Impact of Electric Vehicle Charging on the Portuguese Electricity Demand Curve

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Declaration

I declare that this document is an original work of my own authorship and that it fulfils all the requirements of the Code of Conduct and Good Practices of the Universidade de Lisboa.

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In loving memory of my grandfathers, Ângelo and Michael. Until the next walk of life…

Resumo

Este estudo tem como objetivo analisar o impacto do carregamento de veículos elétricos (VEs) ligeiros-passageiros no diagrama de carga português em 2030. Especificamente, a meta deste trabalho prende-se em identificar, para diferentes potenciais níveis de penetração de VEs em 2030, as estratégias de carregamento que possibilitam uma configuração sustentável do diagrama de carga português nesse ano. Com isto, este estudo tenciona informar os setores energético e político nacionais dos perigos e soluções que diferentes estratégias de carregamento de VEs terão no sistema elétrico nacional em 2030.

Esta investigação será feita para os dias de semana e fins-de-semana de todas as estações do ano, e basear-se-á numa análise teórica desenvolvida no âmbito desta tese. Esta análise teórica tem em vista elaborar uma metodologia direcionada a conceber, desenvolver e testar o conjunto de modelos usado para estabelecer as condições de simulação necessárias.

Os resultados foram estabelecidos de acordo com três níveis de penetração de VEs: *pessimista* (85.925 VEs,), *base* (442.445) e *otimista* (2.008.717). As simulações relativas aos cenários *pessimista* e *base* indicam que não será necessária uma rede elétrica inteligente para executar as operações de carregamento. Porém, o carregamento coordenado de VEs, segundo uma smart grid (SG), será imperativo diante do cenário *otimista*, uma vez que, caso contrário, níveis insustentáveis de potência serão atingidos no sistema elétrico. Adicionalmente, sessões de carregamento durante a manhã terão de ser igualmente abordadas, visto que poderão induzir novos picos de consumo diário devido ao número elevado de atividades de carregamento executadas nesse período.

Palavras-Chave:

Veículo elétrico; Diagrama de carga; Portugal; Padrões de mobilidade; Padrões de carregamento; Estratégias de carregamento

Abstract

This study aims to explore the impacts of light-duty passenger (LP) electric vehicle (EV) charging on the Portuguese national load diagram (LD) in 2030. Specifically, the goal of this work is to identify the EV charging strategies that enable a sustainable configuration of the Portuguese LD under different potential levels of LP EV penetration in 2030. By doing so, this research attempts to offer information to Portuguese utilities and policy makers regarding the potential threats and solutions of distinct EV charging strategies on the national power system in 2030.

The research will be carried out for week and weekend days within all seasons of the year, and will be based on a theoretical analysis developed within the scope of this research. Specifically, the theoretical analysis is directed to designing a methodology aimed at conceiving, developing, and testing the set of models used to establish the simulation conditions required for the practical analysis of this research.

The results were established according to three levels of EV penetration: *pessimistic* (85,925 EVs)*, base* (442,445) and *optimistic* (2,008,717). Within the *pessimistic* and *base* scenarios, results indicate that an intelligent grid is not necessary to perform charging activities. However, coordinating EV charging in the evening, via a smart gird (SG), is imperative in the *optimistic* scenario, as unsustainable levels of demanded power will be reached otherwise. Furthermore, morning charging sessions must be equally addressed, as they may induce new peaks of daily consumption given the significant amount of charging activity taking place within that period.

Keywords:

Electric vehicle; Load diagram; Portugal; Mobility patters; Charging patterns; Charging strategies

Index

Declaration ii

Acknowledgments iv

Resumo vi

Abstract vii

List of Figures x

List of Tables xii

Glossary xiv

1. Introduction 1
   1.1. Topic and Context 1
   1.2. Motivation 3
   1.3. Aims and Objectives 4
   1.4. Dissertation Structure 5

2. Literature Review 6
   2.1. UC Charging and Non-Optimised Controlled Charging Solutions 7
   2.2. Optimised Controlled Charging Solutions 11
   2.3. Vehicle-to-Grid (V2G) and Additional UC Charging Operations 15
   2.4. Additional Research 17

3. Methodology and Simulation Conditions 18
   3.1. Prediction of the Portuguese Baseline Load Diagram (BLD) for 2030 18
   3.2. Prediction of Light-Duty Passenger (LP) EV Penetration in Portugal for 2030 21
      3.2.1. Pessimistic Scenario 21
      3.2.2. Base Scenario 22
      3.2.3. Optimistic Scenario 24
   3.3. Mobility Patterns of Portuguese Drivers and EV Consumption Rates 25
      3.3.1. Mobility Patterns 25
         3.3.1.1. Mobility Patterns of Metropolitan Areas of Porto and Lisbon 25
         3.3.1.2. Combined Mobility Pattern for Metropolitan Areas of Porto and Lisbon 26
         3.3.1.3. Mobility Patterns of Portuguese Drivers 28
      3.3.2. EV Consumption Rates 32
   3.4. Charging Infrastructure, Patterns and Strategies 34
      3.4.1 Charging Infrastructure 34
         3.4.1.1. Charging Infrastructure: Charging Modes and Plugs 35
      3.4.2. Charging Patterns and Strategies 36
         3.4.2.1. Charging Patterns 36
            3.4.2.1.1. Charging Patterns: Selected Charging Modes 36

3.4.2.1.2. Charging Patterns: Time and Location of Charging Events 37
3.4.2.1.3. Charging Patterns: Quantification of Charging Events 43
3.4.2.2. Charging Strategies 47
3.4.2.2.1. Charging Strategies: Uncontrolled (UC) Charging 48
3.4.2.2.2. Charging Strategies: Time-of-Use (TOU) Controlled Charging 48
3.4.2.2.3. Charging Strategies: Smart Grid (SG) Controlled Charging 48

4. Results and Discussion 50
4.1. Pessimistic Scenario 50
4.2. Base Scenario 51
4.2.1. Base Scenario – Weekdays 51
4.2.2. Base Scenario – Weekends 56
4.3. Optimistic Scenario 57
4.3.1. Optimistic Scenario – Weekdays 57
4.3.2. Optimistic Scenario – Weekends 64

5. Conclusions 66
5.1. Methodology 66
5.1.1. Prediction of the Portuguese BLD for 2030 66
5.1.2. Prediction of the LP EV Penetration in Portugal for 2030 66
5.1.3. Mobility Patterns of Portuguese Drivers and EV Consumption Rates 67
5.1.4. EV Charging Patterns 67
5.1.5. EV Charging Strategies 69
5.2. Main Findings 69
5.2.1. Main Findings – Pessimistic EV Penetration Level 69
5.2.2. Main Findings – Base EV Penetration Level 70
5.2.3. Main Findings – Optimistic EV Penetration Level 70
5.3. Future Work 71

References 73

Appendix .... A
List of Figures - Appendix .... A
Appendix A .... D
Appendix B .... F
Appendix C .... G
Appendix D .... J
Appendix E – Results .... K

List of Figures

Figure 1. RLD for Weekday of Winter 2017 [48]. 19
Figure 2. Prediction of Portuguese Yearly Electric Energy Consumption (Without EVs) [44]. 20
Figure 3. RLD (2017) and BLD (2030) for Winter Weekday in MW. 21
Figure 4. Prediction of LP EV fleet – Pessimistic Scenario [44]. 21
Figure 5. Evolution of Portuguese LP Vehicle Fleet 1991-2018. 22
Figure 6. Linear Regression of LP Vehicle Fleet 1991-2018. 23
Figure 7. Prediction of LP EV Fleet in 2030 – Base Scenario. 24
Figure 8. Number of Journeys per TM in MAP. 27
Figure 9. Number of Journeys per TM in MAL. 27
Figure 10. NUTS I, II and III of Portugal [55]. 29
Figure 11. Results of Linear Extrapolation – Weekdays. 31
Figure 12. EV Energy Consumption vs. Ambient Temperature [67]. 33
Figure 13. Distribution of Arrival Times on a Workday in MAL [52]. 38
Figure 14. Distribution of Arrival Times on a Weekend Day in MAL [52]. 39
Figure 15. Distribution of a) Private and b) Commercial Vehicle Fleets in Motion and Parked during the Week [80]. 40
Figure 16. Normal Probability Density Distribution of EV Arrivals on an Evening Weekday. 41
Figure 17. Cumulative Values of EV Arrivals on an Evening Weekday (%). 42
Figure 18. Distribution of EV Arrivals on an Evening Weekday (%). 43
Figure 19. Public Charging Events – Weekdays [84]. 44
Figure 20. Distribution of Energy Demanded/Charging Event in Fast Charging Stations [85]. 47
Figure 21. Baseline Load Diagram Corresponding to the Weekdays of Winter Season in 2030. 51
Figure 22. Load Diagram corresponding to the Weekdays of the Winter Season in 2030, under the Base EV Penetration Level following the Uncontrolled Charging Strategy. 52
Figure 23. Load Diagram corresponding to the Weekdays of Winter Season in 2030, under the Base EV Penetration Level following the Original Time-of-Use Charging Strategy. 53
Figure 24. Load Diagram corresponding to the Weekdays of Winter Season in 2030, under the Base EV Penetration Level following the Alternative Time-of-Use Charging Strategy. 54

Figure 25. Load Diagram corresponding to the Weekdays of Winter Season in 2030, under the Base EV Penetration Level following the Smart Grid Charging Strategy. 55

Figure 26. Load Diagram corresponding to the Weekdays of Winter Season in 2030, under the Optimistic EV Penetration Level following the Uncontrolled Charging Strategy. 57

Figure 27. Load Diagram corresponding to the Weekdays of Winter Season in 2030, under the Optimistic EV Penetration Level following the Original Time-of-Use Charging Strategy. 58

Figure 28. Load Diagram corresponding to the Weekdays of Winter Season in 2030, under the Optimistic EV Penetration Level following the Alternative Time-of-Use Charging Strategy. 59

Figure 29. Load Diagram corresponding to the Weekdays of Winter Season in 2030, under the Optimistic EV Penetration Level following the Smart Grid Charging Strategy. 60

Figure 30. Load Diagram corresponding to the Weekdays of Winter Season in 2030, under the Optimistic EV Penetration Level following the Additional Measures of Smart Grid Charging Strategy. 62

Figure 31. Baseline Load Diagram corresponding to the Weekdays of Summer Season in 2030. 62

Figure 32. Load Diagram corresponding to the Weekdays of Summer Season in 2030, under the Optimistic EV Penetration Level following the Smart Grid Charging Strategy. 63

Figure 33. Load Diagram corresponding to the Weekdays of Summer Season in 2030, under the Optimistic EV Penetration Level following the Additional Measures of the Smart Grid Charging Strategy. 64

List of Tables

Table 1. Size of the LP EV Fleet per Scenario. 24

Table 2. TM Characteristics for MAP during Weekday. 25

Table 3. TM Characteristics for MAP during Weekend. 25

Table 4. TM Characteristics for MAL during Weekday. 26

Table 5. TM Characteristics for MAL during Weekend. 26

Table 6. TM Characteristics for MAP + MAL during Weekday. 28

Table 7. TM Characteristics for MAP + MAL during Weekend. 28

Table 8. Geographical Areas of MAP and MAL [52]. 30

Table 9. TM Characteristics for Portuguese Population during Weekday. 31

Table 10. TM Characteristics for Portuguese Population during Weekend. 32

Table 11. Consumption Rates of EVs [64]. 32

Table 12. Arithmetic Average Temperature/Season for Weekdays [71]. 34

Table 13. EV Energy Consumption Ratings per Season. 34

Table 14. Characteristics of Charging Methods [72]. 35

Table 15. Private and Public Charging Characteristics. 37

Table 16. Charging Pattern Characteristics for Weekdays and Weekends. 40

Table 17. Characteristics of EV Arrival Distributions. 42

Table 18. Share of EV Fleet Charging under Private/Public Chargers. 43

Table 19. Share of EV Fleet associated with Public Charging Stations during Weekdays [84]. 45

Table 20. Share of EV Fleet associated with Public Charging Stations during Weekend Days. 46

Table 21. Energy Demands from EV in Fast Charging Stations [85]. 46

Table 22. Daily Cycle of TOU Tariff [86]. 48

Glossary

BLD – Baseline Load Diagram

CCS – Combined AC/DC Charging System

CGR – Consumption Growth Rate

CO2 – Carbon Dioxide

DEED – Dynamic Economic/Emissions Dispatch

DGEG – Direção-Geral de Energia e Geologia

DN – Distribution Network

EDP – Energias de Portugal

EU – European Union

EV – Electric Vehicle

GHG – Greenhouse Gases

HEV – Hybrid Electric Vehicle

IC – Intermunicipal Communities

IC-CPD – In-Cable Control and Protective Device

ICE – Internal Combustion Engine

IE – Intermunicipal Entities

IEC – International Electrotechnical Committee

IMOB – Mobilidade e Funcionalidade do Território nas Áreas Metropolitanas do Porto e de Lisboa

IMT – Instituto de Mobilidade e Transportes

INE – Instituto Nacional de Estatística

IPCC – Intergovernmental Panel on Climate Change

LD – Load Diagram

LP – Light-duty Passenger

LV – Low Voltage

MAL – Metropolitan Area of Lisbon

MAP – Metropolitan Area of Porto

MAP+MAL – Combined Mobility Pattern of MAP and MAL

MAS – Multi-Agent Solution

NHTS – National Household Travel Survey

NUTS – Nomenclature of Territorial Units for Statistics

PEV – Pure Electric Vehicle

PHEV – Plug-in Hybrid Electric Vehicle

PSO – Particle Swarm Optimization

QP – Quadratic Programming

RCD – Residual Current Protective Device

RE – Renewable Energy

REN – Redes Energéticas Nacionais

RLD – Reference Load Diagram

RTP – Real-Time Price

SCC – Smart Charging Controller

SG – Smart grid

SOC – State-of-Charge

TM – Travel Motive

TOU – Time-of-Use

UC – Uncontrolled

UK – United Kingdom

UN – United Nations

V2G – Vehicle-to-Grid

VE – Veículo Elétrico

1. Introduction

This chapter is dedicated to presenting an introductory overview of the work developed within this dissertation. The first section contextualises the topic considered by the research. A brief description of the work developed by this thesis, as well as the main motivations and objectives which underpin it are then provided. In doing so, this chapter intends to justify why this research will make a valuable contribution to the field.

Given the above, this introductory chapter is divided into four sections: i.) *Topic and Context*; ii.) *Motivations*; iii.) *Aims and Objectives*; and iv.) *Dissertation Structure*.

1.1. Topic and Context

According to the United Nations (UN), after more than a century and a half of industrialisation, deforestation and large scale agriculture, quantities of greenhouse gases (GHGs) in the atmosphere have risen to record levels which have not been witnessed in three million years. Moreover, as populations, economies and standards of living continue to grow, so do the cumulative levels of GHG emissions, leading to further aggravation [1].

Carbon dioxide (CO2) is the most abundant GHG, accounting for approximately two-thirds of the total amount of GHG emissions. CO2 emissions are largely a product of combustion reactions associated with the burning of fossil fuels [1]. The aforementioned chemical reaction is currently prevalent in the most common economic sectors of society, such as: *Energy*; *Industry*; *Residential*; *Agriculture, Forestry, and Fisheries*; and *Transportation* [2].

According to the *Intergovernmental Panel on Climate Change* (IPCC), between 2007 and 2014, the transportation sector alone accounted for approximately 14% of the total global GHG emissions, in which 71% of the respective emissions were directly associated with road transportation [3].

The emission of GHGs within the road transportation sector is caused by the use of internal combustion engine (ICE) vehicles. In brief, the process carried out in an ICE consists in igniting fuel and air within a small cylinder, called a combustion chamber. Within this chamber, the described combustion reaction creates expanding gases of high temperature and pressure, which subsequently cause pistons to move up and down with the purpose of, ultimately, inducing a rotational movement on the wheels of a vehicle. One of the main components present in the gases resulting from the described procedure is CO2, which, after being exhausted from the engine, contributes to toxic air pollution and the aforementioned emission of GHGs which induce climate change [4].

Bearing the above in mind, in general, two approaches have been adopted with the intent of reducing the levels of CO2 emitted by ICE vehicles. The first one involves manufacturing engines with a higher-level efficiency or adopting alternative fuels. The second consists in promoting the use of electric vehicles (EVs) [2].

The basic difference between traditional ICE vehicles and EVs is that the former, as the name indicates, are solely run on an ICE, while the latter are predominately operated via an electric motor, which in some cases is combined with an ICE. Presently, there are three types of EVs: i.) *Pure electric vehicles* (PEVs), in which the electricity fed to the electric motor is provided from a rechargeable battery that has access to the national electric grid; ii.) *Hybrid electric vehicles* (HEVs), which are run on a traditional ICE combined with an electric motor that is equally fed by batteries; and iii.) *Fuel cell electric vehicles*, where the electricity powering the electrical machine is provided from fuel cells [5]. The second category of EVs, namely HEVs, are subsequently split into categories according to how their battery is charged, in which the vehicles which are capable of connecting to the grid are known as *Plug-in hybrid electric vehicles* (PHEVs).

Given the abovementioned descriptions, depending on the vehicle, promoting the use of EVs can guarantee mobility with zero CO2 emissions from the vehicle itself, which is why several governing bodies have taken impressive measures to encourage the implementation of this technology. For example, in 2008, the European Union (EU) created the *European Green Cars Initiative*, which financed €5 billion to boosting the automotive industry and supporting the development of new, sustainable forms of road transport, in particular EVs [6].

Although the use of EVs does provide a potentially cleaner future within the transportation sector of the global economy, their emergence has brought forth additional problems that require carefully considered solutions.

Analysing specifically the category of EVs capable of connecting to the grid, *i.e.* PEVs and PHEVs, which from this moment forth will be merely designated as EVs, one finds several predictions that EVs will make up a considerable portion of worldwide vehicle fleets by 2050 [7, 8, 9]. The increase in national daily electric energy demand that could take place given the potential rise in the use of EVs has drawn multiple concerns, particularly regarding the impact of EVs on national electric grids. Some examples include: degraded power quality; overall reduction in the system reliability; power losses; overloads in the distribution network; increase in production costs; and voltage variations and unbalance [10, 11, 12, 13].

The abovementioned threats associated with EVs are attributed to charging activities which occur in an uncontrolled (UC) fashion. UC charging has been identified as taking place during the morning hours, when users arrive at their respective workplaces, and more predominately, in the evening, after users arrive at their respective households. As these times correspond to the same periods in which the traditional daily peak loads of national energy demand are registered, UC charging behaviour will increase the maximum daily levels of demanded power, subsequently inducing further strain on the grid. Ultimately, this may threaten national power systems in the ways described above [14, 15, 13].

Thus, to enable a swift transition to the use of these vehicles in society, the integration of EVs into national grids must be rigorously studied, with the purpose of guaranteeing that their incorporation into national power systems is carried out in a safe manner.

One of the main fields of study associated with the literature on the aforementioned topic is directed at investigating charging strategies that maintain authorised levels of power within national grids. The research is carried out by analysing how different charging methods and schedules impact on daily national load diagrams (LDs).

LDs, also known as *load profiles*, *load curves* or even *electricity demand curves* consist of graphical plots that register the demanded power of a population over a given timespan, which in this case is assumed as a day. By plotting the demanded energy associated with different sized EV fleets and distinct charging strategies on daily LDs, it is possible to predict the extent to which EV charging events present a threat to a national power system. As such, these diagrams make for useful tools in the planning of EV integration [16, 10, 17, 11].

Existing research carried out with the use of LDs has long identified unsustainable levels of demanded power within national grids due to the significant sizes of EV fleets charging in an UC manner. To ensure that EV charging activities do not inflict an additional burden on power systems, much of the current research is directed at studying the outcome of alternative charging strategies on the configuration of LDs, with the intent of identifying which strategies ensure sustainable levels of demanded power within the national grids.

1.2. Motivation

As stated above, the most active sectors of the global economy must be reformed with the goal of promoting safe and sustainable economic development for present and future generations. To achieve these goals, the implementation of new sustainable technologies such as EVs must be thoroughly researched, with the purpose of guaranteeing that the solutions developed to mitigate past mistakes do not develop into new unpredicted problems of their own.

Furthermore, although these novel technologies generally have the capability of being used in a unilateral manner around the world, their implementation may result in distinct problems for different countries. Therefore, before establishing a commitment to new sustainable technologies, countries need to investigate the possible liabilities associated with existing infrastructure, following the integration of new technologies.

In light of the above, this research aims to investigate how the findings in the literature can be used to enable a swift and sustainable adoption of EVs and their respective charging strategies in the Portuguese national grid.

The results obtained are intended to alert and advise Portuguese utilities and policy makers of the potential threats and solutions presented by distinct EV charging strategies for the Portuguese national power system. Moreover, the present study offers a methodology that can be used as a guideline for other countries to study similar problems.

1.3. Aims and Objectives

By applying the discussed developments within the research field dedicated to analysing the impact of EV charging on national LDs, and by using present and predicted simulation conditions for Portugal, the present thesis aims to identify the charging strategies that will enable a healthy working Portuguese national power system in the year of 2030.

Specifically, the principal objective of the present thesis is to identify the charging strategies, discussed within the literature, that guarantee sustainable configurations of the Portuguese LD under different potential levels of EV penetration identified for 2030. This practical analysis will be carried out via a series of simulations that are aimed at depicting possible configurations of the Portuguese LD under different EV penetration levels and charging strategies for said year. This way, independently of the size of the EV fleet in 2030, the charging strategies that ensure a compatible relationship between the national grid and the charging of EVs will be well identified. The results obtained from the simulations will enable the planning and implementation of the EV charging infrastructure to be carried out in a reliable and secure manner.

