payback period compared to Lisboa. The payback period results present a very low number. This is due to high revenues returned from EVs usage of the charging posts as well as the high number of photovoltaic panels installed producing more energy, injected more energy in the grid (more revenue), or storing the energy to use during the peak hours when the energy bought from the grid is super expensive (revenue savings).

The best chosen scenario, among the three different presented in Chapter 4, results from the optimization method. As the last conclusion, the optimal scenario chosen is always scenario three with an energy storage system and PV installed.

6.2.2. Constant arrival distribution

By having an arrival distribution following the Poisson distribution, it can happen that a lot of EV customers can arrive at the EV fast-charging station during nighttime and a small percentage of EV customers arriving during the daytime, or even during the peak hours. However, nowadays it isn't common to have those types of distribution. For this reason, a constant arrival distribution, in accordance with the values used from EDP, is also simulated and analyzed for the three different cities. For this case, it is therefore assumed a constant arrival distribution of four EV arrivals per hour between 7h-22h and just one EV arrival per hour from 22h-7h. As used for the other simulations with Poisson arrival distribution, in this case, it is also increased by one EV arrival per hour every year from 7h-22h, whereas from 22h-7h it maintains one EV arrival per hour. In Figure 52 is represented the arrival distribution from the 20th year with the constant arrival distribution with a constant value of EV arrivals of 23 per hour from 7h-22h and one EV arrival from 22h-7h.

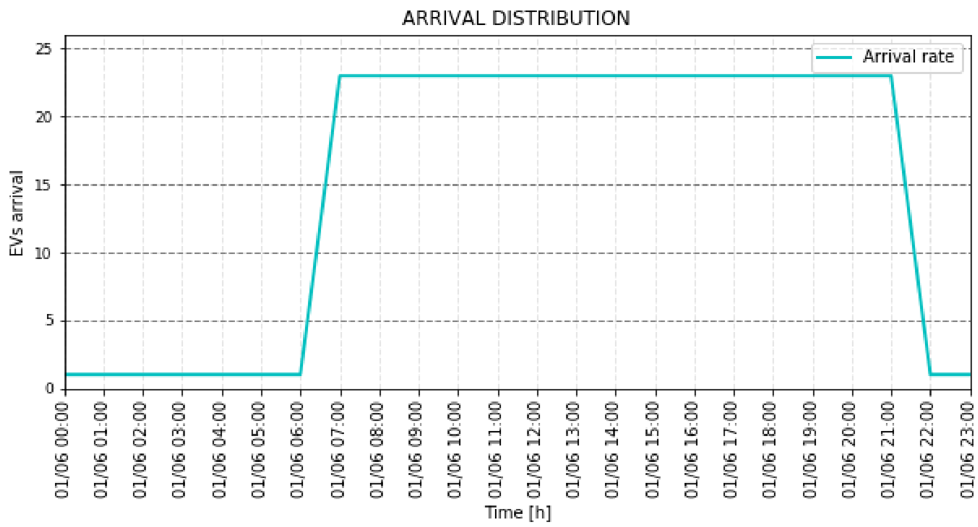


Figure 52 - Constant arrival distribution

Below, the economic values for Lisboa, Faro, and Porto are presented for a constant arrival distribution.

Table 20 - Economic analysis for the three different cities for constant arrival distribution

	NPV (€)	IRR	Payback period (years)	Ideal configuration
LISBOA	4 650 888	0,496	2,31	[11 8 5000]
PORTO	4 687 366	0,532	2,12	[11 7 5000]
FARO	4 665 891	0,473	2,43	[11 9 5000]

From Table 20 is possible to verify that, for a constant arrival distribution, the NPV returned values for the three different cities are considerably lower, almost two million €. Comparing to Table 19, the number of batteries for every city increases. This can be a reason for the lower NPV value returned. However, it is not enough to justify the two million € difference. Another reason is that by taking into account a Poisson arrival distribution with a certain value for the mean, the value can vary from that number up and down. In addition, the number of EV arrivals can vary every day, i.e. the number of arrivals for one day is not always the same, it can be higher or lower. In contrast, the constant arrival distribution always returns the same arrival number for each day. In case the EV arrival values returned from the Poisson distribution are higher than those returned from the constant distribution, the revenue increases for the Poisson distribution model, thereby increasing its NPV. Likewise, the Poisson and constant arrival distribution might not be taking into account daily similar values for the simulation, i.e. by having a Poisson distribution with a mean value of three and a constant distribution with a constant EV arrival of four EVs/hour from 7h-22h and one EV/hour from 22h-7h most likely will not return similar daily totals for EV arrivals.

Also, compared to Table 19, as the NPVs are lower for the three cities, the payback periods are higher and the IRR is lower.

Below is presented Figure 53, with the energy consumption of the EV fast-charging station for Lisboa in the last year of the project lifetime, i.e. 20th year with constant arrival distribution of 23 EV arrivals/hour during daytime. According to the figure, it is possible to verify that the energy consumption from the EV fast charging is mostly done between 7h-22h according to the constant distribution.

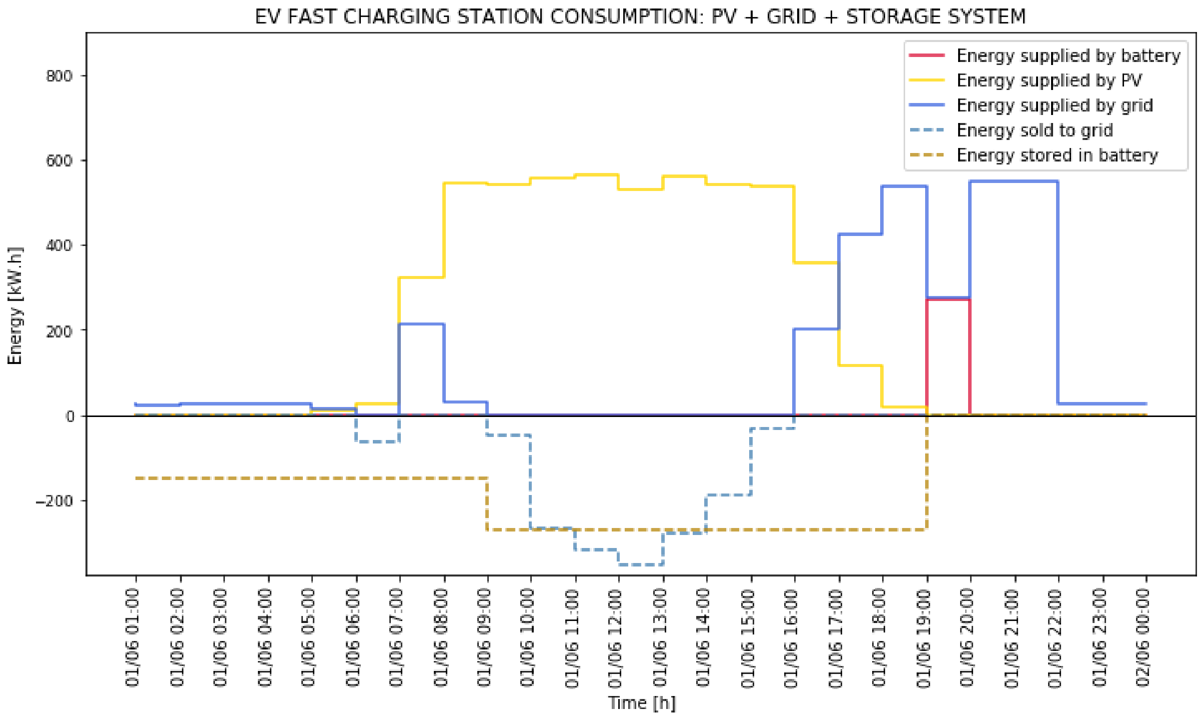


Figure 53 - EV fast-charging station consumption at year t=20 for ideal configuration for Lisboa and constant arrival distribution

Chapter 7

7. Conclusion and Future Work

The final chapter aims to conclude with a brief summary of the work, the accomplishments made and its conclusions as well as give suggestions on how the project could potentially be extended further and analyzed.