Additionally, the identified charging strategies will be tested under the different seasons of the year and days of the week, *i.e*. weekdays and weekends. The objective of these simulations is to verify if the most suited charging strategy identified for each potential level of EV penetration is adequate throughout the whole year, and not merely for a random simulated day.

The input data defining the underlying conditions of the abovementioned simulations will be obtained through an extensive theoretical analysis carried out within this research. Specifically, the theoretical analysis intends to design a methodology for conceiving, developing and testing a set of models used to establish the necessary simulation conditions of the present thesis. These models are:

1. Obtaining a Portuguese LD for 2030 that accounts for all the energy consuming activities excluding EV charging, with the purpose of subsequently overlapping the EV power demands identified through this research with said LD;

2. Identification of three distinct potential sizes of the Portuguese EV fleet in 2030. This phase of the research is fundamental to delivering accurate conclusions regarding the main objective, as different levels of EV penetration will lead to different requirements of charging coordination;

3. An analysis of the daily driving patterns of Portuguese drivers and typical EV consumption rates. This stage is intended to estimate the daily electric energy needs associated with a typical Portuguese EV, and ultimately an entire EV fleet;

4. An assessment of EV charging patterns, *i.e.* the locations, times, portions of fleet and power rates associated with the most common EV charging activities carried out during the day. This analysis will subsequently be used to characterise the most basic form of EV charging – UC charging;

5. Identification and implementation of further charging strategies used within this research, which will be developed from adaptations of the abovementioned UC charging strategy.

1.4. Dissertation Structure

Including the present introductory chapter, this thesis dissertation is divided into five chapters, which are: i.) *Introduction*; ii.) *Literature Review*; iii.) *Methodology and Simulation Conditions*; iv.) *Results and Discussion*; and v.) *Conclusions*.

Chapter 2 – *Literature Review*, is dedicated to analysing and discussing the core research developed within the field of study regarding the impact of EV charging on daily LDs. The discussion carried out in this chapter intends to identify the most common themes of research and findings associated with the respective field, which will subsequently be used as a foundation for the construction of the simulation models used in this thesis.

Chapter 3 – *Methodology and Simulation Conditions*, aims to provide an in-depth description of the methodology used to obtain the necessary models for simulating the impact of EV charging on the Portuguese LD in 2030. The scientific articles discussed in the *Literature Review* chapter will be used as guidelines for building the simulation conditions used in this work.

Chapter 4 – *Results and Discussion*, presents the relevant results obtained from the simulations carried out in the present research. The results will then be discussed and analysed with the intention of identifying the underlying conclusions obtained from all the simulations, and ultimately providing answers to the main research questions established within this introductory chapter.

Chapter 5 – *Conclusions*, intends to describe, in a concise manner, the methodology developed within this research, as well as the results which seek to meet the objectives set out in this chapter. Moreover, a brief section is dedicated at proposing future work on the topic.

2. Literature Review

This chapter is devoted to presenting and discussing the main findings of the literature analysing the present and future influence of different EV charging strategies on power systems and daily LDs. The review aims to highlight the ideas underpinning the simulation models constructed in this thesis, which predict the impact of different EV charging strategies on the configuration of the Portuguese LD in 2030.

As mentioned in the introduction, it is well understood that without proper planning, EV charging will disrupt the normal functioning of national power systems. Within the literature concerning this topic, it is evident that there are several variables threatening the present and, most importantly, future configurations of daily LDs as a result of EV charging, such as: EV penetration levels; typical EV user driving patterns; and EV charging strategies. However, the literature clearly suggests that managing the last-mentioned variable, by ensuring that charging is performed in a sustainable manner, is the most effective way of ensuring stable LD configurations.

As such, the present literature review is dedicated to presenting and discussing the main studies that highlight the abovementioned conclusions. These studies can be grouped into four main themes: i.) *Uncontrolled (UC) Charging and Non-Optimised Controlled Charging Solutions;* ii.) *Optimised Controlled Charging Solutions;* iii.) *Vehicle-to-Grid (V2G) and Additional UC Charging Operations;* and iv.) *Additional Research*.

In the first theme, *UC Charging and Non-Optimised Controlled Charging Solutions*, researchers identify the most common patterns of UC charging behaviour associated with EV fleets. Once those charging patterns have been identified, they are depicted on daily LDs to ascertain the potential impact of UC EV charging on the configurations of future LDs. Further, an analysis of the operating status of power systems where UC charging is accounted for is carried out. With this information, authors study the potential dangers that may arise from UC charging, and subsequently propose non-optimised controlled charging solutions to avoid such problems.

In the second theme, *Optimised Controlled Charging Solutions,* researchers aim to create optimised controlled charging solutions based on the ideas proposed in i.) above. While the studies achieve optimisation through different methods, all the solutions are obtained through optimised algorithms that take into account the economic/technical needs of EV users, grids/utilities and energy producers.

The third theme, *Vehicle-to-Grid (V2G) and Additional UC Charging Operations,* considers how V2G technology can further contribute to coordinated charging, as well as how it can be implemented as a solution to avoid *Additional UC Charging Operations*.

The last theme is dedicated to presenting *Additional Research*. This section discusses adjacent areas of study which rely on the findings produced by the research falling within the first three themes above.

2.1. UC Charging and Non-Optimised Controlled Charging Solutions

In the literature, authors adopt different assumptions regarding UC charging behaviour. Furthermore, the solutions as to how EV charging operations should be coordinated also differ.

Research conducted by *Parks, et al.* [14] concluded that with a large penetration of plug-in hybrid electric vehicle(s) (PHEV(s)) and a lack of charging locations other than users' households, UC charging will increase pressure on peaking units in the evening and therefore create a need to increase grid capacity. The same study presents three different charging strategies to overcome this problem: i.) *delayed charging*; ii.) *off-peak charging*; and iii.) *continuous charging*. *Delayed charging* is confined to the residential area. In this scenario, all users are incentivised to delay their charging to the beginning of the valley hours of national electric consumption, by taking advantage of lower electricity tariffs, also known as time-of-use (TOU) tariffs. *Off-peak charging* also involves PHEVs charging at a residential level and during the valley period, however, in this scenario, PHEV charging is controlled by the local utility, which enables the use of the lowest-cost electricity and improvement of the overall utility system performance. The last strategy, *continuous charging*, is based on UC charging, but with the difference that PHEV owners have the opportunity to charge their vehicle wherever they are parked, thereby reducing both the overall number of vehicles charging at a single moment and the quantity of energy consumed in each charging event. The authors note that any of the abovementioned strategies to control PHEV charging would require no additional grid capacity, even at major PHEV penetration levels. However, the *off-peak charging* strategy produced further benefits, as it would create an additional net benefit in terms of the utilisation of existing plants.

Clement et al. [18] analysed the impact of different charging behaviours on the distribution grid, in the form of power losses and voltage deviations. In this research, uncoordinated charging is defined as charging events in which users do not possess the required information to schedule battery charging with the purpose of optimising grid utilisation. As such, uncoordinated charging encompasses both battery charging that occurs immediately after vehicles are plugged into a socket and, contrary to [14], after a user-adjustable fixed start delay, using off-peak electricity tariffs (TOU tariffs). In coordinated charging, the user makes no decision as to when the vehicle initiates its charging operation. As such, the charging event is determined by smart-metering and signals sent to the individual vehicles with the purpose of minimising power losses. The results obtained from the simulations showed that coordinated charging would increase the load factor of daily LDs, as well as reduce power losses and voltage deviations.

In a study by *Peças et al.* [16], research was carried out to quantify the maximum possible EV deployment in a typical Portuguese low voltage (LV) residential grid, under two different charging scenarios: i.) *dumb charging* and ii.) *smart charging*. *Dumb charging* assumes that users are free to charge their vehicles whenever they please, while *smart charging* incorporates a strategy managed through a control structure that continuously monitors all elements in the grid, providing the most efficient usage of energy and dealing with restrictions, such as branch congestions and voltage drops. An analysis was also carried out to measure renewable energy (RE) surplus wastage, as well as to evaluate the impact on the network voltage profiles, branch congestion levels, and imbalances between the three phases of power flow under both charging scenarios. The results concluded that without reinforcement of the grid, only 11% of the traditional ICE vehicle fleet could be replaced by EVs under *dumb charging* conditions without transgressing the grid capacity. In contrast, 61% of the ICE fleet could be replaced without transgressing grid capacity under *smart charging* conditions. When compared to *dumb charging*, *smart charging* showed significant improvements in branch congestion levels and voltage profiles. However, load imbalance values related to both *dumb* and *smart charging* are relatively similar and considerably higher than the values obtained in the baseline scenario (no EVs connected to the grid). Under the *dumb charging* scenario, EVs charge in afternoon peak hours and therefore do not absorb any RE surplus. In the *smart charging* scenario, EVs carry out their charging operation at night, during the valley period, and therefore do not allow for any RE wastage.

Research by *Putrus et al.* [19] analyses the performance of three different charging scenarios, with respect to peak-valley load difference. It also evaluates voltage level deviations and imbalance under different levels of EV penetration on a typical distribution network (DN) model. Three charging scenarios are considered: i.) *uncontrolled charging*; ii.) *off-peak domestic charging*; and iii.) *smart charging*. In the first scenario, users are offered no incentives to modify the scheduling of their EV charging operation. As such, all users begin charging their vehicles at 18:00, after returning home from work. In the second scenario, users time the charging operation to begin at 01:00, through the use of a timed controller. In the third scenario, EVs are scheduled, through a control system, to start charging in one of four existing charging schedules during Winter (23:00-05:00, 00:00-06:00, 01:00-07:00 and 02:00-08:00), or one of three existing charging schedules during Summer. The charging schedules for Summer and Winter are different since the baseline load (load without EV) during Summer is significantly lower than the one registered in Winter. As such, if EV charging during Summer were to appropriate the *smart charging* schedules applied during Winter, it would induce a new peak load in the valley period. The results from the simulations of the different charging scenarios showed the greatest reduction in peak-valley difference, along with a flattening and smoothing of the daily LD, when *smart charging* was applied. In Summer, higher values of power, in comparison with the Summer baseline curve, were demanded from the grid due to the introduction of EVs. However, charging operations scheduled throughout the whole day resulted in a daily LD with low fluctuations. In Winter, the peak value of power demanded from the grid continued to be registered at its original baseline value, with the valley-filling phenomenon resulting in a flatter daily LD. Additionally, through performing simulations on a typical DN model, the research concludes that a large deployment of EVs could result in violations of statutory voltage limits. Furthermore, operating under certain conditions may also lead to power quality issues and voltage imbalance.

In addition to the topics discussed above, other publications have also studied the impacts of using different levels of power in EV charging. These studies have compared the benefits and weaknesses of charging at a faster rate, using high power, against charging in a more moderate fashion (commonly referred to as normal charging), using limited power.

Research by *Shao et al.* [20] analyses the difference between UC charging without incentives, through the use of a flat rate, and controlled charging, using time-of-use (TOU) tariffs to incentivise demand response. Within each of these charging strategies, the study also compares the impacts of fast and normal charging under the combined scenarios of high-low EV penetration and Winter-Summer LDs. The results show that normal charging does not present a big increase in the demanded power, as it extends the period in which peak power is registered. In contrast, fast charging induces higher values of demanded power within the LDs, which last for shorter periods. The research concludes that if TOU tariffs succeed in encouraging users to charge at special off-peak price rates, EV charging will be transferred from peak hours to off-peak hours, thereby reducing the peak load and flattening the LD for high/low EV penetrations, during both Summer and Winter, using both normal and fast charging.

Other research is focused on analysing the impacts of UC charging in a more meaningful manner. These studies develop a more realistic set of information regarding UC charging behaviours by retrieving and organising statistical information about driving patterns provided from travel surveys.

For example, *Shafiee* and *Rastegar* [21] develop a more insightful analysis of UC charging behaviour through relying on statistical information provided from the National Household Travel Survey (NHTS). EV user behaviour, reflected through variables such as mileage, arrival times of journeys, and type of vehicle used, are analysed to determine EV impact on the electrical grid, under an UC charging strategy. This information is then applied to build daily LDs under different seasons (Summer and Winter), EV penetration levels, and time horizons (for which different annual load growth rates were used). A relevant weakness of this research is that it merely assumes UC charging takes place at home, and as such, that all charging operations begin immediately after users arrive at their respective households. This analysis does, however, help to demonstrate the problems that may arise if precautions are not taken to shift the EV charging load from the traditional periods of peak energy consumption. Using the input data described above, simulations were executed on an IEEE 34-node test feeder during peak consumption hours. Results showed that voltage deviations are a lesser concern when compared to capacity limitations and power losses in the electric system, leading to the conclusion that EV load shifting is imperative.

The studies presented in [17], [10] and [22] below consider all of the abovementioned topics.

Darabi and *Ferdowsi* [17] compare UC charging scenarios, using two different power rates, with three controlled charging scenarios implemented through distinct policies (one of them being TOU price tariffs). This work is notable for using real driving data provided from the NHTS to determine, under a UC charging scheme, when each EV begins its charging operation (which is defined as the time of arrival of the last journey), and how much electric energy is demanded from each vehicle. Resembling the LD results of [16], the UC charging scenario results show that, although the highest values of daily demanded power from low charging power rates are noticed for longer periods of time, they do not result in a significant increase in the daily peak load. On the contrary, charging operations with fast charging power rates are registered for much shorter periods, as EVs are charged more rapidly, and therefore induce a significant increase in power usage registered during peak hours. This work, like other publications, concludes that the TOU price tariff policy may successfully shift EV charging loads to the desired off-peak period. However, if EV charging is indeed transferred to the off-peak slot, with the result that all vehicles begin charging at the same time, the power level demanded from vehicles charging is similar to that which is registered under the UC charging scheme with a high power rate. To address this problem, the paper suggests alternative policies which flatten the LD more effectively, by transferring the load in a distributed manner to off-peak hours. The two policies mentioned are: i.) users arriving home during peak hours charge their EVs at a lower power rate, while others charge with a higher power rate; and ii.) users arriving home during peak hours are obliged to wait for two hours after their arrival to begin their charging operation.

Research conducted by *Dogan et al.* [10] analyses the effects of UC charging and presents alternative controlled charging strategies. It also studies the differences between normal and fast charging. By studying the results obtained from the LDs of different charging strategies and power levels, the authors are able to analyse the percentage increase of system peak loads and differences in system load factors under different EV penetration levels. The UC charging model is based on data retrieved from the NHTS, in which EVs are charged in the afternoon at home, after users' arrival from work. By identifying the afternoon arrival patterns reflected in the information provided from the NHTS, the authors adopted a Gaussian distribution with an average charging commencement time of 17:30 and a standard deviation of 1 hour to establish the pattern associated with UC EV charging. The results are similar to those of the studies discussed above, as UC charging strategies contribute to an increase in the daily peak load; and fast charging shortens the charging period of EVs while simultaneously increasing the power demanded from the grid. Further results obtained from this research present evidence that charging with a normal power rate, following a TOU price scheme charging strategy, for example, can drastically improve the grid's performance – inducing no further increases in the peak load of the LD, while raising the load factor at a 50% EV penetration level.

Qian et al. [22] compare daily LDs of four different charging strategies: i.) *UC domestic charging*; ii.) *UC off-peak domestic charging* – through the use of TOU tariffs; iii.) *"smart" domestic charging*; and iv.) *UC public domestic charging*. The distribution which describes the initial state-of-charge (SOC) of the various EV batteries at the beginning of the charging sessions follows a Gaussian-type probability density function. The work also develops daily LDs for UC charging through public infrastructure located in industrial, commercial and residential settings. Furthermore, it presents an innovative strategy for the *"smart" domestic charging* strategy, in which electricity real-time price (RTP) rates are employed to determine the most economic start time of EV battery charging. Lastly, the study applies real lead-acid and lithium-iron battery charging profiles to build the EV charging profiles used in the daily LDs. The research concludes that UC charging will result in an increase in daily peak power demand of 17.9% and 35.8% with EV penetration levels of 10% and 20%, respectively; and that the *"smart"* charging method is the most beneficial strategy for both the DN operator and EV customers. The authors also suggest that the loads associated with the abovementioned sectors of society need to be analysed separately, as the impact of certain loads on distinct feeders will be disguised if an overall LD is adopted. Finally, the study concludes that sufficient network capacity to support the integration of EVs is not a reason to neglect studying the adverse effects of EV charging.

The research presented above belongs to a broad body of literature dedicated to studying the LD configurations and power system operating points under UC charging strategies. Furthermore, these publications discuss multiple strategies that aim to contain potential threats to grid stability by proposing methods to control EV charging. While the strategies presented by the authors have their differences, the core results obtained from all the studies share a number of common features. *Wang et al.* [7] discuss these similarities, mentioning that if EV charging is not controlled, peak loads of LDs will increase further and present unsustainable values for national grids in the future. As such, controlled EV charging is imperative and must be used to shave additional peak load induced by EVs. Peak shaving can be achieved by shifting EV load to off-peak hours through financial incentives, such as TOU tariffs to promote user controlled charging, or by using smart grids (SG), in which the charging operation is scheduled by either an EV aggregator or the EV user. In the scope of this dissertation, the last-mentioned charging operations have been identified as *optimised controlled charging solutions*. These charging operations rely on real time information about technical and economic constraints on national grids and EV users, and/or financial incentives, such as TOU and RTP tariffs. The following sub-section is dedicated to discussing this field of research.

2.2. Optimised Controlled Charging Solutions

An extensive number of studies have been dedicated to researching and proposing optimum EV charging schedule algorithms to be applied in an SG environment. According to *Masoum et al.* [23], the charging coordination schedules are, in general, either defined through centralised or decentralised (distributed) programmes. In decentralised coordination strategies, EV users have the ability to decide the time and level of power at which their vehicles will be charged based on real time information provided from the utility company. Alternatively, in centralised coordination strategies, an EV aggregator acts as a middleman between the utilities and the users, by scheduling the charging operation of the entire EV fleet with the intent of maximising the benefits for both sides. While decentralised charging aims to allocate greater agency to the users, it fails to guarantee an optimal usage of the grid. The inverse can be said for scheduling the charging operations in a centralised fashion.

Following up on the research conducted in [22], *Zhang et al.* [24] use a normal distribution stochastic model to determine the initial SOC of the battery. The authors also use the battery charging profile of lithium-iron batteries to build their EV charging profiles. The research presents a centralised quadratic programming (QP) solution to optimise the charging schedule of a fleet of EVs, with the purpose of shifting the EV load to valley hours and flattening the overall daily LD. The QP solution is applied to several levels of EV penetration under four different charging strategies: all EVs charged at home by mode 1; all EVs charged at home by mode 2; all EVs are charged in public stations by mode 3 or 4; and half of private EVs are charged at home by mode 1, while the other half are charged at home by mode 2. All company EVs are charged at public stations by mode 3 and 4. This work distinguishes itself from others by using charging power rates based on existent charging modes. Results from the study demonstrate that the model flattens the LD more significantly when applied to higher charging power rates and levels of EV penetration.

Sun et al. [25] introduce a real-time centralised optimal EV charging scheduling solution. The proposed algorithm works in two stages. The first stage of the programme is characterised by a binary QP solution, the purpose of which is to perform valley-filling with the load allocated for EV charging. This stage pays special attention to restrictions imposed at the distribution level by complying with constraints defined for distribution transformers. The second stage, implemented by using a heuristic algorithm, looks at minimising the total number of on-off switching activities of all EV charging operations. The LDs obtained from the simulations show that the programme achieved reasonably good results under a low level of uncertainty and in cases without perfect predictions, for low EV penetration levels.

Research conducted by *Vandael et al*. [13] attempts to compare two different demand side management solutions of controlled EV charging, implemented by a SG, with the intention of avoiding further burden on the grid during peak consumption hours. The abovementioned strategies are a decentralised multi-agent solution (MAS) and a centralised quadratic programming (QP) schedular solution. The LD obtained from simulations demonstrated that while the QP schedular is able to optimally control the charging operations, by transferring and flattening the charging load of EVs within the valley period, it is poorly scalable and requires perfect information related to all the charging operations, providing little adaptability and flexibility. On the contrary, the MAS only manages to coordinate EV charging with an efficiency up to 95% of the QP schedular solution. However, it proves to be more scalable and flexible than the QP schedular, and is able to deal with incomplete and unpredictable information far better than the latter.

Martinenas et al. [26] propose a decentralised algorithm to implement smart charging based on electricity RTP tariffs. The purpose of said algorithm is to schedule an EV’s charging operation through the use of a smart charging controller (SCC). The SCC runs an external network-connected computer, with the intent of: monitoring RTP stream and EV battery status; calculating and updating the charging schedule according to changes in the electricity price; and dispatching control signals to the EV. The price signal followed by the algorithm is based on the results of the EcoGrid EU project, which produces dynamic tariffs built on current and predicted future grid status. The SCC algorithm operates by: i.) reading and processing price stream data; ii.) reading the actual EV SOC; iii.) calculating the optimal charging schedule; and iv.) actuating charging power for the EV. The algorithm was tested on two separate cases, namely, one where the charging operation can take place anytime between 17:00 – 01:00, and the other between 22:00 – 08:00. Results showed that in both cases, the algorithm managed to charge the vehicle to the desired battery level. However, the latter scenario achieved a quicker charge with less financial expenses.

Research by *Li et al.* [27] presents a two-stage distributed coordination algorithm for optimising EV charging in the context of a community microgrid. The charging coordination is achieved through multiple agents, which in the context of the framework are the SCCs belonging to each individual EV. The algorithm is operated in two separate stages: a planning stage and an operation stage. The planning stage is dedicated to scheduling the charging operations according to the day-ahead market price, which subsequently calculates an ideal optimal charging power. Once the RTPs are established, the operation stage is designed to minimise the deviations from the ideal charging power and the real charging power, as well as consider the constraints of power balance and load and supply.