7.1. Discussion and Conclusions

The initial task carried out was an analysis of literature, which contributed to provide support in the development of this work while at the same time allowing to differentiate itself from other works. The literature analyzed the current state of the art involving the models developed for the design of an EV charging station taking into account the different technologies used to supply the EV owners such as wind and solar energy, storage systems, grid network and so on. It was also analyzed which models were developed and used for the queuing models, charging demand models and energy management models. To finalize, some literature involved the usage of a genetic algorithm presenting its objective function in order to find the optimal solution.

The results from the [15] return a lower NPV and charging posts number and a higher payback period, since in this case the EV station is fed from a mix of renewable energy, solar and wind source, and by the grid, i.e. increases the initial investment cost due to wind turbines. And the system doesn't include batteries to store the energy plus in order to reduce the utilization from the national grid.

Afterward, the chosen framework to carry out the models developed of this work, Python programming language was considered. In order to use it, some specific packages and libraries were used and understood so that the models could be combined all together. By understanding how to use its packages and both integrate and unite the various models, the next step was to create the different models.

The first model, allowed to find the energy demand annually for every city in accordance to the market share of EVs in Portugal, the correspondent battery capacities of the top ten cars from Portugal and the dynamic charging parameter, the state of charge for each EV arrival considered for the charging station. Following this, the queuing model allowed us to identify the arrival distribution daily for the charging station, the waiting time tolerance of EV customers and the service time of each EV charged as well as the maximum service time tolerated for each EV. From these two models, the consumption profile of the EV fast-charging station was created.

The development of the solar photovoltaic model was focused on creating the production profile required to meet the consumption profile. However, solar energy most of the time aren't enough to fulfill the requirements and meet the consumption profile because it is an intermittent energy source. Therefore, the inclusion of the storage system model allows the creation of an alternative way to supply energy to EV customers. The energy management model includes these two models, and an algorithm to return where the energy supplied to the EV fast-charging station is coming from, grid network, solar panels or the storage system per hour. It likewise returns the amount of energy sold to the grid and the energy which is stored in the battery storage system.

Following this, the economic assessment is completed, considering the CAPEX and OPEX values for the batteries, PVs and charging points, and also the energy prices from the energy sold to the grid, the energy purchased from the grid and the revenue from EV customers usage. From this analysis, the NPV, the IRR and the payback period are obtained taking into account a lifetime of 20 years.

With these models in place, the genetic algorithm is performed for two different convergence criteria for the difference between NPVs from every iteration: 1% and 0,1%. The optimal population size evaluated is 200 which performed and returned the best three NPV values concisely. For a value of 0,1%, for the convergence criteria, the NPV difference presented for every solution is within $\pm$2%.

By comparing among the returned NPV values for the different population size and generation limit combinations, it is possible to validate that the IRR and payback period variations are related to the number of batteries installed. The greater the number of batteries installed, the lower is the IRR and the higher is the payback period since these are very expensive. For this reason, charging posts and PV panels dictate the economic viability of the business model. It is possible to verify, that generally a high number of PVs installed are associated with a high NPV returned. This is due to its low investment value as well as the significant decrease in the grid network usage, which is very expensive and increases the cash outflows. It is also possible to conclude that the higher the number of charging points and the lower the number of batteries, the highest is the NPV. With more charging points, there are more EV customers charging throughout the year, increasing the revenue. Likewise, with fewer battery storage systems, the CAPEX of the batteries decreases substantially, decreasing the investment made in the beginning. For a constant arrival distribution, the NPV returned values for the three different cities are considerably lower.

The payback period results in general present a very low number. This might happen because the batteries are undervalued, but at the same time is due to high revenues returned from EVs usage of the charging posts as well as the high number of photovoltaic panels installed producing more energy, injected more energy in the grid (more revenue), or storing the energy to use during the peak hours when the energy bought from the grid is super expensive (revenue savings).

The best-chosen scenario, among the three different presented in Chapter 4, results from the optimization method. As the last conclusion, the optimal scenario chosen is always scenario three with the storage system and photovoltaic panels installed. The optimal solution for Lisboa, Porto, and Faro is:

- Lisboa – nº of charging points: 12; nº of batteries: 6; nº of PV: 4955; NPV: 6.315.087€
- Porto – nº of charging points: 14; nº of batteries: 4; nº of PV: 5000; NPV: 6.349.288€
- Faro - nº of charging points: 12; nº of batteries: 7; nº of PV: 5000; NPV: 6.342.947€

The model developed in this thesis is therefore necessary and important to be used as a tool for enterprises, such as EDP, Prio, Galp and so on which aim to install and increase its capital on fast-charging stations, to help dimensioning its ideal configuration of charging points installed, photovoltaic panels installed and batteries for the storage system installed.

7.2. Potential improvements and Future Work

Some areas that could be further developed and possibly extended include:

- In order to make the model more realistic, one could take into account the waiting times assumed for cable changes and other random things that might happen which increases the customer waiting time, instead of being only the charging time;
- It could be interesting to consider the real charging state of an EV, since the charging rate of an EV changes throughout its charging time. The charging rate is high when the SOC is low and it is low when the SOC is high;
- Concerning the actual implementation of the energy tariffs of the energy purchased from the grid, it could be more realistic taking into account the energy tariffs for each quarter of the year for the medium voltage tariffs;
- Concerning the actual implementation of the scheduling of the energy purchased from the grid, it could be more realistic to take into account the summer and winter schedules;
- Likewise, it could be more realistic to consider the weekdays and weekends for the energy tariffs and scheduling of the energy purchased from the grid as well as for the arrival distribution which becomes lower for those periods;
- The integration of a more coherent way of distributing hourly arrivals while keeping the average, for instance, a multiplier factor depending on the hour of the day;
- It could also be interesting to associate a logistic curve to the arrival distribution for the lifetime of the project taking into account the EVs growth in the following 20 years;
- It would be wise to validate an analysis taking into account not only its maximum capacity but also the size variation of the batteries for the storage system instead of a constant capacity of 50 kW.h;
- One of the main problems of the fast-charging stations regarding the EV owners is the charging time exceeded even after the car battery is completely full since the owners let their cars charging and leave them for a long time. The car battery is already filled and is taking charging time from another user. Therefore, as the main solution for this problem, the charging time in the model could take into account a variable price taking into account the total time charging in the charging station, i.e., for instance, every 10 minutes could have a different price per minute,

and the higher the charging time the higher the price per minute. Likewise, there could be a price for users to book a particular time for charging paying an extra fee for this service. However, it would have the charging station available for its utilization;

- Considering that a user with a state of charge of 20% would be willing to wait more time to charge its car than a user with a state of charge of 60%, a more realistic waiting time variable for the model could take into account that, i.e. the charging time would be associated to the battery's state of charge;
- Lastly, for the CAPEX and OPEX of the batteries, photovoltaic panels, and charging posts were only considered costs taking into account one source. Likewise, for instance, for the batteries, the prices could be taken into account when buying the second batteries for replacement a different price than the actual price since in 10 years the battery costs will be less. Or it could be taken into account that the batteries used in the beginning could be recycled batteries. For this reason, would be more reasonable to perform a sensitivity analysis for these three technologies costs.

References

[1] Till Bunsen *et al.*, “Global EV Outlook 2019 to electric mobility,” *OECD iea.org*, p. 232, 2019.

[2] “Electric car models to triple in Europe by 2021 – market data | Transport & Environment.” [Online]. Available: https://www.transportenvironment.org/press/electric-car-models-triple-europe-2021-—-market-data. [Accessed: 08-Aug-2019].

[3] O. S. Till Bunsen, Pierpaolo Cazzola, Marine Gorner, Leonardo Paoli, Sacha Scheffer, Renske Schuitmaker, Jacopo Tattini, Jacob Teter, Simon Bennett, Emanuele Bianco, Paul Hugues, George Kamiya, Sarbojit Pal, Kate Palmer, Apostolos Petropoulos, “Global EV Outlook 2018 Towards cross-modal electrification,” *OECD iea.org*, p. 147, 2018.

[4] F. Sioshansi, *Innovation and Disruption at the Grid’s Edge. How Distributed Energy Resources are Disrupting the Utility Business Model*. 2017.