Liu et al. [28] present a two-stage (day-ahead stage and a real time stage) decentralised programme via stochastically staggered dual-tariffs to schedule EV charging. The objective function of the constructed algorithm is to minimise wind power curtailment. The first stage of the algorithm is divided into two further phases: the first phase is intended to identify the dual tariff charging scheme, based on a charging coordination integrated unit commitment; the purpose of the second phase is to adjust the charging scheme at the feeder level, via a security check and correction algorithm, with the intent of guaranteeing bus voltages, feeder currents and losses within the desired limits. In the second stage of the decentralised programme, an individual charging pattern is drawn out for cost minimisation at the charging device level. The results obtained from the simulations were subsequently compared with results obtained from the use of flat tariffs, TOU tariffs and RTP tariffs, to which, comparatively, the proposed scheme presents greater absorption of surplus wind energy efficiency, at the transmission level. However, although the algorithm works within the established regulation limits for the feeder-level, results show that tight feeder regulation constraints degrade the overall optimality of the programme.

Jiang et al. [29] propose a decentralised coordinated scheduling strategy based on a multi-objective optimisation algorithm. The proposed strategy attempts to meet the needs of both the power grid and its users, by maintaining the stability of the power system and minimising the user’s costs, using TOU tariffs. The results obtained from the optimised solution were compared with an uncoordinated charging scenario. Based on data retrieved from the NHTS, a Monte Carlo simulation was carried out to establish daily energy demands of the EVs (applied in both coordinated and uncoordinated charging scenarios). Additionally, Gaussian distributions were applied to the uncoordinated charging scenario to describe charging start times in the afternoon, after users’ arrival home from work, as well as in the morning, after their arrivals at work. Results from the simulations showed the algorithm was successful in satisfying the needs of EV charging while making full use of the valley period of the LD. As such, the proposed model can significantly reduce the cost of EV charging compared to UC charging.

Research carried out by *Shi et al.* [8] presents an optimised solution for EV charging schedules through a Particle Swarm Optimization (PSO) algorithm. The solution of the PSO algorithm is based on TOU price tariffs and has an objective function of guaranteeing user satisfaction (based on charging cost and battery SOC) and minimising curtailment of wind energy. The results from the application of the PSO algorithm are compared to a UC charging scenario. The results obtained highlight that the proposed algorithm effectively optimises the overall objective function and manages to flatten the overall LD.

Zhao et al. [30] propose an innovative set of pricing measures applied on a heuristic algorithm for EV charging to encourage users to participate in peak shaving and ultimately reduce the difference between the peak and valley load of the LD. The strategy is primarily based on TOU price tariffs, which present a considerable difference in electricity cost between peak and valley hours, and the selected charging mode, *i.e.* charging power of the charging operation. Moreover, an additional EV charging service fee is implemented for EV owners who do not participate in coordinated charging. Simulations of the strategy showed positive results by managing to shift the EV charging load to the valley period.

Studies by *Sheikhi et al.* [31] also use normal distribution functions to determine the start time of charging operations, in a UC charging scenario, and the EVs' respective initial SOC. The work presents the results of an algorithm developed for a controlled charging scenario in which users make decisions in an interactive manner, using smart meters to obtain real time information on RTP and generation capacity limitations to achieve peak load shaving. The algorithm establishes the users' charging decisions through a game theory model which determines a Nash equilibrium point that minimises all car owners' cost of charging. The algorithm is subsequently tested on three different EV penetration levels, in which peak load shaving and valley-filling is most noticeable in the results for the highest penetration level.

In [32], *Marmaras et al.* present an innovative approach for studying the difference between controlled and UC EV charging. In this research, the coordinated and uncoordinated strategies are based on the awareness of the EV drivers, which were simulated through Aware or Unaware EV agents. The multi-agent simulation takes place in a complex network with several avenues connecting different districts, in which EV agents live, move and interact amongst each other. The environment built for the simulation consists of a road transport network, an electricity grid and EV agents. Aware EV agents drive and charge their vehicles according to real time information about the status of the transport network and the electricity grid. As such, they travel through avenues with the least levels of congestion and charge in public or private infrastructure according to electricity grid limitations. Unaware EV agents' travelling and charging behaviour is not influenced by the environment surrounding them, as such, they operate in a UC fashion, inducing greater impacts on the transport network and the electric grid. Results from the simulation revealed that the Aware EV agents, who operate in a controlled manner, present the most promising results of all three interacting entities.

Optimised charging algorithms tend to deal with grid constraints, such as overloading, power balance and voltage deviation. However, the optimisation of controlled charging strategies through the use of an EV aggregator typically focus on maximising the economic benefit in the electricity market, or minimising the operating cost without transgressing the constraints of grid stability [25]. Since distribution transformers are the weakest infrastructure in distribution systems, *Masoum et al.* [11, 33] carried out studies to analyse the impacts of UC and optimised controlled charging strategies on distribution transformers, as opposed to other publications, which neglect transformer stresses and losses. Results from the research identified that UC charging could have significant impacts on transformer losses in LV residential networks, as well as lead to serious transformer overloading with large EV penetration levels. The studies also highlight that, as some strategies developed for optimised controlled charging operations neglect transformer stresses and losses, they produce charging schedules which can induce transformer overloading in cases of high EV penetration.

Muñoz et al. [34], for example, create a decentralised algorithm to coordinate charging in a manner that addresses grid level (utility level economics) and local level (safety and maintenance) concerns, dedicating special attention to infrastructure restrictions on the local level side, namely, transformers. The solution is subsequently compared with three different charging scenarios: UC charging; TOU charging; and grid valley-filling charging. Results from the simulations showed that all three charging strategies overloaded the transformers, particularly UC charging and TOU charging. In contrast, the authors' proposed algorithm prevented transformer overloading while managing to achieve a satisfactory level of valley-filling within the LD.

2.3. Vehicle-to-Grid (V2G) and Additional UC Charging Operations

A number of studies have also been dedicated to researching the operation known as V2G, in which EVs enhance the reliability of the system by acting as energy suppliers which feed energy stored in their batteries back to the grid. V2G offers several other features, such as: active power regulation; supporting reactive power; load balancing through valley-filling; current harmonics filtering; peak load shaving; reducing utility operating cost and overall cost of service; improving load factors; generating revenues; reducing emissions; and tracking of RE resources [35].

Wang and *Infield* [36] propose an optimised charging schedule solution that implements the concept of V2G in a SG. Through shifting EV consumption to periods of low demand and providing V2G services during peak demand, EV users interact with an EV aggregator that schedules an optimum charging and discharging session according to RTPs. The scheduling solution also takes into consideration battery degradation, EV availability and network constraints, such as voltage deviations and grid capacity. The research only considers charging and discharging in a household environment, therefore, discharges are only performed during afternoon peak hours and charging operations are only carried out in valley hours.

Research conducted by *López, et al.* [37] is similar to [36] above. The main difference is that the optimisation model in this study aims to maximise the profits of all agents involved in the energy market operation. Further, it also considers RE integration.

As already discussed, much of the literature only focuses on the impact that UC charging has on evening peak hours, under the assumption that EV charging will mostly take place at the user's home. However, research has shown that as EVs become more financially accessible, a significant proportion of future EV charging will take place not only at home, but also within public infrastructure, throughout the whole day; and at work, primarily in the morning [38]. These predictions, related to *additional UC charging operations*, have led to further studies which present distinct daily LDs according to different assumptions of UC charging patterns.

For example, *Weiller* [15] proposes alternative configurations of the daily LD given the *additional UC charging operations*. Relevant conclusions point to the fact that EV charging will generate three distinct daily spikes during weekdays: two of the three spikes are registered significantly at workplaces and homes during the morning and the evening, respectively; and a more subtle spike is registered at commercial places during the afternoon. During weekends, the results point to a less distinctive configuration, with a varying load that distributes itself throughout the entire afternoon.

Zhang et al. [39] analyse the EV load of UC charging behaviours with a special focus on the influence that social attributes have on charging patterns, arguing that ignoring such information deteriorates the accuracy of the charging load model. The results confirmed that charging load profiles vary with different demographics and social attributes, such as gender, age and education level. These demographic factors have a considerable effect on charging patterns during peak hours, especially during weekdays at the workplace.

Given the potential rise in load demand due to *additional UC charging operations*, with a special notice to charging carried out at work in the morning, it is important to identify studies that have found solutions which coordinate charging in every identified period of EV charging activity. However, unlike charging at home, EVs that charge at work do not benefit from the charging flexibility that home-charging vehicles present, *i.e.* their ability to postpone charging operations into the valley period in early morning hours. As such, authors have proposed models in which V2G operation is used to support the grid in morning charging activities.

Research presented by *Sufyan et al.* [40] proposes an optimised charging coordination solution through the implementation of a firefly algorithm. By including a V2G operation and incorporating battery degradation cost and RE integration, the proposed model coordinates battery charging in the most economically optimal way for both the grid and user. Results from simulations identified that, compared to UC charging, the model improves the voltage profile of the test system and increases the profits of EV users, by selling energy to the grid during morning and evening peak hours and charging during valley hours. Moreover, RE integration further reduces the system costs and losses in the controlled charging scenarios and increases battery lifetime. However, the increase in battery lifetime is due to a gradual reduction in V2G participation as a result of less attractive profits.

In article [41], *Liang et al.* develop an optimised EV coordinated charging procedure that implements dynamic economic/emissions dispatch (DEED) to perform peak shaving and valley-filling within the LD. The paper compares five charging strategies according to their performance in terms of costs and emission: i.) *UC charging*; ii.) *controlled charging*; iii.) *controlled charging with integration of V2G in DEED for afternoon peak hours*; iv.) *controlled charging with integration of V2G in DEED for afternoon and morning peak hours*; and v.) *controlled charging with integration of V2G in DEED according to battery degradation costs*. All the controlled charging operations are implemented via a water-filling algorithm, with the intent of maximising the valley-filling operation. The results indicate that the integration of EV into DEED not only reduces the difference between peak and valley loads, but it also promotes both the reduction of emissions and saving on investments of peak load plants. Scenario iv.) above presents the lowest daily emission levels and fuel costs.

Research carried out by *Sarker et al.* [12] presents a RTP-based model for the implementation of an optimal charging schedule and V2G operation under the coordination of an EV aggregator. The model aims to maximise the aggregator's profits, while minimising the consumer's costs. This is achieved through optimally scheduling EV charging operations and by exploiting the flexibility of some household appliances to operate during off-peak hours. The model is compared to an EV charging and discharging scenario using TOU price tariffs. The work concludes that the greatest benefits are obtained with the implementation of the RTP scheme.

2.4. Additional Research

This subsection is devoted to presenting examples of adjacent research fields which have benefited from studies of EV charging strategies.

A few articles have attempted to study the future composition of energy markets as affected by high penetration of EVs. The studies focus on identifying the main energy producers and the amount of energy dispatched from each producer under UC and controlled charging strategies.

For example, *Foley et al.* [42] compare RE integration in a given UC charging scenario and controlled charging scenario using TOU price tariffs. Further, the authors identify the pool of energy sources that provide energy to EVs under the above charging strategies for the year 2020. Results from the simulations highlight that within the controlled charging scenario, EVs are predominately powered by gas, followed by wind, coal and some interconnection. There was also a reduction in RE curtailment. In the UC charging scenario, EVs were primarily powered by gas, peaking power plants and expensive pumped hydro generation. Interestingly, the UC charging scenario saw a reduction in the dispatch of coal and interconnection, accompanied by an increase in wind power curtailment.

Similarly to [42], *Hanemann et al.* [43] look at the implications which different charging strategies (namely UC, controlled and V2G) will present for the German power system in 2030. For each predicted EV penetration level, the results discuss the changes in various power plant energy production according to CO2 emission price variations. The study also discusses the RE integration which results from the different charging scenarios.

Some research has also been dedicated to analysing the role of EVs in frequency control operations in power systems.

For example, in article [9], *Obaid et al.* present a review of the multiple control methods proposed to support power systems with the challenges associated with frequency control, following the introduction of RE resources. The authors state that frequency control operations can benefit from controlled charging and discharging (V2G) EV strategies.

3. Methodology and Simulation Conditions

This chapter is dedicated to explaining the different stages of theoretical work undertaken to conceive, develop and test the methodology required to simulate electric vehicle (EV) charging within the Portuguese load diagram (LD) in 2030.

The chapter is divided into four sections. Each section sets out how key assumptions were built in respect of each of the four main studied themes, which are: *i) Prediction of the Portuguese baseline load diagram (BLD) for 2030*; *ii.) Prediction of light-duty passenger (LP) EV penetration in Portugal for 2030*; *iii.) Mobility Patterns of Portuguese drivers and EV consumption rates*; and *iv.) Charging infrastructure, patterns and strategies*.

3.1. Prediction of the Portuguese Baseline Load Diagram (BLD) for 2030

The demand for electric energy consumption in Portugal will grow until 2050 [44, 45, 46, 47]. According to the Direção-Geral de Energia e Geologia (DGEG), *i.e.* Ministry of Environment and Energy, in *Relatório de Monitorização da Segurança de Abastecimento do Sistema Elétrico Nacional 2017 - 2030* [44], the aforementioned growth in electric energy consumption will arise not only from the introduction of EVs, but also due to an increase in demand from traditional electric energy consuming sectors [46]. As such, to predict possible configurations of future LDs, it is first necessary to obtain a baseline load diagram (BLD) for 2030 that quantifies the Portuguese growth in electric energy consumption due to activities other than EV charging.

In order to build daily BLDs for different seasons of 2030, it was necessary to obtain daily LDs of the respective seasons relative to a given reference year. Throughout this dissertation, these daily LDs will be designated as reference load diagram(s) (RLD(s)). The RLDs present real measured values associated with daily LDs registered in the past and, in this research, were retrieved from a dataset belonging to the Portuguese National Electricity Transmission Grid Company – Redes Energéticas Nacionais (REN), in *Diagramas de Carga 2017* [48]. The document presents data relative to the load demand, in MW, registered for every 15 minutes of 2017, which is the reference year used in this work. Figure 1 provides an example of an RLD used in this study – weekday of the Winter of 2017.

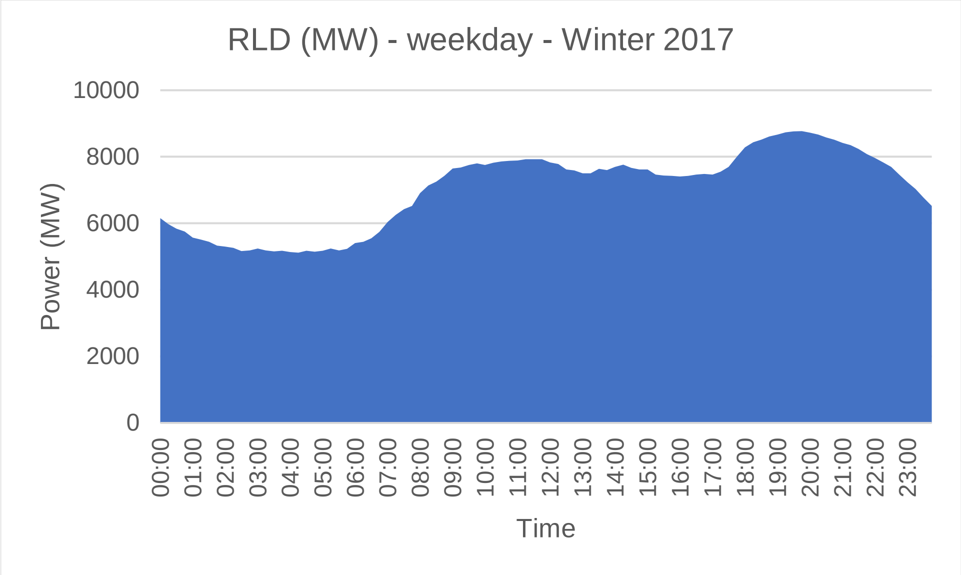

Figure 1. RLD for Weekday of Winter 2017 [48].

For the scope of this research, individual RLDs were obtained for weekdays and weekends of each season. The criteria used for selecting each RLD was the weekday and weekend day with the highest registered demand of energy in each season. For example, figure 1 represents the day of highest electrical energy demand registered in a weekday of Winter 2017.

To identify the weekdays and weekend days registering the highest values of demanded energy, E, within each season of 2017, the set of values of power, P, registered in each weekday and weekend day of the aforementioned document were integrated with respect to time, t, as described in equation 1.

$$E = \int P\,dt \tag{1}$$

Subsequent to obtaining the RLDs, research into the predictions of electric energy consumption for 2030 was conducted with the intention of calculating the growth rate associated with the increase in electric energy demand between 2017-2030. Figure 2 illustrates the registered and predicted values of yearly electric energy demand in Portugal from 2016-2030, without the consumption of EVs [44].

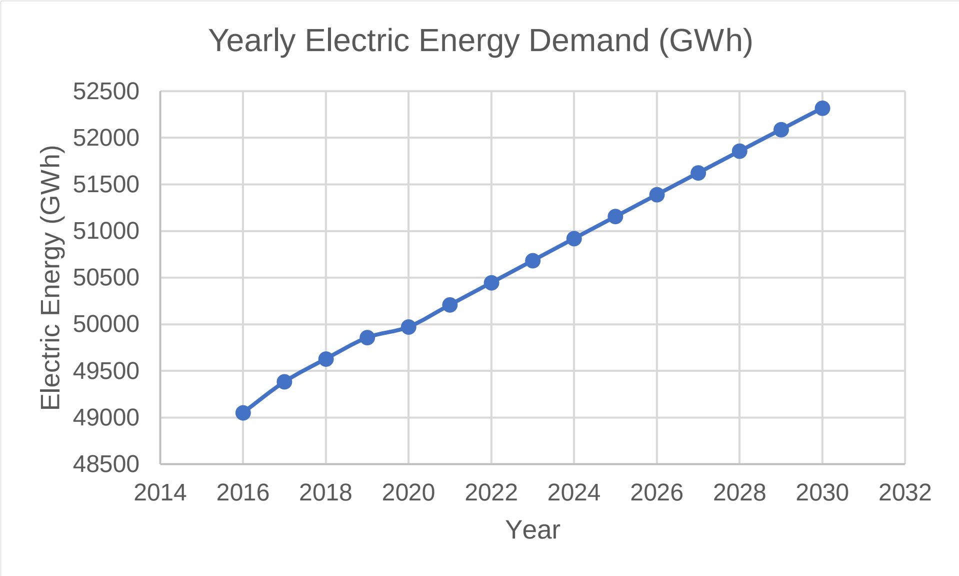

Figure 2. Prediction of Portuguese Yearly Electric Energy Consumption (Without EVs) [44].

According to the information illustrated in figure 2, the total electric energy demand for the years of 2017 and 2030 is 49,383 GWh and 52,319 GWh, respectively. As such, according to equation 2, the electric energy consumption growth rate (CGR) between the years of 2017 and 2030 is approximately 5.95%.

$$CGR(\%) = \frac{E_{BLD} - E_{RLD}}{E_{RLD}} \times 100 \tag{2}$$

Where:

CGR : Consumption Growth Rate

E_{BLD} : Annual Electric Energy Consumption in year of BLD

E_{RLD} : Annual Electric Energy Consumption in year of RLD

On the assumption that demand patterns of traditional electric energy-consuming sectors will not change, the BLDs for 2030 were obtained by applying the calculated CGR to the RLDs of each season. As such, the BLDs present the same configuration as the RLDs. The various BLDs were subsequently used to analyse the potential impacts of EV charging on the LDs of 2030. Figure 3 illustrates both the RLD and BLD for the years of 2017 and 2030, respectively, in a weekday during the Winter season.

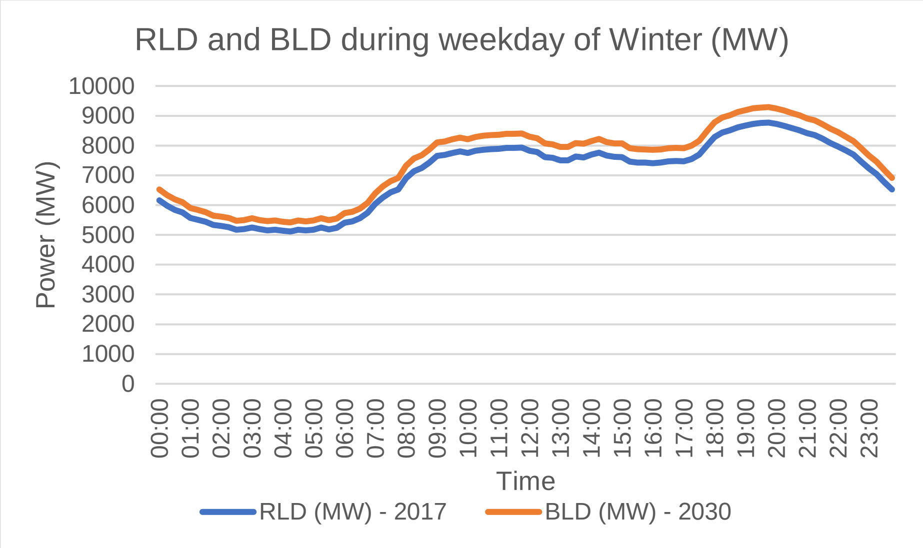

Figure 3. RLD (2017) and BLD (2030) for Winter Weekday in MW.

3.2. Prediction of Light-Duty Passenger (LP) EV Penetration in Portugal for 2030

With regard to the prediction of the light-duty passenger (LP) EV fleet in Portugal for 2030, three different scenarios were considered: a *pessimistic* scenario; a *base* scenario; and an *optimistic* scenario, in which the number of vehicles associated with the EV fleet increases from the *pessimistic* to the *optimistic* scenario, according to different sources of information.

3.2.1. Pessimistic Scenario

The *pessimistic* scenario assumes the predictions made in *Relatório de Monitorização da Segurança de Abastecimento do Sistema Elétrico Nacional 2017 - 2030* [44], illustrated in figure 4.

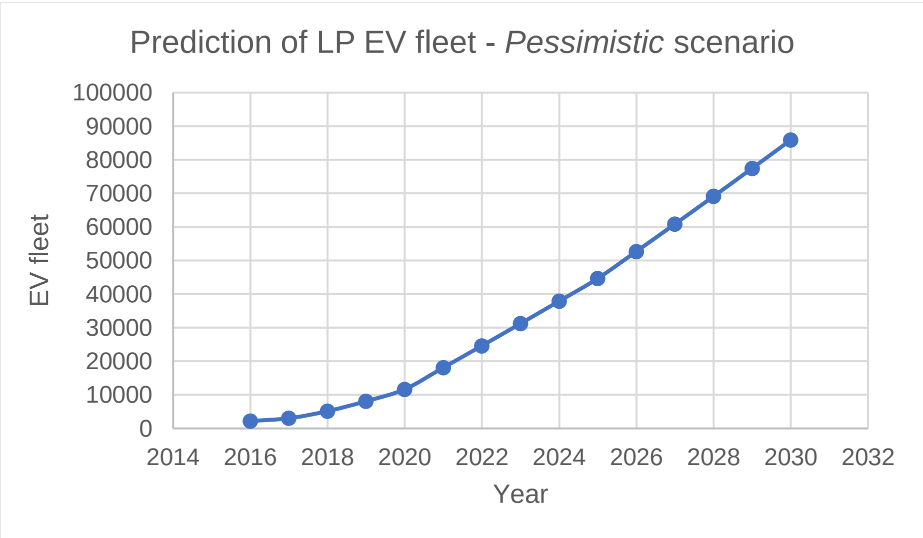

Figure 4. Prediction of LP EV fleet – Pessimistic Scenario [44].

According to the abovementioned information, the assumed value associated with the number of LP EVs for the *pessimistic* scenario in 2030 is 85,925 vehicles.

3.2.2. Base Scenario

The *base* scenario is built according to information provided in the *Directive of the European Parliament and of the Council amending Directive 2009/33/EC on the promotion of clean and energy-efficient road transport vehicles* [49]. The directive sets minimum procurement levels, indicated by the EU, for the percentage share of clean LP vehicles in each of its member states from the 2nd of August 2021 to the 31st of December 2030. In the case of Portugal that target is set at 29.7%.

Bearing this information in mind, it was necessary to produce a yearly prediction for the total number of LP vehicles in Portugal between the years 2021-2030. To make this prediction, data reflecting the annual registered number of LP vehicles in Portugal was used. This data was obtained through information published by the Portuguese National Institute of Statistics – Instituto Nacional de Estatística (INE) – in their yearly reports *Estatística dos Transportes e Comunicações 1991 – 2018* [50] and is illustrated in figure 5 below.

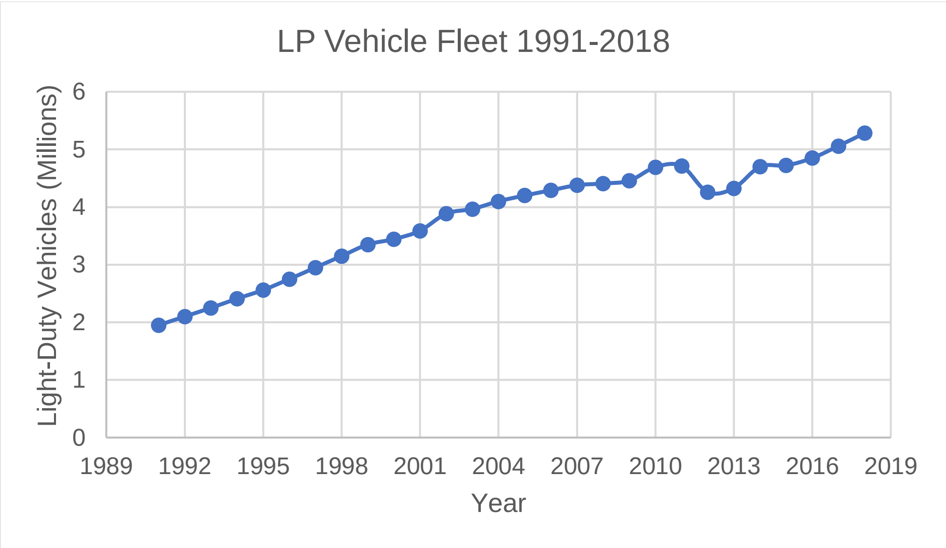

Figure 5. Evolution of Portuguese LP Vehicle Fleet 1991-2018.

The prediction of the yearly LP vehicle fleet for 2030 in Portugal was subsequently obtained by applying a linear regression model on the data presented in figure 5. The purpose of the regression model is to attain a trend line associated with the development of the above sample.

The trend line obtained from the linear regression is expressed in equation 3 and is depicted in figure 6. The mathematical processes used to obtain equation 3 can be found in appendix A.

$$\hat{Y}_i = 2175421 + 113008X_i \quad (3)$$

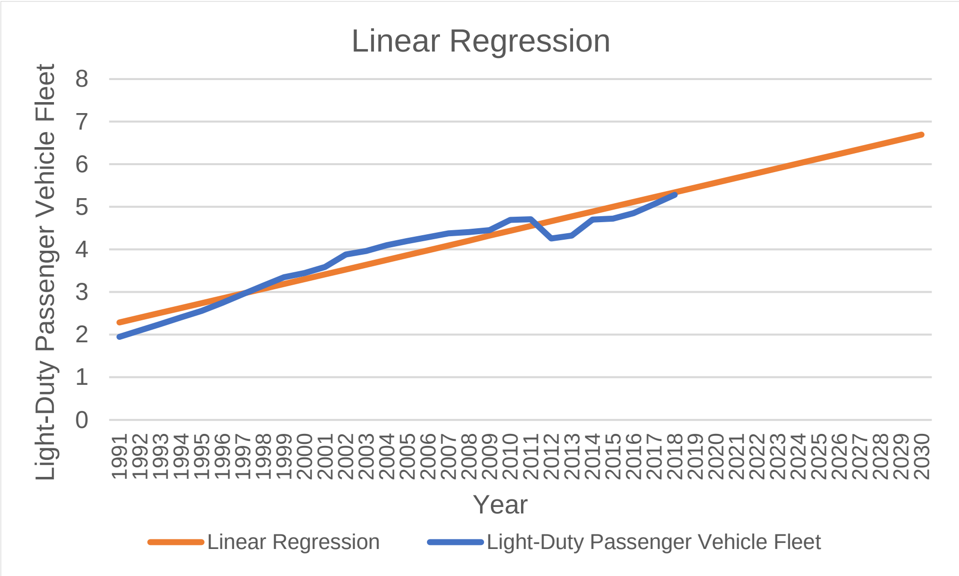

Figure 6. Linear Regression of LP Vehicle Fleet 1991-2018.

Given the results obtained from the linear regression, the prediction for the size of the LP vehicle fleet in 2030 is 6,695,724 vehicles.

As mentioned, the *base* scenario assumes that Portugal achieves a minimum procurement level for the share of clean LP vehicles of 29.7%, over the period from 02 August 2021 to 31 December 2030. As such, within these dates, 29.7% of all LP vehicles sold must be EVs. However, as the annual values associated with the size of the LP EV vehicle fleet in Portugal were only obtained up to 2018, this research assumes that the dates to which regulation [49] is applied are extended to include the period between 01 January 2019 and 01 August 2021.

According to the linear regression model, the LP vehicle fleet increases in annual increments of 113,008. As such, as of 2019, the *base* scenario assumes that the number of yearly LP EV sales in Portugal is approximately 33,563.

According to the Portuguese Institute of Mobility and Transport - Instituto de Mobilidade e Transportes (IMT) – in *Anuário Estatístico da Mobilidade e dos Transportes 2018* [51], the registered number of LP EVs in Portugal at the end of 2018 was 19,689 vehicles. Thus, according to the *base* scenario, the number LP EVs in Portugal by 2030 will be 422,445. Figure 7 illustrates the development of yearly LP EV penetration according to the *base scenario*.

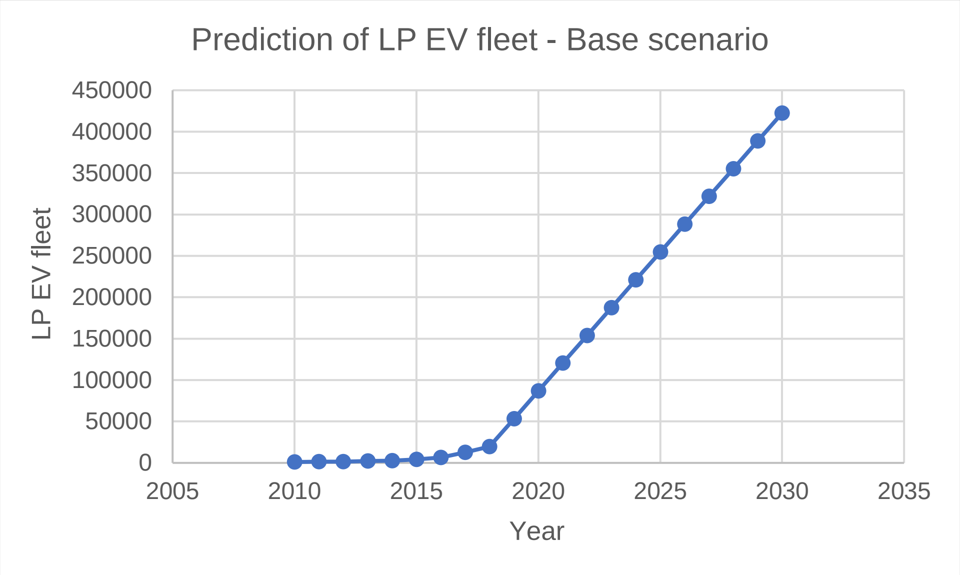

Figure 7. Prediction of LP EV Fleet in 2030 – Base Scenario.

3.2.3. Optimistic Scenario

The *optimistic* scenario is based on information published by the Portuguese government in *Roteiro para a Neutralidade Carbónica 2050 – Estratégia de Longo Prazo para a Neutralidade Carbónica da Economia Portuguesa em 2050* [45]. The document states that within the LP vehicle sector, diesel fuel will no longer be cost-effective by 2030, and gasoline fuel by 2040. As such, the national government has set a target to secure at least 30% of its mobility demand through electrified sources.

Bearing the above in mind and considering the regression model obtained in section 3.2.2, the *optimistic* scenario predicts that, by 2030, 30% of Portugal's LP vehicle fleet is composed of EVs. As the prediction produced by the regression model estimates a total of 6,695,724 LP vehicles in Portugal by 2030, the *optimistic* scenario assumes that the Portuguese LP EV fleet, by 2030, will be made up of 2,008,717 vehicles.

The results obtained for each scenario will be applied to each of the four seasons, as well as to the different charging strategies tested in this research. Table 1 presents the number of LP EVs associated with each scenario adopted for this study. For the remainder of this thesis, LP EVs will be merely designated as EVs.

Table 1. Size of the LP EV Fleet per Scenario.

Scenario	Size of EV fleet
Pessimistic	85,925
Base	422,445
Optimistic	2,008,717

3.3. Mobility Patterns of Portuguese Drivers and EV Consumption Rates

This section of chapter 3 is dedicated to analysing the most common distances travelled by Portuguese drivers, and to determining typical electric energy consumption rates registered in EVs. The purpose of this investigation is to quantify typical values of daily EV electric consumption, per vehicle, with the purpose of generating estimates of the daily electric energy demand of the Portuguese EV fleet.

3.3.1. Mobility Patterns

3.3.1.1. Mobility Patterns of Metropolitan Areas of Porto and Lisbon

The mobility patterns built for this research rely on a study that was conducted by INE – *Mobilidade e funcionalidade do território nas Áreas Metropolitanas do Porto e de Lisboa 2017* (IMOB 2017) [52]. The report presents organised statistical data on mobility patterns associated with the main forms of transport in the Metropolitan Areas of Porto (MAP) and Lisbon (MAL). The results presented in the document are based on a survey performed in the MAP and MAL.

The information from the *IMOB 2017* used in this research quantifies the portion of vehicles associated with a respective *Travelled Distance*, according to specific categories. The categories are defined by the travel motive (TM) of each journey. The *Portion of Fleet* and *Travelled Distance* associated with the journeys of each TM are described in tables 2-5, according to the day of the week and the respective metropolitan area.

MAP:

Table 2. TM Characteristics for MAP during Weekday.

TM	Travelled Distance (km)	Portion of Fleet (%)
Work	13.4	36
Study	7.5	13.3
Friend/Family Accompanying	7.1	19.3
Leisure	16.9	6.6
Shopping	6.9	12.6
Personal Affairs	12	12
Other Activities	16.5	0.2

Table 3. TM Characteristics for MAP during Weekend.

TM	Travelled Distance (km)	Portion of Fleet (%)
Work	13.4	13
Study	7.5	1
Friend/Family Accompanying	7.1	8
Leisure	16.9	21
Shopping	6.9	36
Personal Affairs	12	21
Other Activities	16.5	0

MAL:

Table 4. TM Characteristics for MAL during Weekday.

TM	Travelled Distance (km)	Portion of Fleet (%)
Work	14.8	36.1
Study	6.9	13.7
Friend/Family Accompanying	7.1	18.5
Leisure	14.2	7.1
Shopping	5.7	14
Personal Affairs	16.9	9.9
Other Activities	12.1	0.7

Table 5. TM Characteristics for MAL during Weekend.

TM	Travelled Distance (km)	Portion of Fleet (%)
Work	14.8	16
Study	6.9	1
Friend/Family Accompanying	7.1	7
Leisure	14.2	22
Shopping	5.7	38
Personal Affairs	16.9	16
Other Activities	12.1	0

As can be seen in the tables above, the *Portions of Fleet* associated with each TM differ according to weekday or weekend and metropolitan area. However, unlike the *Portions of Fleet*, the *Travelled Distances* associated to each TM are equal during weekdays and weekends for each metropolitan area.

3.3.1.2. Combined Mobility Pattern for Metropolitan Areas of Porto and Lisbon

This subsection describes the steps carried out to create a unique set of data which combines the mobility patterns of both MAP and MAL (MAP + MAL), described in tables 2-5. To obtain said information, a weighted arithmetic average [53] of the *Travelled Distance* associated with each TM was calculated, according to equation 4.

$$\bar{x}_i = \frac{\sum_{j=1}^{n} w_{ij} x_{ij}}{\sum_{j=1}^{n} w_{ij}} \tag{4}$$

Where:

$\bar{x}_i$: weighted arithmetic average of *Travelled Distance* associated to TM i of MAP + MAL

w_{ij} : weight associated to TM i in metropolitan area j

x_{ij} : *Travelled Distance* for TM i in metropolitan area j

The weights, w_{ij}, were calculated using equation 5, which is based on the number of daily journeys recorded, per TM, in both metropolitan areas (Figures 8 and 9). These input variables were retrieved from *IMOB 2017*.

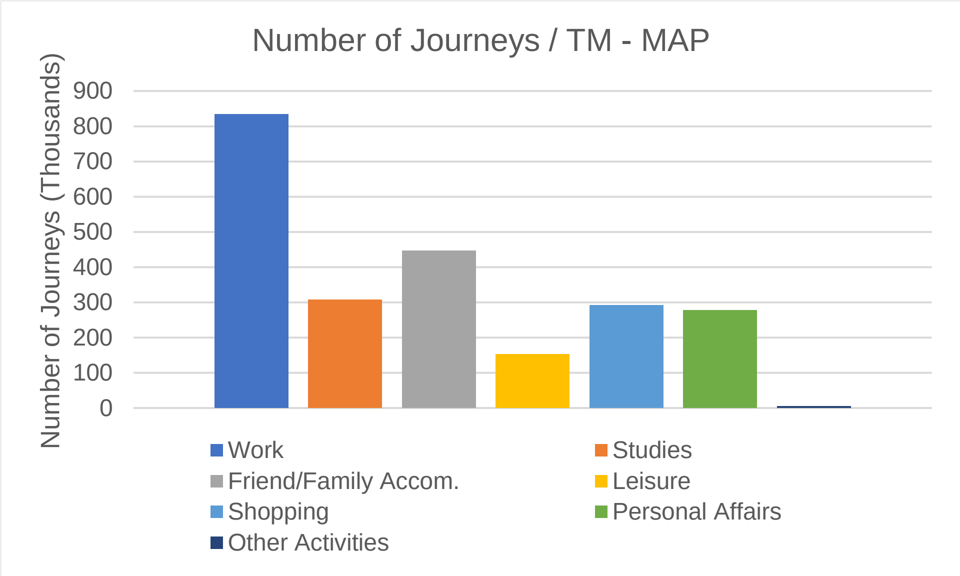

Figure 8. Number of Journeys per TM in MAP.

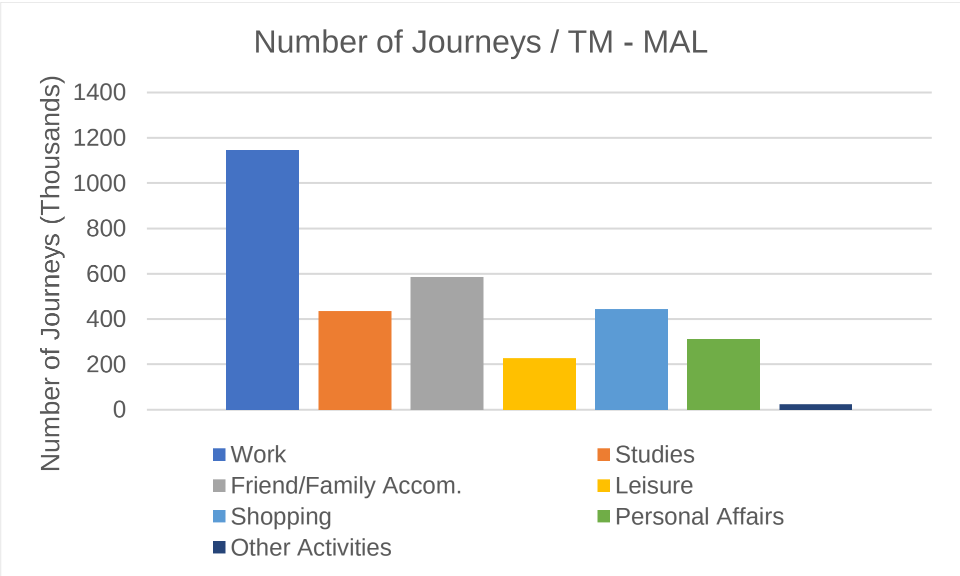

Figure 9. Number of Journeys per TM in MAL.

$$w_{ij} = \frac{Number\ of\ Journeys_{ij}}{\sum_{j=1}^{n} Number\ of\ Journeys_{ij}} \tag{5}$$

Where:

$Number\ of\ Journeys_{ij}$: Number of journeys in metropolitan area j associated to TM i

Similar to the *Travelled Distance*, the *Portion of Fleet* associated with each TM of MAP + MAL was calculated through a weighted arithmetic average which also makes use of the weight values obtained in equation 5. As such, the weighted arithmetic average of the *Portion of Fleet* associated with each TM of MAP + MAL can equally be calculated through equation 4, in which the values associated with x_{ij} correspond to the *Portion of Fleet* associated with TM i in metropolitan area j. A more detailed explanation of the mathematical processes used to achieve this calculation can be found in appendix B – section B.1.

Tables 6 and 7 present the results of the abovementioned computations.

Table 6. TM Characteristics for MAP + MAL during Weekday.

TM	Travelled Distance (km)	Portion of Fleet (%)
Work	14.2	36.06
Study	7.1	13.53
Friend/Family Accompanying	7.1	18.85
Leisure	15.3	6.9
Shopping	6.2	13.44
Personal Affairs	14.6	10.89
Other Activities	12.9	0.61

Table 7. TM Characteristics for MAP + MAL during Weekend.

TM	Travelled Distance (km)	Portion of Fleet (%)
Work	14.2	14.74
Study	7.1	1
Friend/Family Accompanying	7.1	7.43
Leisure	15.3	21.6
Shopping	6.2	37.21
Personal Affairs	14.6	18.35
Other Activities	12.9	0

3.3.1.3. Mobility Patterns of Portuguese Drivers

This section illustrates the steps taken to obtain a set of data resembling mobility patterns of the whole of Portugal. This information was built from the combined mobility patterns of MAP + MAL described in 3.3.1.2.

According to the *Regulation (EC) No 1059/2003 of the European Parliament and of the Council* [54], the *Nomenclature of territorial units for statistics* (NUTS) subdivides the geographical territory covered by the member-states of the EU into three levels for statistical analysis. These three levels are known as NUTS I, NUTS II and NUTS III and are illustrated in figure 10 for the Portuguese territory.

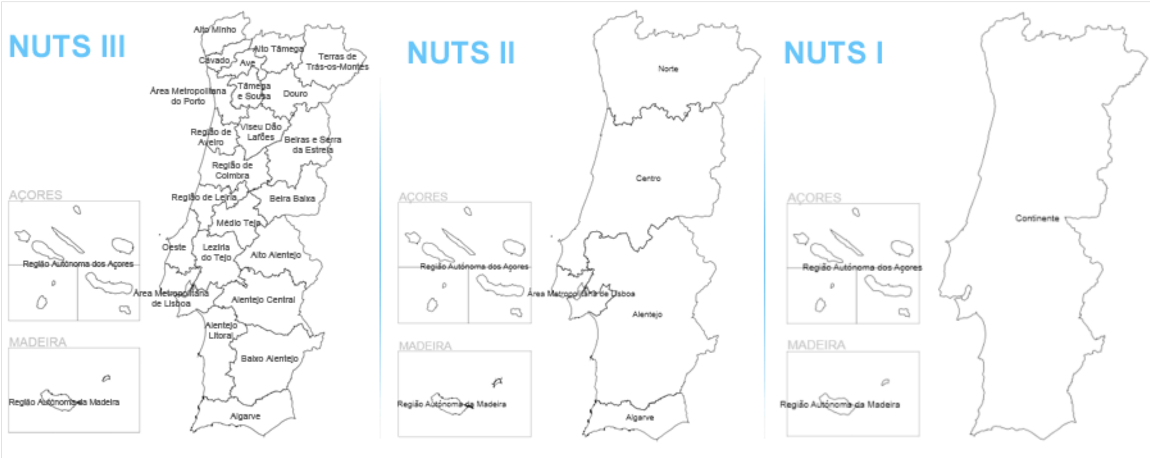

Figure 10. NUTS I, II and III of Portugal [55].