[5] “Mobilidade Elétrica.” [Online]. Available: https://www.edp.pt/particulares/servicos/mobilidade-eletrica/. [Accessed: 25-Sep-2019].

[6] “Home | EAFO.” [Online]. Available: https://www.eafo.eu/. [Accessed: 05-Apr-2019].

[7] “Carregar fora de casa - EDP Comercial.” [Online]. Available: https://www.edp.pt/particulares/servicos/mobilidade-eletrica/carregar-fora-de-casa/. [Accessed: 25-Sep-2019].

[8] “MOBI.E.” [Online]. Available: https://www.mobie.pt/. [Accessed: 01-May-2019].

[9] H. J. Vermaak and K. Kusakana, “Design of a photovoltaic–wind charging station for small electric Tuk–tuk in D.R.Congo,” *Renew. Energy*, vol. 67, pp. 40–45, Jul. 2014.

[10] O. Hafez and K. Bhattacharya, “Optimal design of electric vehicle charging stations considering various energy resources,” *Renew. Energy*, vol. 107, pp. 576–589, Jul. 2017.

[11] V. Viswanathan, D. Zehe, J. Ivanchev, D. Pelzer, A. Knoll, and H. Aydt, “Simulation-assisted exploration of charging infrastructure requirements for electric vehicles in urban environments,” *J. Comput. Sci.*, vol. 12, pp. 1–10, Jan. 2016.

[12] T. N. Le, S. Al-Rubaye, H. Liang, and B. J. Choi, “Dynamic charging and discharging for electric vehicles in microgrids,” *2015 IEEE Int. Conf. Commun. Work. ICCW 2015*, pp. 2018–2022, 2015.

[13] A. El-Zonkoly and L. dos Santos Coelho, “Optimal allocation, sizing of PHEV parking lots in distribution system,” *Int. J. Electr. Power Energy Syst.*, vol. 67, pp. 472–477, May 2015.

[14] C. Hutson, G. K. Venayagamoorthy, and K. A. Corzine, “Intelligent scheduling of hybrid and electric vehicle storage capacity in a parking lot for profit maximization in grid power transactions,” *2008 IEEE Energy 2030 Conf. ENERGY 2008*, pp. 1–8, 2008.

[15] J. A. Domínguez-Navarro, R. Dufo-López, J. M. Yusta-Loyo, J. S. Artal-Sevil, and J. L. Bernal-Agustín, “Design of an electric vehicle fast-charging station with integration of renewable energy and storage systems,” *Int. J. Electr. Power Energy Syst.*, vol. 105, pp. 46–58, Feb. 2019.

[16] A. Cavaco, H. Silva, P. Canhoto, S. Neves, J. Neto, and M. Collares Pereira, “Annual Average Value of Solar Radiation and its Variability in Portugal,” 2016.

[17] “Optimization methods - genetic algorithm.” .

[18] A. Gad, “Introduction to Optimization with Genetic Algorithm,” 2018. [Online]. Available: https://towardsdatascience.com/introduction-to-optimization-with-genetic-algorithm-2f5001d9964b. [Accessed: 14-Sep-2019].

[19] “Compare hybrid and electric vehicles - EV Database.” [Online]. Available: https://ev-database.org/. [Accessed: 16-May-2019].

[20] “120. Generating log normal samples from provided arithmetic mean and standard deviation of original population – Python for healthcare modelling and data science.” [Online]. Available: https://pythonhealthcare.org/2019/02/07/120-generating-log-normal-samples-from-provided-arithmetic-mean-and-standard-deviation-of-original-population/. [Accessed: 01-Oct-2019].

[21] “Queuing Theory Tutorial - What is Queuing?,” 2017. [Online]. Available: https://people.revoledu.com/kardi/tutorial/Queuing/Queuing-What-Is.html. [Accessed: 05-Apr-2019].

[22] “Queuing Theory Tutorial - What is Queuing Theory?,” 2017. [Online]. Available: https://people.revoledu.com/kardi/tutorial/Queuing/Queuing-Theory-What-Is.html. [Accessed: 05-Apr-2019].

[23] “Queuing Theory Tutorial - Queuing Optimization,” 2017. [Online]. Available: https://people.revoledu.com/kardi/tutorial/Queuing/Queuing-Optimization.html. [Accessed: 25-Sep-2019].