As is evident from figure 10, MAL is taken into consideration in NUTS II and III. However, MAP and MAL are both considered only under NUTS III. As such, NUTS III was used to establish the desired mobility patterns of the remaining Portuguese regions, in accordance with the variables expressed in tables 6 and 7.

According to the *Diário da República, 1ª série – N.º 176 – 12 de setembro de 2013* [56], NUTS III subdivides the Portuguese territory into intermunicipal communities (IC) and metropolitan areas, which together make up intermunicipal entities (IE). Apart from the difference in population scale, the two sets of IEs present similar features, such as:

1. *Networks of public water distribution, basic sewage infrastructure and treatment of wastewater and urban waste;*
2. *Network of Health care facilities;*
3. *Networks of education and professional training;*
4. *Territorial planning, nature conservation and natural resources;*
5. *Security and civil protection;*
6. *Transports and mobility;*
7. *Network of public facilities;*
8. *Promotion of economic, social and cultural development;*
9. *Networks of cultural, sports and leisure equipment.*

Given the abovementioned similarities between IEs, the *Travelled Distances* of Portuguese drivers in the ICs were linearly extrapolated from the distances obtained in MAP + MAL according to the difference between the geographical areas of said metropolitan areas and respective ICs. Equation 6 presents the formula used to perform the linear extrapolation [57]. Note that both MAP + MAL and the ICs are identified with the subscript of IEs – k.

$$y_{ik} = \frac{y_{i1} - y_{i0}}{x_1 - x_0}(x_k - x_0) + y_{0k}, \qquad where\ x_0 = y_{i0} = 0 \tag{6}$$

Where:

y_{ik} : *Travelled Distance* of TM i in IC k

x_k : Area of IC k

y_{i1} : *Travelled Distance* of TM i in MAP + MAL ($k = 1$)

y_{i0} : *Travelled Distance* of TM i inexistent location ($k = 0$)

x_1 : Area of MAP + MAL ($k = 1$)

x_0 : Area of inexistent location ($k = 0$)

The area and *Travelled Distances* associated with the inexistent location, x_o and y_{i0}, and the MAP + MAL, x_1 and y_{i1}, respectively, are used as references to indicate how the area of each IC impacts on the calculation of its *Travelled Distances*. Specifically, the inexistent location indicates that if the area of a certain IC is zero, the *Travelled Distance* associated with any of its TMs will also be zero. Furthermore, if a certain IC presents an area equal to that of MAP + MAL, the *Travelled Distance* associated with each TM will be equal to that which is registered in MAP + MAL. As such, according to equation 6, the *Travelled Distance* associated with the TMs of each IC will depend on the linear relationship between the *Travelled Distances* and areas of the inexistent location, on the one hand, and those of MAP + MAL, on the other.

With regard to the input information associated with MAP + MAL in the computation of the linear extrapolation, the *Travelled Distances*, y_{i1}, correspond to the data presented in tables 6 and 7. Moreover, the single area of MAP + MAL, x_1, was calculated through a weighted arithmetic average which combines the area of both locations according to their proportional difference. The areas of both MAP and MAL are indicated in table 8.

Table 8. Geographical Areas of MAP and MAL [52].

Metropolitan Area	Geographical area ($\boldsymbol{km^2}$)
Porto	2041
Lisbon	3015

Accordingly, the combined area of MAP + MAL, x_1, is 2621.85 km^2. The mathematical formulations corresponding to the weighted arithmetic average of the single area associated with MAP + MAL can be consulted in appendix B – section B.2. The areas associated with the ICs, x_k, were obtained from a set of documents named *Statistical Yearbook of Alentejo, Algarve, Centro and Norte Region* [58, 59, 60, 61], published by INE.

Figure 11 illustrates the results of the linear extrapolation for weekdays. The set of points represent the *Travelled Distances* associated with the TMs of each IC. The group of points belonging to a common value on the x-axis identify the *Travelled Distances* of all the TMs in a particular IC.

Lastly, a weighted arithmetic average was also used to develop a set of data representing the combined mobility patterns of the entire Portuguese population. This weighted arithmetic average was used to calculate the *Travelled Distance* of each TM in Portugal according to the size of the population of each IE. Hence, the weight of each *Travelled Distance* used in the computation is dependent on the population size of its respective IE. The size of the populations associated with each IE was also obtained from the aforementioned *Statistical Yearbook* [58, 59, 60, 61] collection, and the mathematical processes used to produce the weighted arithmetic average can be consulted in appendix B – section B.3.

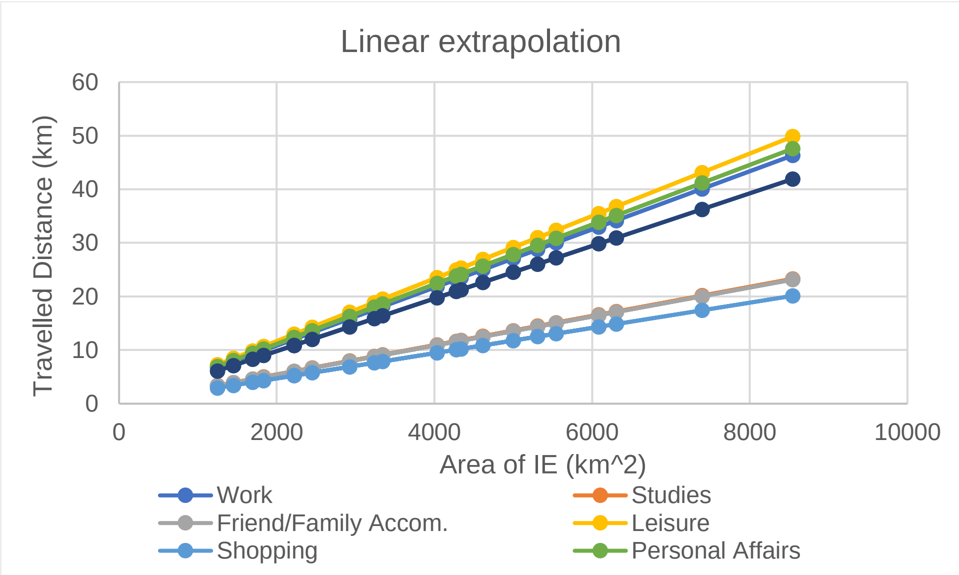

Figure 11. Results of Linear Extrapolation – Weekdays.

Tables 9 and 10 present the data associated with the mobility patterns of Portuguese drivers. For simplicity, the *Portion of Fleet* associated with the mobility patterns of Portugal was assumed as being equal to that of MAP+MAL. This information was subsequently used in the various simulations carried out to identify the configuration of the daily LDs in Portugal in 2030.

Table 9. TM Characteristics for Portuguese Population during Weekday.

TM	Travelled Distance (km)	Portion of Fleet (%)
Work	16.6	36.06
Study	8.4	13.53
Friend/Family Accompanying	8.3	18.85
Leisure	17.9	6.9
Shopping	7.2	13.44
Personal Affairs	17.1	10.89
Other Activities	15.1	0.61

Table 10. TM Characteristics for Portuguese Population during Weekend.

TM	Travelled Distance (km)	Portion of Fleet (%)
Work	16.6	14.74
Study	8.4	1
Friend/Family Accompanying	8.3	7.43
Leisure	17.9	21.6
Shopping	7.2	37.21
Personal Affairs	17.1	18.35
Other Activities	15.1	0

3.3.2. EV Consumption Rates

This section is dedicated to analysing EV electrical energy consumption ratings with the purpose of validating the particular EV consumption rates used in the simulations performed in this research.

Examples of common EVs are the midsize 2016 Nissan Leaf and the SUV 2016 Tesla Model X, which are rated at 0.19 kWh/km and 0.24 kWh/km, respectively [62]. Although the values associated with the electrical energy consumption of EVs are unique to each vehicle, in general, the consumption ratings of EVs of a similar size do not differ significantly from one another. This is evident in the studies performed by *Perujo et al.* [63] and *Loisel et al.* [64], in which the authors have classified EV consumption ratings into categories according to the size of the respective vehicle – see table 11.

Table 11. Consumption Rates of EVs [64].

EV size	Electricity consumption (kWh/100km)
Mini	11
Small	15
Compact	18
Large	23

Studies that have made use of EV consumption rates to carry out simulations typically use the values within the ranges mentioned above. For example, *Darabi et al.* [17], *Wu et al.* [65] and *Chen et al.* [66] rely on consumption rates of 0.22 kWh/km, 0.15 kWh/km and 0.19 kWh/km, respectively.

Yuksel et al. [67] studied the variation of the Nissan Leaf's energy consumption rate according to the ambient temperature in which the vehicle is being driven. Multiple tests, in which the EV was driven in different ambient temperatures, were carried out to draw conclusions about the vehicle's energy consumption ratings. Figure 12 illustrates the results obtained from the various tests, as well as a curve (red), obtained through a least squares regression using the lowest polynomial order which follows the trend of the acquired data.

Since part of the objective of this dissertation is to obtain the daily LD for different seasons of the year, and since the Nissan Leaf is a predominant vehicle within the Portuguese EV fleet [68], the curve illustrated in figure 12 was used to determine the energy consumption levels registered in the different seasons of the year. The curve is described mathematically by equation 7.

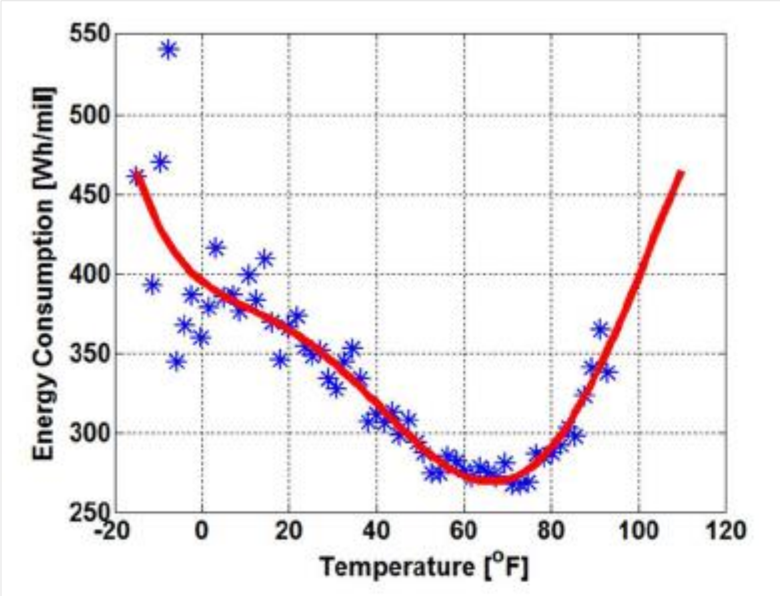

Figure 12. EV Energy Consumption vs. Ambient Temperature [67].

$$c_i(T_i) = \left(\sum_{n=0}^{5} a_n T^n\right) \quad (7)$$

Where:

$c_i(T_i)$: Energy consumption rate in season i (kWh/mi)

T : Arithmetic mean of temperatures registered in season i (ºF)

a_n : coefficients of polynomial regression (kWh/mi/ºF)

In which:

$$a = [0.395 \quad -0.0022 \quad 9.1978 * 10^{-5} \quad -3.9249 * 10^{-6} \quad 5.2918 * 10^{-8} \quad -2.0659 * 10^{-10}]$$

As is noted from equation 7, the input values associated to temperature, T, are expressed in Fahrenheit. As the data relating to temperature acquired for the present thesis is expressed in Celsius, equation 7 was mathematically manipulated so that the input values for T could be converted from Celsius to Fahrenheit [69]. Furthermore, as the present work required the values of energy consumption rate, $c_i(T_i)$, to be expressed in kWh/km, equation 7 was multiplied by 0.62, which corresponds to the conversion factor required to convert kWh/mi to kWh/km [70]. The above manipulations to equation 7 result in equation 8, which was used to calculate the energy consumption rates in kWh/km.

$$c_i(T_i) = 0.62 * \left[\sum_{n=0}^{5} a_n (1.8T_i + 32)^n\right] \quad (8)$$

As the RLDs, mentioned in section 3.1 of this chapter, are all in respect of the year 2017, the temperatures of each season used to calculate the EV energy consumption rates were obtained from the document *Boletim Climatológico Anual – Portugal Continental – 2017* [71], which indicates the arithmetic mean temperature associated with each season of 2017, presented in table 12. The temperatures presented in table 12 were subsequently used to calculate the EV consumption rates for both weekdays and weekend days of the respective seasons in 2017.

Table 12. Arithmetic Average Temperature/Season for Weekdays [71].

Season	Arithmetic mean temperature (ºC)
Winter	9.9
Spring	15.6
Summer	30.2
Autumn	24.4

Given equation 8 and the data established in table 12, the values associated with the electric energy consumption of EVs used in the simulations carried out in this thesis are presented in table 13.

Table 13. EV Energy Consumption Ratings per Season.

Season	EV energy consumption rates (kWh/km)
Winter	0.180
Spring	0.168
Summer	0.195
Autumn	0.172

Comparing the values of table 13 with the abovementioned reference values, it is clear that they fall roughly into the same range. As such, the values of table 13 are valid to use in the simulations performed in this thesis.

3.4. Charging Infrastructure, Patterns and Strategies

As the title indicates, this section is dedicated to analysing and defining the EV charging infrastructure, patterns and strategies used in the simulations performed in this thesis. *Charging infrastructure* identifies and discusses the charging conditions used in the simulations within this research, *i.e.* the type of charging modes/power for public and private charging infrastructure. *Charging patterns and strategies* discusses the times and locations of different EV charging operations during the weekdays and weekend days, as well as the portion of vehicles charging at such times and locations. Finally, this section also describes the charging strategies considered in this dissertation.

3.4.1 Charging Infrastructure

As this dissertation focuses on EV charging within Portugal, the charging infrastructure assumed for the simulations is that which is required by the European Standard. The standards for EV charging infrastructure (*i.e.* charging systems, plugs and sockets) in Europe are defined by the International Electrotechnical Committee (IEC). In the document *IEC – 61851*, the IEC defines three different charging categories as a function of the rated power used and the recharging time, which are subsequently indicated [72]:

1. ***Low power or slow charging****:* Rated power less than 3.7kW; used in a domestic environment or long-time EV parking.

2. ***Medium power or normal charging:*** Rated power from 3.7 to 22kW; used for private and public EV charging (semi-public).

3. ***High power or fast charging:*** Rated power greater than 22kW; used for public EV charging.

The main connection types associated with each category are indicated in table 14:

Table 14. Characteristics of Charging Methods [72].

Charge Method	Connection	Power (kW)	Location
Slow Charging	1-Phase AC	≤ 3.7	Domestic
Normal Charging	1- or 3-Phase AC	3.7 – 22	Semi-public
AC Fast Charging	3-Phase AC	> 22	Public
DC Fast Charging	DC	> 22	Public

3.4.1.1. Charging Infrastructure: Charging Modes and Plugs

As mentioned, the type of charging equipment used has a clear influence on charging operations. As such, this section is dedicated to briefly presenting and defining the attributes of the different charging modes used in the simulations carried out in this research. A more detailed analysis of charging components, which discusses charging modes and the most commonly used plugs in the EU, can be found in appendix C - sections C.1 and C.2.

Currently, there are four charging modes used in Europe, which are respectively designated as: *Mode 1*; *Mode 2*; *Mode 3*; and *Mode 4*. *Modes 1* to *3* use AC current, while *Mode 4* uses DC current.

Charging *Mode 1* and *2* are both carried out through conventional household sockets or monophasic/triphasic industrial plug sockets. With reference to table 14, both charging modes can be carried out using *Slow Charging* or *Normal Charging*. However, since *Mode 1* is regarded as a charging mode with a low level of safety, its usage is not recommended. As such, it will be disregarded in this research.

Mode 3 charging uses a charging station or a wallbox (EV charging equipment capable of being installed in a private setting) equipped with a dedicated EV charging plug. Within the EU, the charging plugs used for *Mode 3* charging are the *IEC 62196-2 "Type 2"*, also known as *Mennekes connector*. With reference to table 14, *Mode 3* can be operated using *Normal Charging* or *AC Fast Charging*.

Similarly, *Mode 4* also uses a dedicated EV charging station with a specific plug for its charging operation. Within the EU, the charging plug associated with *Mode 4* charging is the *Combined AC/DC*

Charging System, also known as *CCS - Combo 2*. With reference to the information illustrated in table 14, this charging mode is operated using *DC Fast Charging* [38].

3.4.2. Charging Patterns and Strategies

3.4.2.1. Charging Patterns

This section is dedicated to analysing the most common daily EV charging patterns. Specifically, it intends to investigate the charging times, modes, and locations associated with the current EV fleet in Portugal. Further, the portions of EV fleet associated with the most common charging times, modes, and locations are quantified. The collection of such data is intended to indicate how current EV charging patterns should be mathematically modelled in the simulations.

3.4.2.1.1. Charging Patterns: Selected Charging Modes

As mentioned in chapter 2, the literature typically divides all charging operations into two major categories: private and public charging. Private charging encompasses charging events which take place in a household or a workplace environment. In contrast, public charging refers to charging operations that take place in public charging stations, in which any car is entitled to make use of the equipment [73, 74, 75, 76, 77].

Analysing the European context, *Wirges* [38] states that several pilot projects, carried out in a number of countries, have shown EV user preference for charging in private settlements as opposed to public charging infrastructure. Citing information from the *MINI E trial* conducted in Berlin, charging events taking place on public infrastructure only accounted for 3% of the total EV charging. Furthermore, 46% of the users had never used a public charging station. Similar to the studies discussed in the *Literature Review*, other projects have also identified that private charging operations took place in two environments: workplace and home. For example, the United Kingdom (UK) project *Plugged in Places* found that 42% of charging operations were carried out at home, and 23% at workplaces, respectively. The remaining 35% were carried out in public, *i.e.* commercial places and on-street charging points.

The preference for private charging is noticeable. However, in some European countries, the prevalence of detached housing is low, which contributes to a lack of private charging points, especially at home. The Netherlands, for example, has invested heavily in public charging infrastructure and now has one of the highest shares of *Low Power* public charging points in the world, making it the country with the lowest number of PEVs per charging point [76]. Since Portugal is a European country, it is important to factor in public charging events.

Given the above information regarding charging modes and public/private charging events, this research applies different charging power rates according to the environment in which the charging operation is carried out, as indicated in table 15, which specifies the values of power associated to the various charging events considered in this research.

As already explained, charging via *Mode 1* has been excluded from this research, as it is unsafe and therefore unlikely be used in 2030. Further, this research assumes that the demand for charging EVs with the *Slow charging* method, *i.e.* with rated power of 3.7kW, will be reduced by 2030. As such, the minimum power rate assumed to charge EVs in a private setting, be it through a normal household socket or a wallbox, corresponds to the lowest power rate associated with the *Normal charging* method – 7.4kW [38].

Table 15. Private and Public Charging Characteristics.

Charging Event	Charge Method	Charging Mode	Power (kW)
Private	Normal – Home	Mode 2 or 3 (AC)	7.4
	Normal – Work	Mode 2 or 3 (AC)	7.4
Public	Normal – Home	Mode 3 (AC)	22
	Normal – Work	Mode 3 (AC)	22
	Normal – Other	Mode 3 (AC)	22
	Fast – Other	Mode 3 or 4 (AC or DC)	50

Within the EU, *Normal charging* in public stations presents a maximum value of 22kW [78]. As such, this is the value assumed for such charging events. Furthermore, the power rate value assumed for *Fast charging* is 50kW, as it is the maximum value associated with *Fast charging* operations [38].

In addition to *Slow*, *Normal* and *Fast charging*, a more recent form of charging has emerged, designated as *Ultra-fast charging*. However, presently, this charging method is not commonly used. As such, it will not be included in this thesis as predicting the penetration of this charging method is difficult given the scarcity of data on its use.

3.4.2.1.2. Charging Patterns: Time and Location of Charging Events

As mentioned in the *Literature Review*, private charging operations are easily identifiable, as they mostly take place in the morning, upon the user's arrival at work, or in the evening, following the arrival of the EV user at home.

Public charging events are typically carried out in two different settings: *1.* Where users do not have access to private charging sources and therefore carry out their EV charging via a public charging station either in the morning, upon arrival at work during workdays, or in the evening, upon arrival at home during workdays and weekends; and *2.* in commercial places, where vehicles are parked for a considerable amount of time due to leisure, shopping, sports or other activities, during both workdays and weekends [15, 79].

To determine the time of arrival of vehicles throughout weekdays and weekends at the abovementioned locations, data from *IMOB 2017* [52] was retrieved (depicted in figure 13 and 14, respectively). These figures illustrate the arrival times of journeys undertaken in the MAL.