[24] S. Edition, *Solar Energy Engineering*. 2009.

[25] D. Syntax, *Photovoltaic Energy - Chapter 3 - class slides*. .

[26] W. F. Holmgren, C. W. Hansen, and M. A. Mikofski, “Pvlib Python: a Python Package for Modeling Solar Energy Systems,” *J. Open Source Softw.*, vol. 3, no. 29, p. 884, 2018.

[27] “Google Earth.” [Online]. Available: https://earth.google.com/web. [Accessed: 21-Sep-2019].

[28] “JRC Photovoltaic Geographical Information System (PVGIS) - European Commission.” [Online]. Available: https://re.jrc.ec.europa.eu/pvg_tools/en/tools.html#PVP. [Accessed: 01-Oct-2019].

[29] G. Lorenzi, R. da Silva Vieira, C. A. Santos Silva, and A. Martin, “Techno-economic analysis of

utility-scale energy storage in island settings,” *J. Energy Storage*, vol. 21, no. January 2019, pp. 691–705, 2019.

[30] “Horários Média Tensão - Inverno e Verão.” [Online]. Available: https://www.edpsu.pt/pt/tarifasehorarios/horarios/Pages/HorariosMT.aspx. [Accessed: 11-Oct-2019].

[31] “Tarifas de Média Tensão.” [Online]. Available: https://www.edpsu.pt/pt/tarifasehorarios/Pages/TarifaMT.aspx. [Accessed: 11-Oct-2019].

[32] “MINISTÉRIO DO AMBIENTE, ORDENAMENTO DO TERRITÓRIO E ENERGIA Decreto-Lei n.º 153/2014 de 20 de outubro.”

[33] “Inicio | OMIE.” [Online]. Available: http://www.omel.es/pt/inicio. [Accessed: 21-Oct-2019].

[34] “Efacec Electric Mobility | EV QC45 Quick Charger.” [Online]. Available: https://electricmobility.efacec.com/ev-qc45-quick-charger/. [Accessed: 21-Oct-2019].

[35] “Efacec QC45 - 50kW CHAdeMO/SAE Combo Dual Charger ChargePoint Enabled – Best EV Chargers.” [Online]. Available: https://www.bestevchargers.com/products/efacec-ocpp-50kw-chademo-single-port?_pos=1&_sid=068930b86&_ss=r. [Accessed: 21-Oct-2019].

[36] C. H. Villar, D. Neves, and C. A. Silva, “Solar PV self-consumption: An analysis of influencing indicators in the Portuguese context,” *Energy Strateg. Rev.*, vol. 18, pp. 224–234, 2017.

[37] N. Sandia, S. Alliance, S. Pv, and M. W. Group, “Best Practices in Photovoltaic System Operations and Maintenance 2 nd Edition NREL / Sandia / Sunspec Alliance SuNLaMP Best Practices in Photovoltaic System Operation and Maintenance 2 nd Edition,” no. December, 2016.

[38] “GitHub - ahmedfgad/GeneticAlgorithmPython: Genetic Algorithm Implementation in Python using NumPy.” [Online]. Available: https://github.com/ahmedfgad/GeneticAlgorithmPython. [Accessed: 27-Oct-2019].

[39] A. Cavaco, H. Silva, P. Canhoto, S. Neves, J. Neto, and M. Collares Pereira, “Radiação Solar Global em Portugal e a sua variabilidade, mensal e anual,” 2016.