When analysing the arrival times of journeys undertaken during weekdays (figure 13), two peaks are easily distinguished. The first peak is registered in the morning, and the other in the evening. These peaks are a result of the fact that the highest number of arrivals are registered at approximately 09:00 and 19:00, when users arrive at work in the morning, and at home in the evening, respectively. As such, these peaks encompass both private and public charging. Additionally, a smaller peak is noticeable during the early afternoon hours, with the highest number of arrivals registered at roughly 14:00. This peak represents journeys completed during lunch hours and therefore have commercial places and other locations as their destination. The charging activities associated with these journeys only use public charging infrastructure [52, 80, 15, 81].

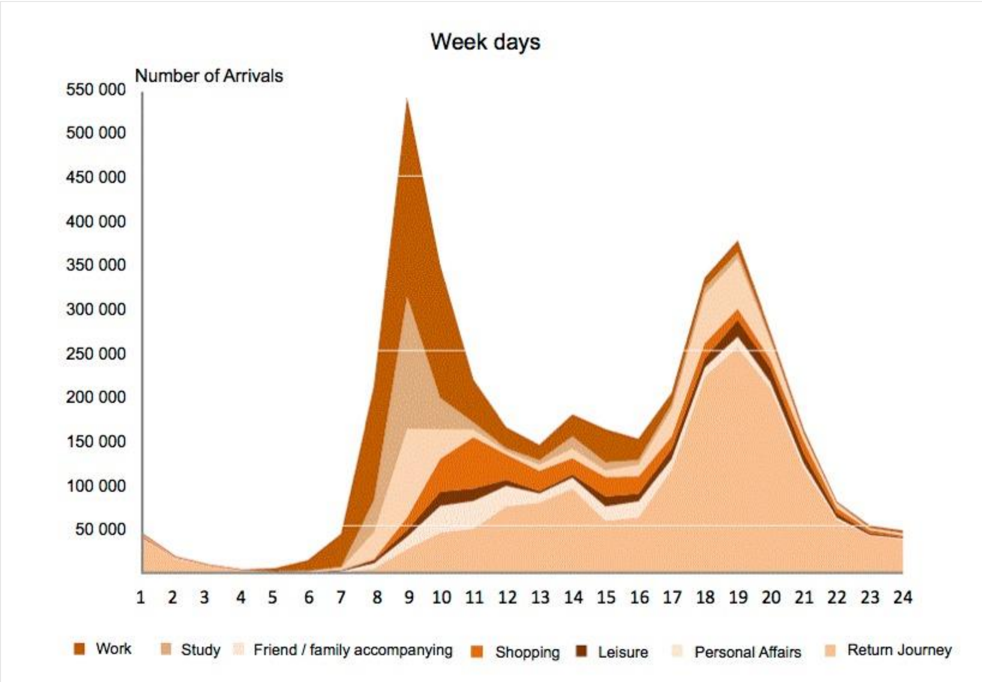

Figure 13. Distribution of Arrival Times on a Workday in MAL [52].

The configurations of arrival times during the weekend, shown in figure 14, are less obvious. To better understand the data, the distributions represented in figure 14 were compared with the results obtained from the study *European-wide study in big data for supporting road transport policy* [80]. This study identifies, by collecting data from navigation systems, the travel behaviours of commercial and private vehicles within fifteen different cities in the EU, one of them being Lisbon. The results of the research can be found in figure 15.

Contrary to figures 13 and 14, figure 15 represents the number of vehicles *en route* instead of arrivals. However, it is nevertheless possible to note that the configuration of figure 13 resembles a very similar pattern to that which is represented in figure 15 during weekdays. As such, for the purposes of this research, the results of 15 are assumed as arrival times for weekends.

Taking the above into consideration, it is possible to identify two distinct arrival peaks for commercial vehicles during the weekend in Lisbon, as reflected in figure 15. The highest number of vehicles are registered at 12:00 and 19:00, thus creating the two peaks. Although there is no data available in respect of private vehicles in Lisbon, the results obtained for commercial vehicles in Lisbon and private vehicles in other cities during the weekend are relatively similar [80]. Thus, for the weekend, the present thesis assumes that all EV arrival times follow the configuration represented by commercial vehicles in Lisbon in figure 15, in which two distinct arrival peaks are noticeable – where the highest number of arrivals are registered at 12:00 and 19:00. These assumptions are similar to those adopted in *Electric Vehicle Charging Behaviour Study* [81], which identifies no morning peak charging events over the weekend due to a 73% reduction in drivers travelling into work. As such, during the weekend, EV users arriving in the first peak charge their vehicle using public charging infrastructure, and charging events belonging to the second peak are made up of a combination of private and public charging. Although evidence has been provided to support the adoption of this assumption in this research, weekend charging patterns differ between studies. For example, *Weiller* [15], who analyses EV charging patterns in the United States, identifies only one peak of consumption during the weekend, which corresponds to the first peak assumed for this research.

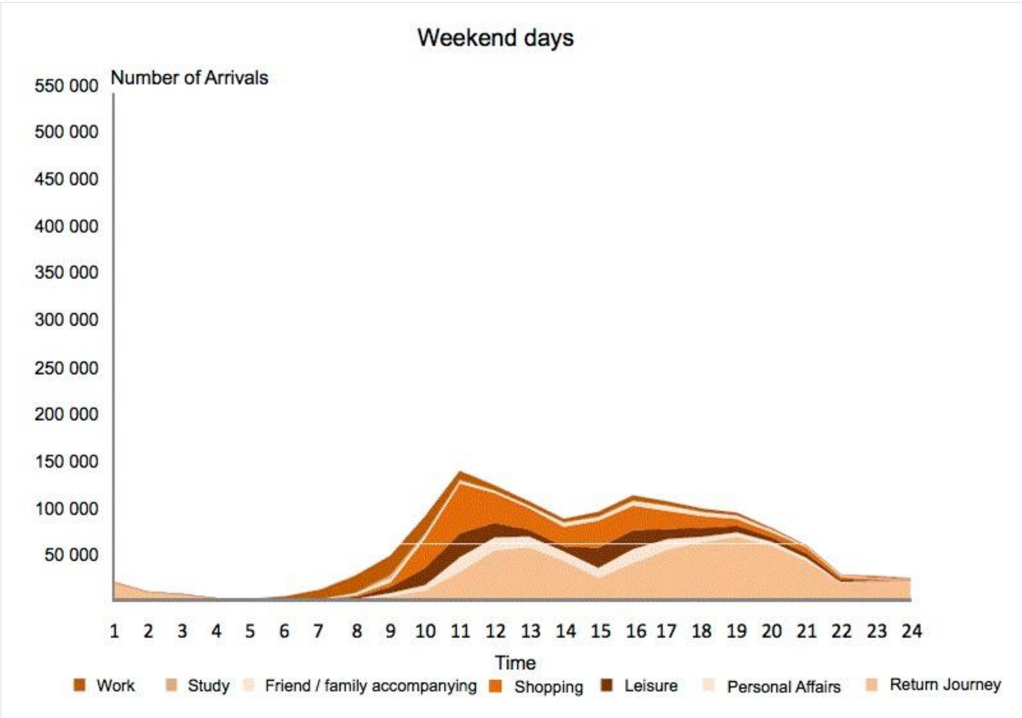

Figure 14. Distribution of Arrival Times on a Weekend Day in MAL [52].

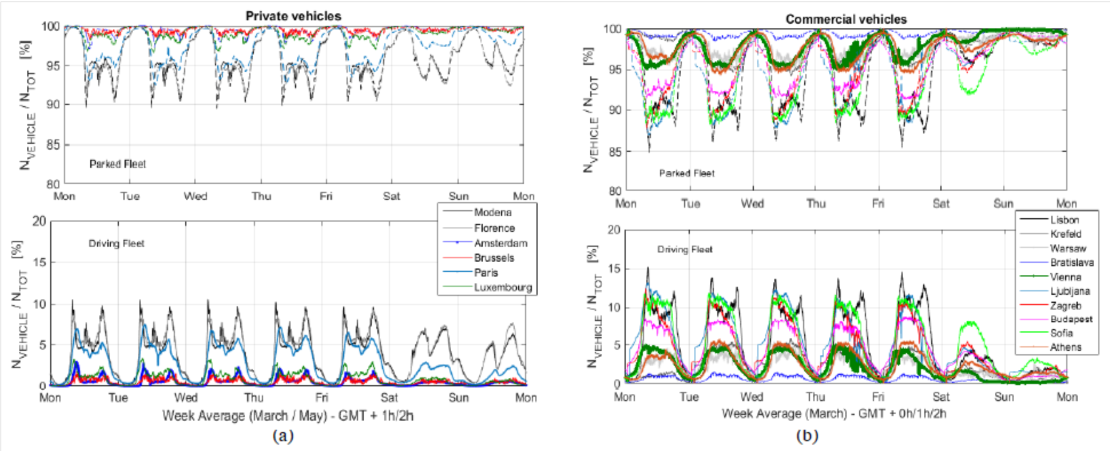

Figure 15. Distribution of a) Private and b) Commercial Vehicle Fleets in Motion and Parked during the Week [80].

Table 16 presents the aforementioned charging behaviour patterns for weekdays and weekends, which were subsequently used in the simulation models of this thesis.

Table 16. Charging Pattern Characteristics for Weekdays and Weekends.

Day	Peaks	Charging Point	Location
Weekday	Morning – 09:00	Private + Public	Work + Other
	Afternoon – 14:00	Public	Other
	Evening – 19:00	Private + Public	Home + Other
Weekend	Afternoon – 12:00	Public	Other
	Evening – 19:00	Private + Public	Home + Other

Similar to the research discussed in the *Literature Review*, the curves describing the start time of the charging activities (*i.e.* the arrival times of EVs) were mathematically modelled by the Gaussian distribution for the purposes of this research. This modelling was chosen because of the close resemblance between the arrival times of vehicles throughout the week, and the configuration of the Gaussian probability distribution. Equation 9 presents the formula associated with the normal probability density function [82].

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} \tag{9}$$

Where:

$f(x)$: probability density of EV arrivals at time x

x : time

σ : standard deviation (hours)

μ : mean

Figure 16 presents an example of the application of equation 9, where μ = 19:00 and σ = 3 hours, which corresponds to the distribution of EV arrivals at home in the evening, during a weekday.

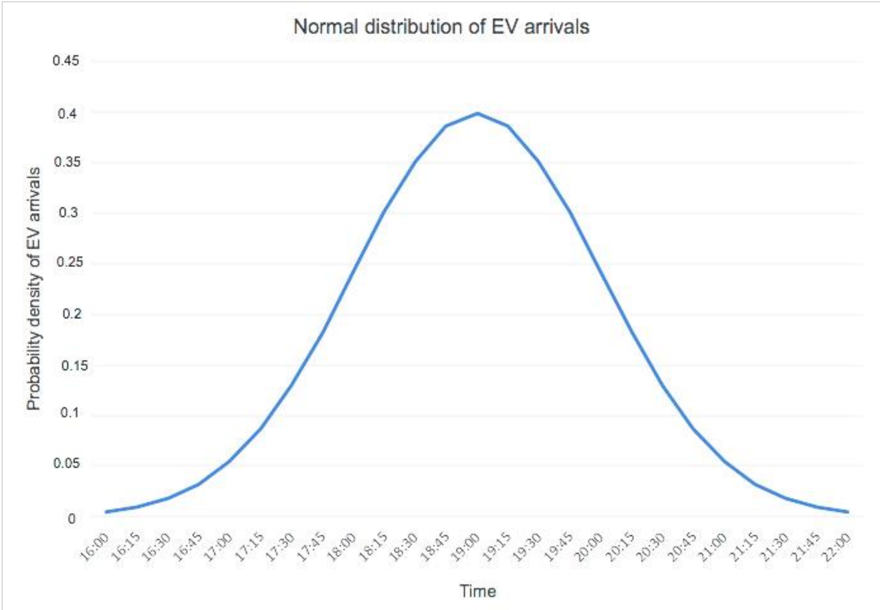

Figure 16. Normal Probability Density Distribution of EV Arrivals on an Evening Weekday.

The BLDs acquired for this research depict the daily load demand represented in 15-minute increments. As such, the normal distribution applied in this work represents the number of EV arrivals in 15-minute increments, as is clear in figure 16.

Since the normal distribution is a continuous probability distribution, it is impossible to assign a discrete value to the percentage of EV arrivals for each 15-minute increment [82]. As such, the normal cumulative distribution function, shown in equation 10, was applied to determine the increase in percentage of EV arrivals for each 15-minute increment.

$$F(x) = \phi\left(\frac{x-\mu}{\sigma}\right) = \phi(Z) \tag{10}$$

Where:

$F(x)$: Cumulative percentage of initiated charging events at time x (%)

Z : standard deviation associated to time x

The cumulative number of EV arrivals, reflected as a percentage, associated with each value of Z can be found in the spreadsheet of appendix D [83]. Figure 17 illustrates the results of the normal cumulative distribution obtained for the example depicted in figure 16.

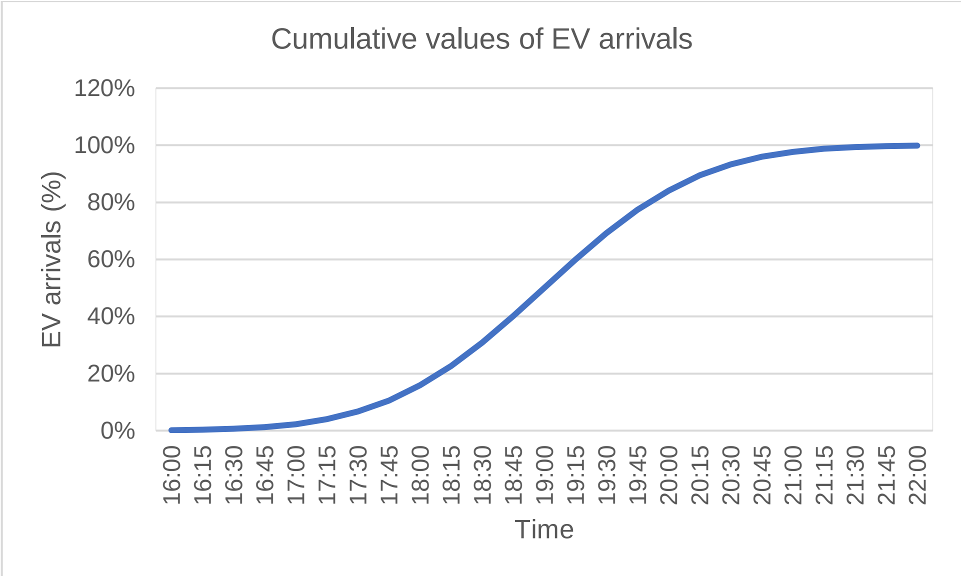

Figure 17. Cumulative Values of EV Arrivals on an Evening Weekday (%).

After obtaining results for the cumulative values of EV arrivals, it was possible to determine the number of EVs arriving every 15 minutes using equation 11.

$$P(x-1 \leq Z < x) = F(x-1) - F(x) \tag{11}$$

Where:

$P(t \leq Z < t+1)$: Percentage of EVs arriving between time $x-1$ and x

The results obtained from the application of equation 11 to the values depicted in figure 17 are illustrated in figure 18.

Figure 18 illustrates the number of EV arrivals, as a percentage, for each 15-minute increment. Similar to the aforementioned figures, figure 18 depicts the configuration of EV arrivals at users' homes, in the evening during a weekday. As equation 11 shows, the values attributed to each 15-minute increment in figure 18 represent the number of arrivals between the indicated time and 15 minutes prior to the indicated time.

The characteristics associated with the normal distribution of the three charging sessions considered in this thesis are set out in table 17.

Table 17. Characteristics of EV Arrival Distributions.

Day	Peak – Mean (μ)	Standard Deviation (σ)
Weekday	Morning – 09:00	1 Hour
	Afternoon – 14:00	40 Minutes
	Evening – 19:00	1 Hour
Weekend	Afternoon – 12:00	1 Hour
	Evening – 19:00	1 Hour

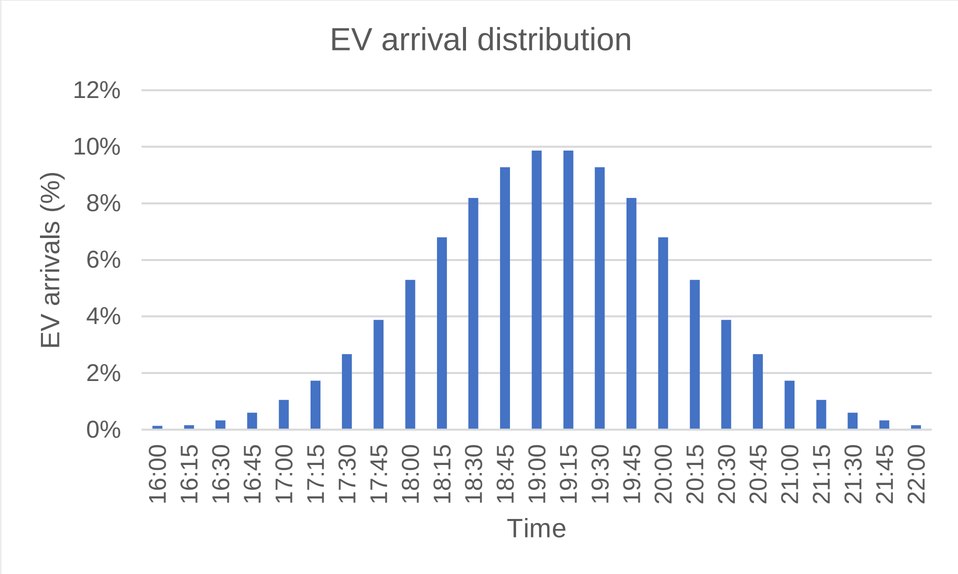

Figure 18. Distribution of EV Arrivals on an Evening Weekday (%).

3.4.2.1.3. Charging Patterns: Quantification of Charging Events

This section attempts to determine the portions of EV fleet charging within each of the periods mentioned in table 17.

Since Portugal is a member of the EU, the information used in the simulations to represent the proportions of EV fleet charged using private infrastructure and public infrastructure for 2030 was obtained from the report *Recharge EU: how many charge points will Europe and its Member States need in the 2020s* [79], authored by *Transport & Environment*. Table 18 indicates the referenced values, in which public charging events are subdivided according to the rated power used.

Table 18. Share of EV Fleet Charging under Private/Public Chargers.

Type	Location	Portion of EV fleet (%)
Private	Home	45
	Work	24
Public	Other – Normal	22
	Other – Fast	9

With regard to public charging, the same report [79] indicates that fast public charging will be overwhelmingly implemented via the abovementioned *Ultra-fast charging* (as opposed to simply *Fast charging*). However, as previously mentioned, information about *Ultra-fast charging* is presently limited. Therefore, in this research, these public charging operations are reflected as being implemented only by *Fast charging*.

Public charging activities take place in the morning, afternoon and evening. As such, it was necessary to quantify the incidence of public *Fast charging* and *Normal charging* taking place in each of the aforementioned periods.

The different portions of EV fleet charged publicly during the abovementioned periods were quantified using research by *Helmus et al.* [84], which analyses public charging events carried out in The Netherlands. Although the present thesis is focused on studying EV charging in Portugal, The Netherlands presents one of the highest numbers of public charging points per EV in the world, and therefore presents a reliable database for information regarding public charging [76]. The results obtained from [84] used in the present thesis are depicted in figure 19.

Figure 19 illustrates two types of charging points: *demand driven* (blue) and *strategic* (red) charging points. According to *Helmus et al.* [84], the *demand driven* charging points are defined as having at least one dedicated user, and as such, have a higher probability of being located in a residential area; on the contrary, the *strategic* charging points are characterised as being used by a wide range of EV users. The latter charging points are typically located in public facilities or strategic locations where occasional use is expected, *i.e.* sporting grounds and leisure locations. However, these charging point classifications are not taken into account for the analysis of the present thesis, and therefore the number of charging activities represented in figure 19 is to be interpreted as the sum of both classifications.

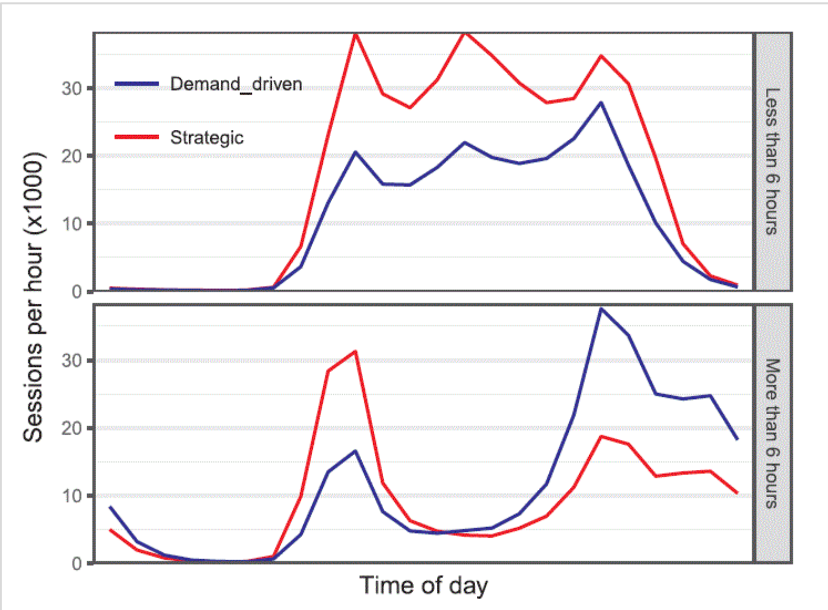

Figure 19. Public Charging Events – Weekdays [84].

The results illustrated in figure 19 represent two categories of public charging during weekdays – public charging with less than 6 hours of charge time (<6h) and with more than 6 hours (>6h). When analysing both categories, it is possible to identify patterns of charging events similar to those previously discussed in this research, with 3 distinct peaks occurring in the <6h category – morning, afternoon and evening – and 2 peaks in the >6h category, which coincide with the morning and evening peaks of the former category.

As such, for the purposes of this research, the >6h category was assumed to represent the charging events initiated by users who do not possess a private charging outlet at work or at home, and therefore charge their vehicle via a public charging point in the vicinity of these locations during the morning and evening, respectively. As these charging operations present some flexibility due to the large amount of time in which the EVs are connected to the grid, these public charging events are assumed to be carried out using *Normal charging* – 22kW.

The <6h category is assumed to encompass charging events that present short connection times [84], and is therefore associated with users who need to charge their vehicle through *Fast charging* – 50kW. These types of public charging activities take place during the morning, afternoon and evening.

The approximated values associated with the overall number of charging sessions per hour in each category are shown in table 19.

Table 19. Share of EV Fleet associated with Public Charging Stations during Weekdays [84].

Charging duration	Time	Charging session/hour	Portion of EV fleet (%)
<6h (Fast) (9%)	Morning	60	3
	Afternoon	60	3
	Evening	60	3
>6h (Normal) (22%)	Morning	45	9.5
	Evening	60	12.5

As is clear from the above column *charging session/hour* in respect of *Fast charging*, the number of charging sessions per hour for Morning, Afternoon and Evening are proportionate to one another in the ratio 1:1:1. This ratio was applied to the corresponding value for *Fast charging* in table 18 (*i.e.* 9%) to distribute the portion of the EV fleet in the same ratio across the three time categories. Similarly, in respect of *Normal charging*, the number of charging sessions per hour for Morning and Evening are proportionate to one another in the ratio 3:4. This ratio was applied to the corresponding value for *Normal charging* in table 18 (*i.e.* 22%) to distribute the portion of EV fleet in same ratio. The results of the application of the ratios are reflected in the column titled *Portion of EV fleet* in table 19.

The results obtained from [84] regarding charging patterns for weekend days relied on different assumptions to those made in this thesis, and were therefore not taken into account. Instead, the reports authored by *Transport and Environment* [79] and *IMOB 2017* [52] were used to determine the share of EVs charging during the established weekend charging schedules.

According to *Transport and Environment* [79], commercial areas should equip 50% of their public or semi-public parking spots with charging infrastructure by 2030. Given this recommendation, the present research assumes that on the weekend, 50% of all public charging activities take place during the aforementioned weekend afternoon timeslot. Furthermore, as private charging activities taking place in workplaces during the week do not occur on the weekend, 50% of private charging events carried out in workplaces during the week are instead completed using commercial public or semi-public charging infrastructure during the weekend. The remaining 50% of public charging activities (*i.e.* those which do not take place during the afternoon) are carried out in the evening slot. Lastly, private home charging takes place in the same way as weekdays. Table 20 identifies the share of EV charging more clearly.

Table 20. Share of EV Fleet associated with Public Charging Stations during Weekend Days.

Charging duration	Time	Portion of EV fleet (%)
<6h (Fast) (9%)	Afternoon	4.5
	Evening	4.5
>6h (Normal) (46%)	Afternoon	23
	Evening	23

As mentioned previously, the share of EV charging events which use private outlets in workplaces during the week use public charging infrastructure during weekends. As such, *Normal charging* public activities during the weekend account for 46% of the fleet.

According to *Morrissey et al.* [85], *Fast charging* stations register a higher quantity of demanded energy per vehicle than *Normal charging* points. As such, for the purposes of the present research, the energy demanded under *Fast charging* adopts a distribution based on the results obtained from [85], which is shown in table 21.

Table 21. Energy Demands from EV in Fast Charging Stations [85].

Energy demanded (kWh)	Proportion of *Fast charging* fleet (%)
2	15
4	11.5
6	15.5
8	15
10	13
12	10
14	7
16	6
18	4
20	3

The results presented in table 21 were obtained by determining the approximated arithmetic average of the values presented in figure 20, which illustrates data retrieved from a study performed in Ireland.

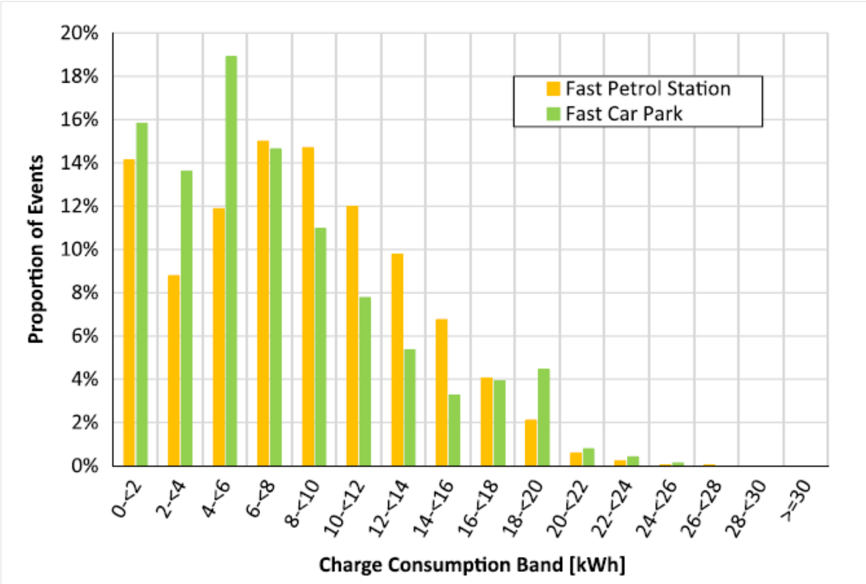

Figure 20. Distribution of Energy Demanded/Charging Event in Fast Charging Stations [85].

Lastly, according to the *IMOB 2017* [52], MAL registers a reduction of approximately 16.7% in its mobility level during the weekend. As MAL accounts for a considerable proportion of journeys executed in Portugal, the size of the EV fleet considered under each scenario (*pessimistic*, *base* and *optimistic*) during the weekend is 83.3% of the fleet registered during weekdays.

3.4.2.2. Charging Strategies

As the charging patterns discussed thus far in section 3.4 are carried out according to the individual needs of users and not a partially or globally optimised system, they are regarded as uncontrolled (UC) charging events. As the *Literature Review* demonstrates, the growth of EV fleets will pose increasingly greater threats to national grids should UC charging continue to be the default charging behaviour. As such, new controlled charging strategies are necessary to guarantee a sustainable relationship between EV recharging operations and national grid stability.

This final section therefore aims to present the three different charging strategies simulated in this research: *1. Uncontrolled (UC) charging; 2. Time-of-Use (TOU) controlled charging;* and *3. Smart grid (SG) controlled charging.*

3.4.2.2.1. Charging Strategies: Uncontrolled (UC) Charging

As already stated, the UC charging strategy is defined by all the steps described in sections 3.4.2.1.2. and 3.4.2.1.3. Overall, the UC charging strategy is characterised by EV owners who charge their vehicles immediately after their arrival at a certain destination.

3.4.2.2.2. Charging Strategies: Time-of-Use (TOU) Controlled Charging

The TOU strategy is based on users charging their vehicles according to the TOU price tariff. A TOU price tariff sets variable prices of electricity according to the time when it is being demanded. Typically, prices of electricity following a TOU price tariff offer electricity at a cheaper rate during off-peak consumption periods, when load demand is lower and the grid is less strained. The purpose of said tariff is to balance the load of national grids by incentivising users to shift their load demanded from peak hours, when electricity is more expensive, to off-peak hours. This phenomenon is known as peak shaving or load shifting [37, 40].

The TOU charging strategy used in this work is based on the TOU price tariff set by *Energias de Portugal* (EDP), the biggest electric utility in Portugal. EDP offers several TOU price tariff schemes that vary according to days of the week and time of the year. In this research, the TOU price tariff considered corresponds to the daily cycle during Summer and Winter, from Monday to Sunday [86], which is described in table 22.

As the cheaper tariff begins at 22:00, only evening charging activities adopt this method, namely *Normal charging* in private and public settings. It is assumed that public *Fast charging* is not carried out using the TOU price tariff, as users who charge with this method are typically seeking to recharge their vehicle on demand, *i.e.* as soon as possible. The remaining charging activities take place using the UC strategy.

Table 22. Daily Cycle of TOU Tariff [86].

Consumption	Time (Beginning – End)
Peak	8h – 22h
Off-Peak	22h – 8h

3.4.2.2.3. Charging Strategies: Smart Grid (SG) Controlled Charging

In the present research, the charging activities associated with the SG charging strategy also follow the timetables of the TOU price tariffs reflected in table 22. As such, evening charging events are also shifted to 22:00. However, in this case, by interacting in real time with a central aggregator, each EV is charged only with the minimum required power level necessary to fulfil its respective energy needs until 06:00 – when users begin travelling to work. The purpose of said strategy is to simultaneously avoid sudden peaks of power demand from the grid, which potentially occur when several EVs initiate their charging at the same time; and to promote valley-filling in the off-peak hours.

The power with which each EV is charged using the SG controlled charging approach is calculated using equation 12.

$$P = \frac{dE}{dt} \tag{12}$$

Where:

P : Power (kW)

E : Energy demanded from charging event (kWh)

t : Charging event duration (hours)

Where the timespan in which the considered charging events all take place is from 22:00 to 06:00.

EVs that connect to the grid in the evening present a greater margin of flexibility with regard to the period in which their actual charging operation can be initiated. This is because these EVs are connected to the grid until the early hours of the following day, and as such, have the advantage of being able to charge during the evening peak hours, or shift their charging operation to off-peak hours, when the price of electricity is cheaper. Users charging their EVs in the morning and afternoon do not have the aforementioned flexibility as they do not have the option to shift the charging operation to an off-peak period. As such, similar to the TOU charging strategy, vehicles charging in the morning and afternoon charge in a UC manner. Additionally, and as is the case with the TOU charging strategy, public *Fast charging* also takes place in a UC fashion.

4. Results and Discussion

This chapter is dedicated to presenting and discussing the results obtained from the simulations, which were performed using the conditions developed with the methodology described in the previous chapter.

Since the results obtained from the simulations were extensive, this chapter will only present and discuss the results from the simulation conditions that significantly distort the baseline load diagram (BLD) or lead to unforeseen outcomes, and therefore potentially threaten the stability of the national power system.

As the primary goal of this thesis is to identify the most suitable charging strategies for each of the EV penetration levels, this chapter is divided into three main sections, according to the different EV penetration levels considered in the simulations: 4.1.) *pessimistic scenario*; 4.2.) *base scenario*; and 4.3.) *optimistic scenario*. As mentioned, the results that do not present any significant differences or unexpected changes to the configurations of the load diagrams (LDs) prior to electric vehicle (EV) charging will be omitted.

4.1. Pessimistic Scenario

As explained in the previous chapter, the *pessimistic* scenario is that which presents the lowest number of EVs within the light-duty passenger (LP) vehicle fleet in 2030. The results obtained from the simulations carried out for the *pessimistic* scenario are of little relevance, as the load demanded from the different EV charging strategies does not reveal any significant changes to any of the BLDs for the weekdays and weekends of the different seasons. As such, the results obtained from the *pessimistic* scenario will not be presented in this chapter. However, the following paragraphs provide a brief description of the main conclusions drawn from the simulations.

As expected, within the *pessimistic* EV penetration level, the uncontrolled (UC) charging strategy presents the greatest rise in demanded power during the evening. However, as the size of the EV fleet is small, the increase in power consumption is of no major concern, as the load induced by EV charging during said period is relatively flattened. As such, EV charging using the UC strategy does not lead to any significant additional loads when compared to the traditional loads already observed in the BLDs.

The Time-of-Use (TOU) charging strategy shifts public and private *normal charging* events during the evening to a later period. As such, this charging strategy presents an LD with almost no charging events during the evening. However, the reduction in evening demand due to the TOU price tariff is somewhat negligible given the significantly higher values of power registered in the BLD. Moreover, although the TOU charging strategy presents a lower value of maximum daily registered power when compared to the UC strategy, it also results in a sudden rise in demanded power at a later period, due to EVs initiating their charging operation simultaneously under the TOU price tariff.

The SG charging strategy does, as expected, present the most beneficial results out of all three strategies. However, much like the TOU strategy, the differences are not sufficiently significant to lead to an LD with a notably different configuration from the one presented under the UC strategy. Furthermore, the desired valley-filling phenomenon is almost unnoticeable given the reduced number of EVs.

Overall, the results obtained from the simulations indicate that carrying out charging activities using UC charging will not pose significant threats to the national power system in the *pessimistic* EV penetration scenario.

4.2. Base Scenario

In the *base* scenario, EV charging does, as anticipated, induce greater differences in the LD when compared to the *pessimistic* scenario. However, despite this greater impact, the LDs associated with UC charging in the *base* scenario still do not present a significant difference when compared to their respective BLDs. Nevertheless, an unexpected outcome does occur when the TOU charging strategy is used, as will be discussed below.

To discuss the outcomes related to the *base* EV penetration level, the results from the simulations carried out during the weekdays and weekends of Winter will be presented. This is because Winter is the season in which the Portuguese daily LDs register their highest levels of consumption, and as such, present the worst-case scenario for the national grid.

4.2.1. Base Scenario – Weekdays

The results for weekdays of Winter will first be discussed. Figure 21 illustrates the BLD of a weekday during the Winter of 2030.

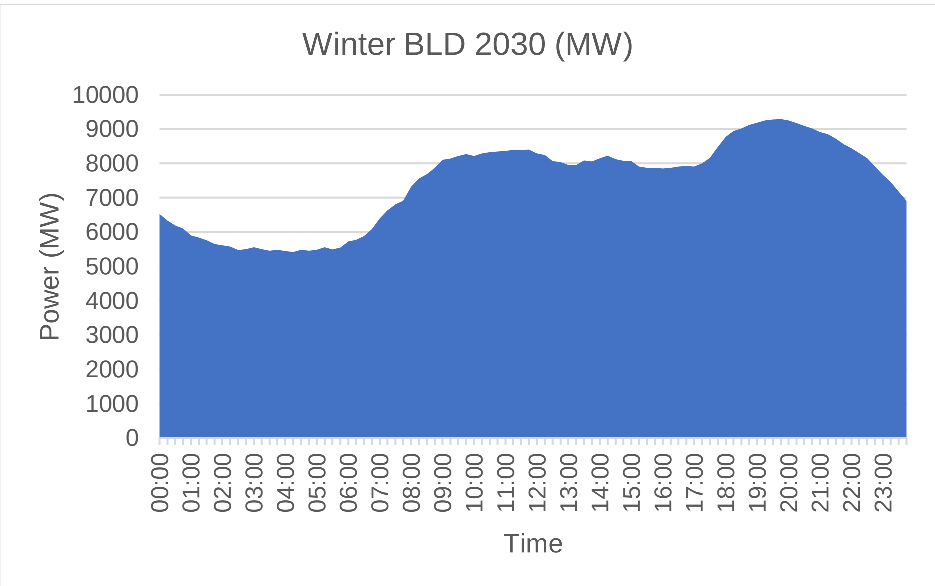

Figure 21. Baseline Load Diagram Corresponding to the Weekdays of Winter Season in 2030.

The LD depicted in figure 22, which shows the results of the UC charging strategy under the *base* EV penetration level, clearly illustrates the weekday EV charging patterns discussed in the previous chapter. When analysing figure 22, it is possible to identify three distinct EV charging sessions: in the morning; the afternoon; and in the evening.

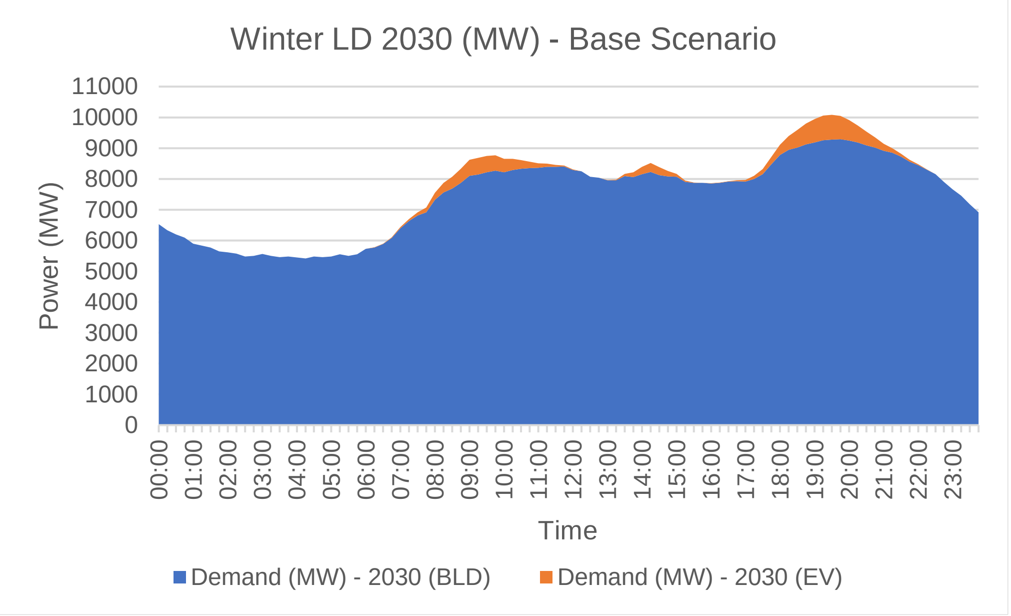

Figure 22. Load Diagram corresponding to the Weekdays of the Winter Season in 2030, under the Base EV Penetration Level following the Uncontrolled Charging Strategy.

By analysing figure 22, it is clear that the *base* scenario does not result in significant changes to the LD. The combination of a relatively small EV fleet with charging events that, given the size of said fleet, are adequately spread apart in time, create distinct peaks of EV load (depicted in orange) which are properly dispersed and therefore do not result in significantly higher levels of demanded power.

The additional loads induced by EV charging in the morning and afternoon hardly present an increase in the demanded power level when compared with the BLD. As expected, the most considerable impact of EV charging is registered in the evening, where a maximum daily registered power of 10,082MW is observed, corresponding to an approximate 9% increase from the maximum daily power recorded in the BLD. However, the new evening peak induced by UC charging should nevertheless be alleviated by implementing the controlled charging strategies presented in the previous chapter, *i.e.* the TOU and SG strategies, although the TOU strategy produces an unforeseen result that raises doubts as to its effectiveness.

Following an analysis of figure 23, which reflects TOU charging under the *base* EV penetration level during a weekday of Winter, it is observed that the load registered in the evening is indeed alleviated by shifting public and private EV *normal charging* activities to a later period. The adoption of the TOU charging strategy induced a maximum registered power of 9,416MW during the evening, which corresponds to an approximate 7% reduction in the maximum power registered for the UC strategy during the same period. However, by shifting most of the charging events which take place in the evening to a later period (specifically, 22:00), and by initiating the respective charging activities simultaneously, a sudden peak in demanded power occurs in the LD. As figure 23 clearly suggests, the abrupt spike in power resulting from shifting the charging sessions leads to a maximum daily recorded power of 11,016MW, which surpasses that which was observed in the UC strategy. Moreover, the load induced by the TOU charging strategy results in a sharp difference in the power registered on the national grid, as opposed to the UC strategy, which presented a gradual and more moderate increase in the EV load.

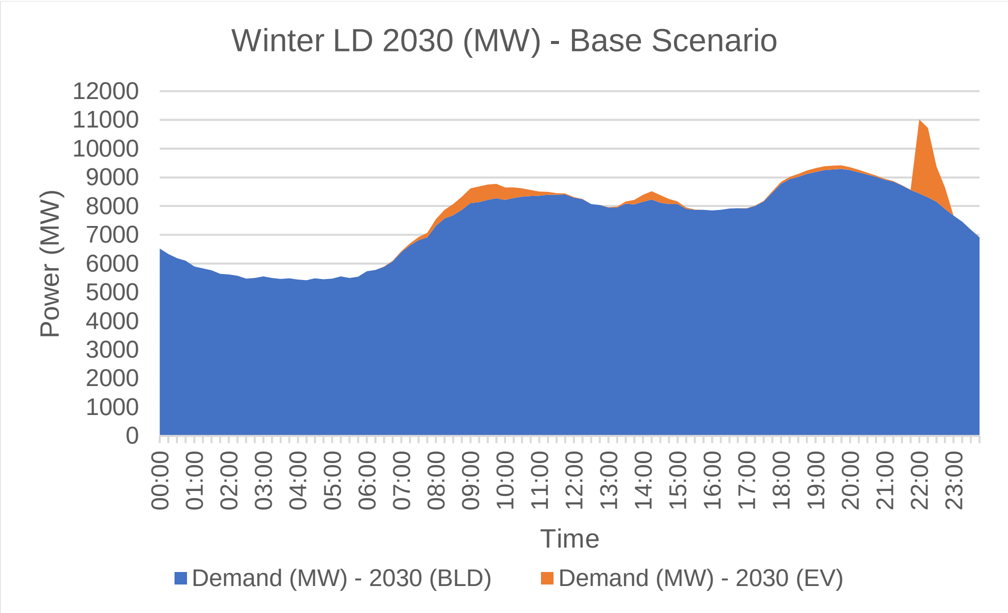

Figure 23. Load Diagram corresponding to the Weekdays of Winter Season in 2030, under the Base EV Penetration Level following the Original Time-of-Use Charging Strategy.

Given the above, it appears that the number of EVs that can charge under the TOU charging strategy and produce results which actually contribute to a healthier and better working power system is limited. As such, the limits to the size of the EV fleet using TOU charging must be carefully analysed.

Despite this outcome, the set of results should not mislead utilities and policymakers into thinking that, under this specific level of EV penetration, UC charging is always more beneficial than TOU charging. For one, as the name suggests, UC charging is not regulated, and is therefore subject to a much greater level of uncertainty regarding changes in traditional user behaviours. Secondly, modifications to the TOU charging strategy can, depending on the size of the fleet, produce more satisfying LDs than the ones obtained in figures 22 and 23.