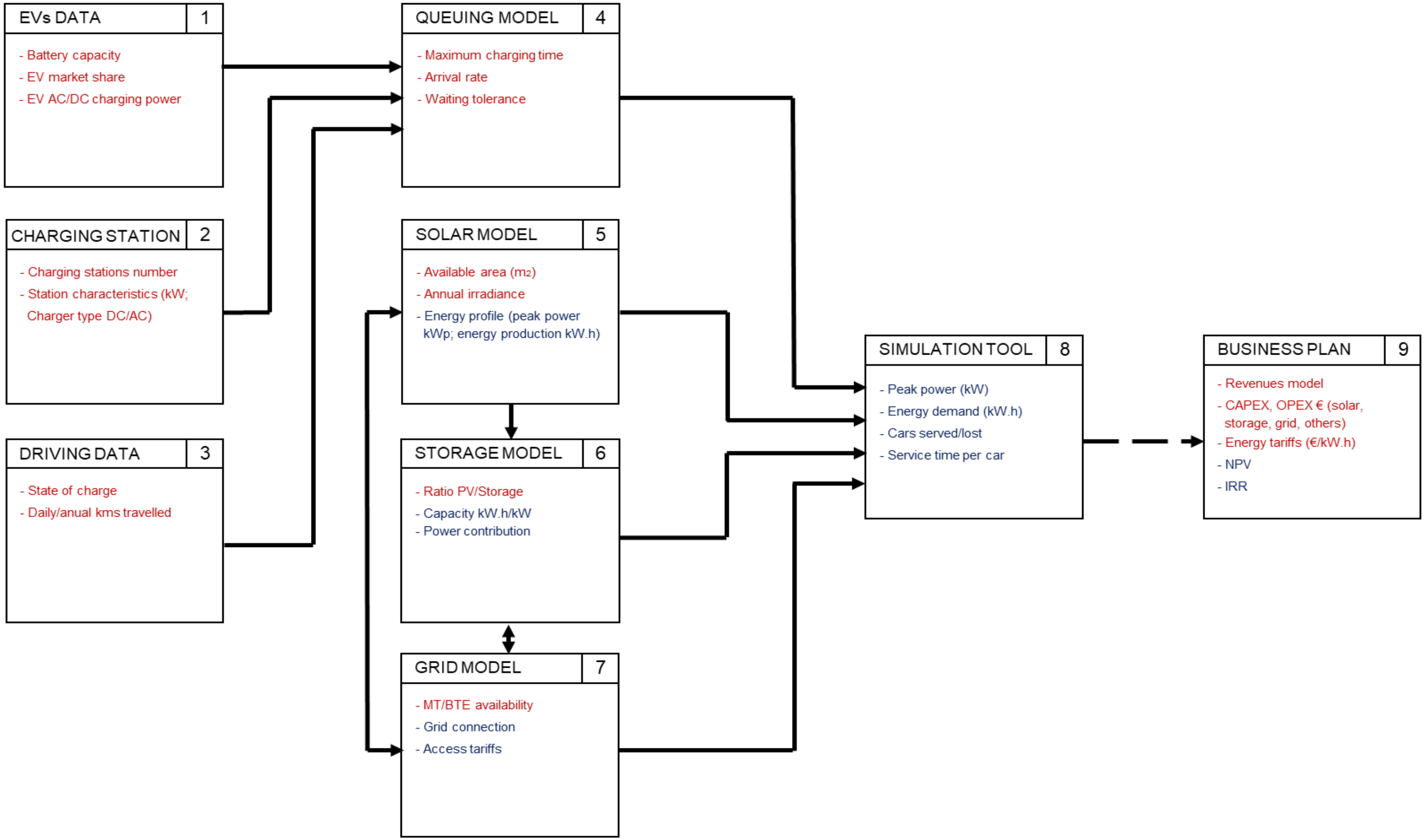
[40] “Queuing Theory Tutorial - Queuing Optimization.” [Online]. Available: https://people.revoledu.com/kardi/tutorial/Queuing/Queuing-Optimization.html. [Accessed: 02-Oct-2019].

[41] “OMIE.” [Online]. Available: http://m.omie.es/files/omie_informe_precios_pt.pdf?m=yes. [Accessed: 21-Oct-2019].

[42] “EDP Relatório & Contas 2018 - WE LOVE ENERGY.” [Online]. Available: https://www.edp.com/sites/default/files/portal.com/documents/rc_2018_pt_compress.pdf. [Accessed: 21-Sep-2019].

Supporting Info

Appendix A: EDP Model



Notes: MT – Média Tensão "Medium voltage"; BTE – Baixa Tensão Especial "Low voltage special"; CAPEX – Capital Expenditure; OPEX – Operational Expenditure; NPV – Net Present value; IRR – Internal Rate of Return.