For example, figure 24 presents an alternative TOU charging strategy that, under the *base* EV penetration level, improves the configuration of the LD when compared to the results of both the UC and TOU charging strategies depicted in figures 22 and 23, respectively.

For the purpose of distinguishing between the TOU strategies, the charging strategies depicted in figures 23 and 24 will be designated henceforth as *original* and *alternative* TOU charging strategies, respectively. The conditions associated with the *alternative* TOU strategy, which will be explained below, were not based on any existing price scheme, and were created only for present research purposes.

The abovementioned *alternative* TOU strategy, illustrated in figure 24, has two main differences from the *original* TOU charging strategy represented in figure 23. Firstly, a lower number of evening charging events are shifted to a later period. Specifically, in the new *alternative* TOU charging strategy, private *normal charging* events are transferred to off-peak hours and public *normal charging* events remain in the evening, and as such use the UC strategy. This is in contrast to the *original* TOU charging strategy, where both public and private *normal charging* events are shifted to the off-peak hours. Secondly, the time at which the price of electricity falls to the off-peak price rate is moved from 22:00 to 00:00, which allows the charging activities to initiate simultaneously during a period in which the BLD registers a lower level of demand. As figure 24 shows, the combination of these two conditions creates a smoother LD than the one presented in figure 23.

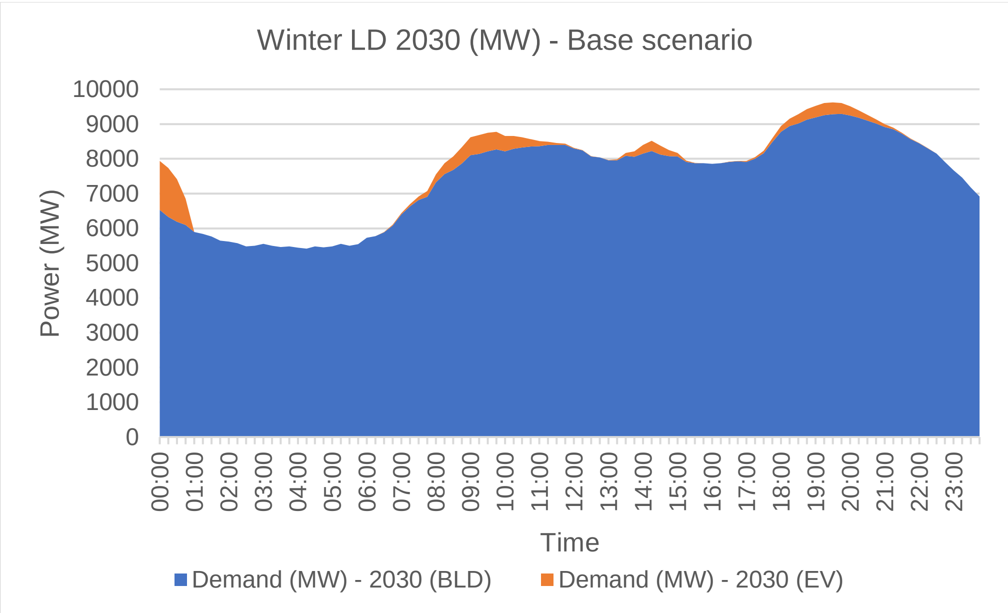

Figure 24. Load Diagram corresponding to the Weekdays of Winter Season in 2030, under the Base EV Penetration Level following the Alternative Time-of-Use Charging Strategy.

As predicted, the evening load in figure 24 presents a slightly higher peak of power than the one shown in figure 23, due to the larger number of charging events taking place at that time. However, shifting a lower number of evening charging events to an even later period produced enhanced results, as the power registered in the *alternative* TOU strategy at the beginning of the off-peak price tariff is 7,934MW, as opposed to the much higher corresponding value of 11,016MW for the *original* TOU charging strategy – a reduction of approximately 28%. Moreover, in comparison to the UC strategy, the *alternative* TOU charging strategy improves the evening load by reducing the maximum registered power during said period from 10,082MW to 9,622MW.

The main objective of developing the *alternative* TOU charging strategy was to obtain a result that i.) reduces the evening load registered under the UC charging strategy and ii.) contains the potential power surge associated with EVs simultaneously initiating their charging operations, thereby avoiding a new maximum daily power level. As this objective was clearly achieved (as evidenced by figure 24), it can be concluded that while the *original* form of the TOU charging strategy may present dangers to certain EV penetration levels, it does not necessarily have to be discarded. Adapting the TOU charging method according to the EV penetration level in which it is being used can help to avoid the problems associated with UC charging in a simple, user-voluntary way.

Although the aforementioned results indicate that, for the *base* EV penetration level, there is no need for a more complex controlled charging strategy, figure 25 illustrates the results obtained when the SG charging strategy is applied to the same conditions.

As clearly demonstrated by figure 25, the SG charging strategy produces the most attractive results out of all four simulations presented thus far, as the evening load is significantly reduced to the same level as the *original* TOU charging strategy, depicted in figure 23. Furthermore, the public and private *normal charging* events that traditionally occur during the evening are shifted to off-peak hours, which results in a lower impact on the LD and minor levels of valley-filling. However, when comparing the results presented in figures 24 and 25, it is clear that the SG charging strategy is not imperative for this specific EV penetration level, as the *alternative* TOU charging strategy guarantees a sufficiently safe and stable use of the national power system.

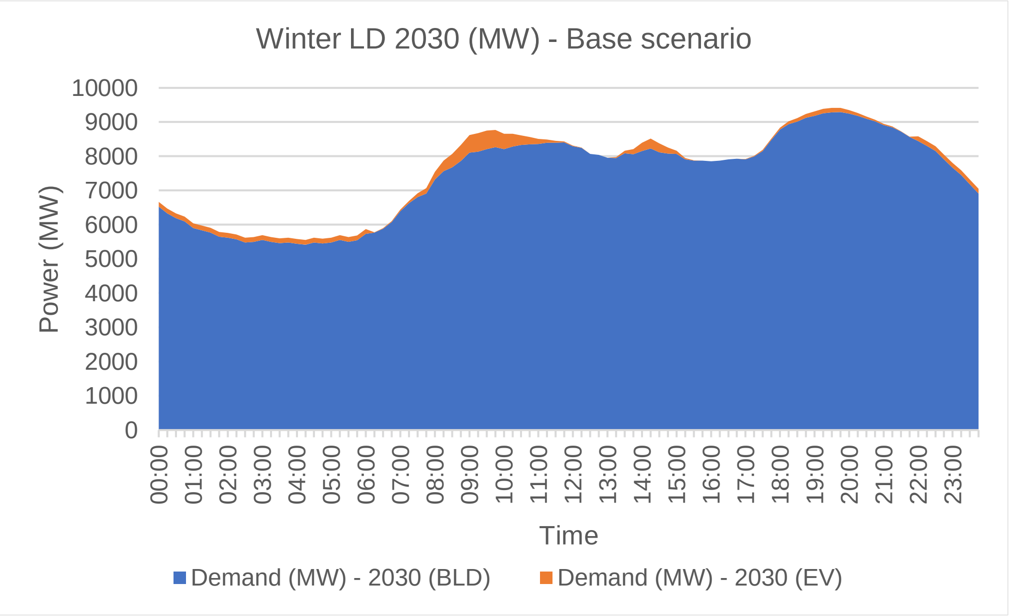

Figure 25. Load Diagram corresponding to the Weekdays of Winter Season in 2030, under the Base EV Penetration Level following the Smart Grid Charging Strategy.

4.2.2. Base Scenario – Weekends

The simulations of the *base* EV penetration level for weekends present similar conclusions to those obtained in respect of weekdays, discussed previously in section 4.2.1. As such, the results produced in relation to weekends will only be briefly discussed. The LDs obtained from the simulations can be found in appendix E.

Similar to weekdays, the results associated with the UC charging strategy during the weekend for the *base* EV penetration level do not indicate any significant changes to the BLD, with two peaks of relatively low EV charging recorded during the afternoon and evening periods. As expected from the simulation conditions, the most significant growth in the LD is recorded during the evening due to a larger number of vehicles charging during this period. Although this evening peak is not alarming, the maximum daily load is increased by approximately 10%, from 8,106MW to 8,897MW. For this reason, it is worth considering applying a controlled charging strategy to reduce this increase.

Applying the *original* TOU charging strategy to the weekend under the *base* scenario results in the same conclusions achieved for weekdays, as shifting traditional evening private and public *normal charging* operations to a later time induces a new daily maximum power level. This is due to the considerable number of vehicles initiating charging activities simultaneously.

As discussed in section 4.1.1 in respect of weekdays, it is important to consider whether the *alternative* TOU charging strategy better accommodates EV charging within the weekend LDs, thus avoiding the need to resort to the SG charging strategy. For the same reasons discussed in respect of weekdays, the results obtained from the simulations of the *alternative* TOU strategy indicate that it is also suitable for carrying out EV charging under the *base* EV penetration level for weekends.

One could also apply the SG charging strategy to weekends, which, as expected, provides the most attractive results. However, since satisfactory results may be obtained by using the *alternative* TOU charging strategy, a more complex controlled charging strategy, such as SG charging, is unnecessary in the *base* EV penetration level.

The configuration associated with the BLDs of Winter, Autumn and Spring are relatively similar. However, during the last two mentioned seasons, there are lower levels of demand recorded on their respective BLDs. The results obtained from the simulations of Autumn and Spring are otherwise similar to those already presented and discussed for Winter, with the main difference lying in the lower levels of power registered during both these seasons. As such, the problems and solutions identified for the TOU charging strategy in respect of Winter relate equally to Autumn and Spring. For this reason, the results associated with the *base* EV penetration level for these specific seasons will not be presented in this chapter. However, the results for Autumn and Spring can be consulted in appendix E.

The configuration of the Summer BLD is, interestingly, distinct from the one registered during Winter. Specifically, the Summer BLD presents a more flattened configuration throughout the whole day. For this reason, the results associated with Summer are worthy of discussion. However, the main conclusions drawn from the simulations carried out for the *base* scenario during Summer are similar to those drawn for the other seasons, and as such, will not be presented in this section. Instead, the results for Summer will be presented in the *optimistic* EV penetration level, where the impact of EV charging is considerably more relevant. The results associated with the *base* EV penetration level for Summer can be consulted in appendix E.

4.3. Optimistic Scenario

This section is dedicated to presenting the main findings from the simulations carried out for the *optimistic* EV penetration level.

The results obtained for the *optimistic* EV penetration level present, as expected, the most adverse impact on the national LD. Given the considerable size of the EV fleet under the *optimistic* scenario, the resulting LDs of every season change significantly when compared to their respective BLDs. As such, controlled charging strategies are imperative to guarantee the sustainable and safe integration of EV charging into the national power system. The results in this section will be presented and discussed with the intent of identifying the most adequate charging strategies to guarantee the aforementioned aims.

Similar to section 4.2, the findings associated with this scenario will be discussed for Winter, as it is the season of the year with highest levels of consumption, and therefore, presents the worst-case scenario.

4.3.1. Optimistic Scenario – Weekdays

The results obtained from the UC charging strategy for the *optimistic* EV penetration level, during the weekdays of Winter, are depicted in figure 26.

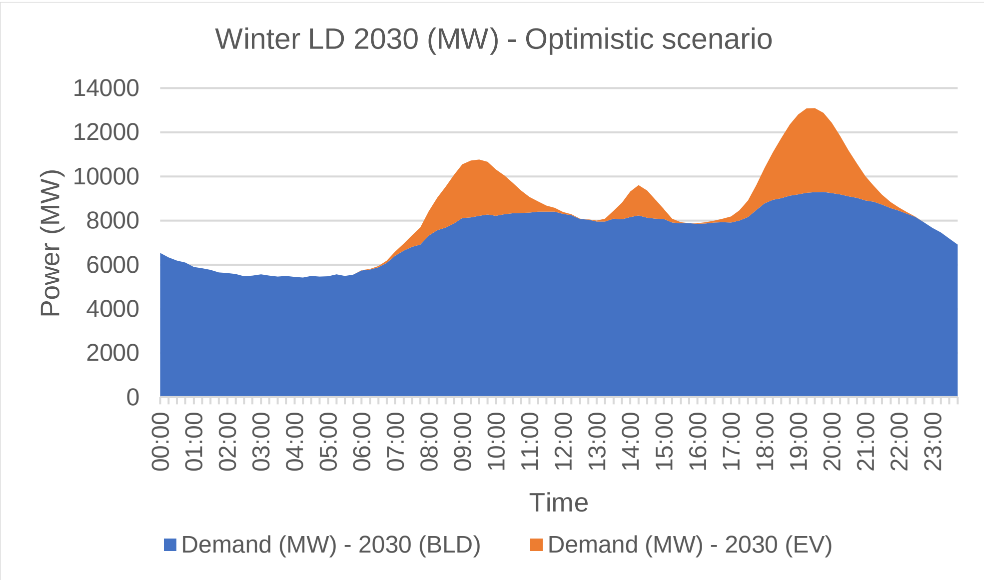

Figure 26. Load Diagram corresponding to the Weekdays of Winter Season in 2030, under the Optimistic EV Penetration Level following the Uncontrolled Charging Strategy.

By analysing figure 26, it becomes clear that the three weekday peaks of EV consumption are even more evident in the *optimistic* scenario. The results from this simulation indicate overwhelming levels of demanded power, as the maximum load registered during the afternoon charging session alone almost reaches the maximum daily registered power for UC charging in the *base* EV penetration level. Moreover, the morning and evening peaks of consumption register power levels of 10,768MW and 13,094MW, respectively, which are approximately 28% and 41% greater than the maximum power levels registered in the respective morning and evening periods of the BLD.

Bearing the aforementioned data in mind, it is clear that the results presented in figure 26 indicate the need for controlled charging strategies to reduce the impact induced by UC charging, under the *optimistic* EV penetration level.

The first controlled charging strategy that will be discussed is the TOU strategy. Figure 27 depicts the results obtained from the simulation in which the *original* TOU charging strategy is applied to the *optimistic* EV penetration level, during a weekday of Winter.

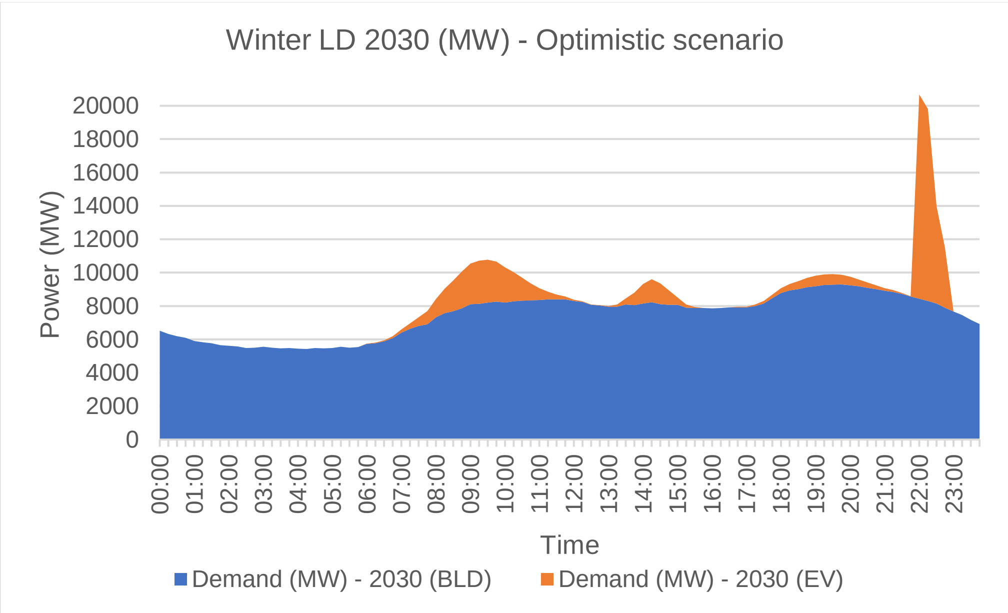

Figure 27. Load Diagram corresponding to the Weekdays of Winter Season in 2030, under the Optimistic EV Penetration Level following the Original Time-of-Use Charging Strategy.

Similar to the results obtained for the *original* TOU charging strategy under the *base* EV penetration level, the results from figure 27 show that this strategy is evidently an inappropriate alternative to UC EV charging under the *optimistic* scenario. By analysing figures 26 and 27, it is clear that the maximum power level registered in the evening has been significantly reduced from 13,094MW, under the UC charging strategy, to 9,917MW, under the *original* TOU charging strategy. Again, this is due to the transfer of public and private *normal charging* events to the off-peak period. However, the significant number of EVs simultaneously initiating their charging activity at a later period induces a large spike in demanded power, which reaches an unprecedented 20,675MW. This value is, as expected, the highest value of power registered during the day, and is approximately 58% greater than the maximum daily power level registered in the UC charging strategy.

Given these results, it is evident that the *original* TOU charging strategy proposed in this work is not suitable for addressing the impacts of UC charging within the *base* and *optimistic* scenarios. However, as shown in the discussion of the *base* scenario, there may be potential benefits in studying the possibility of the *alternative* TOU charging strategy, as it may improve on the results of the UC and *original* TOU charging strategies.

To study this possibility, the same *alternative* TOU charging strategy presented in the *base* EV penetration level was tested for the *optimistic* scenario, for the weekdays of Winter. The results of said simulation are illustrated in figure 28.

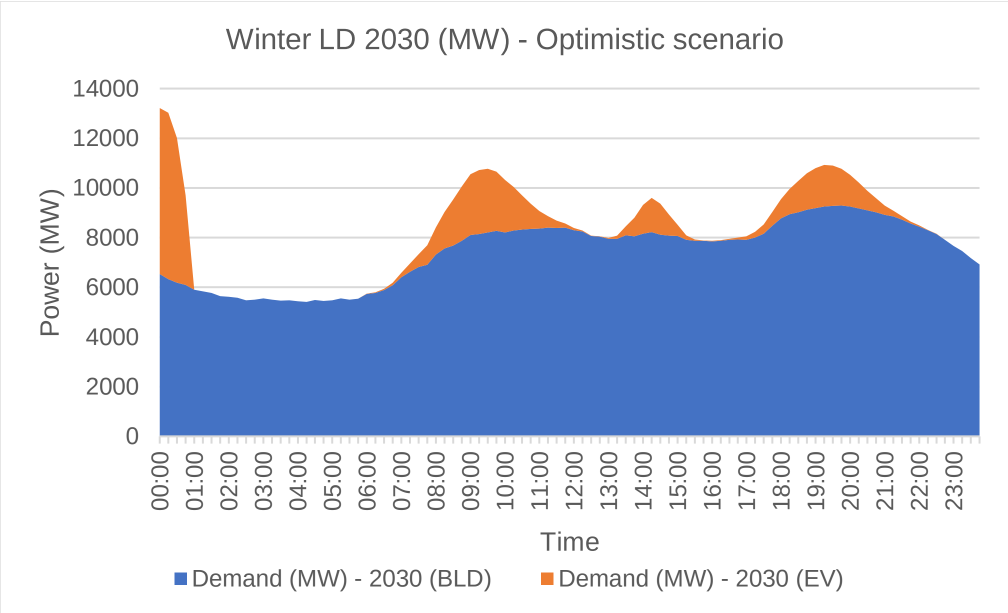

Figure 28. Load Diagram corresponding to the Weekdays of Winter Season in 2030, under the Optimistic EV Penetration Level following the Alternative Time-of-Use Charging Strategy.

As previously mentioned, in the *alternative* TOU strategy, only private *normal charging* events that usually take place in the evening are shifted to 00:00. This is in contrast to the *original* TOU strategy, in which both private and public *normal charging* activities are transferred to 22:00.

By analysing figure 28, it is clear that the outcomes of the *alternative* TOU strategy present more desirable results than those obtained for the UC and *original* TOU charging strategies. For one, the evening load registered in the LD depicting the *alternative* TOU strategy is lower than the load observed for UC charging. Specifically, the evening maximum recorded power of 10,923MW registered under the *alternative* TOU strategy presents an approximate reduction of 17% from the maximum power registered under the UC charging strategy for the same period. Moreover, the load generated from EVs charging simultaneously during off-peak hours is noticeably lower in the *alternative* TOU strategy, as there is a 36% decrease in the power registered at the beginning of off-peak hours (from 20,675MW to 13,216MW) when compared to the *original* TOU strategy. However, as much as this strategy presents enhanced results when compared to the *original* TOU charging strategy, it does not necessarily present an improvement from UC charging (which was not the case under the *base* EV penetration level, where the *alternative* TOU strategy improved upon both the *original* TOU strategy and the UC strategy). This is clear when comparing figures 28 and 26, as the maximum daily load registered under the *alternative* TOU strategy is similar to the one obtained under the UC strategy (13,216MW and 13,094MW, respectively). As such, although the implementation of the *alternative* TOU strategy lowered the power registered in the evening, it achieved a maximum daily registered power that is almost identical the one obtained by using the UC charging strategy.

The results from both TOU charging strategies in the *optimistic* EV penetration level suggest that continuously adapting the TOU strategy according to the different sizes of the EV fleet is complicated. Ultimately, once a certain EV penetration level has been reached, the TOU strategy cannot be adopted as an effective controlled charging strategy to mitigate the problems of UC charging.

Given the above, if Portugal does indeed intend to entirely electrify its vehicle fleet, then, depending on the rate at which EVs substitute ICE vehicles, it will need to implement an intelligent grid which manages all the entities and constraints of the national power system simultaneously. In the present research, this intelligent solution is simulated by the SG charging strategy. Figure 29 presents the results obtained from the SG strategy under the *optimistic* EV penetration level for the weekdays of Winter.

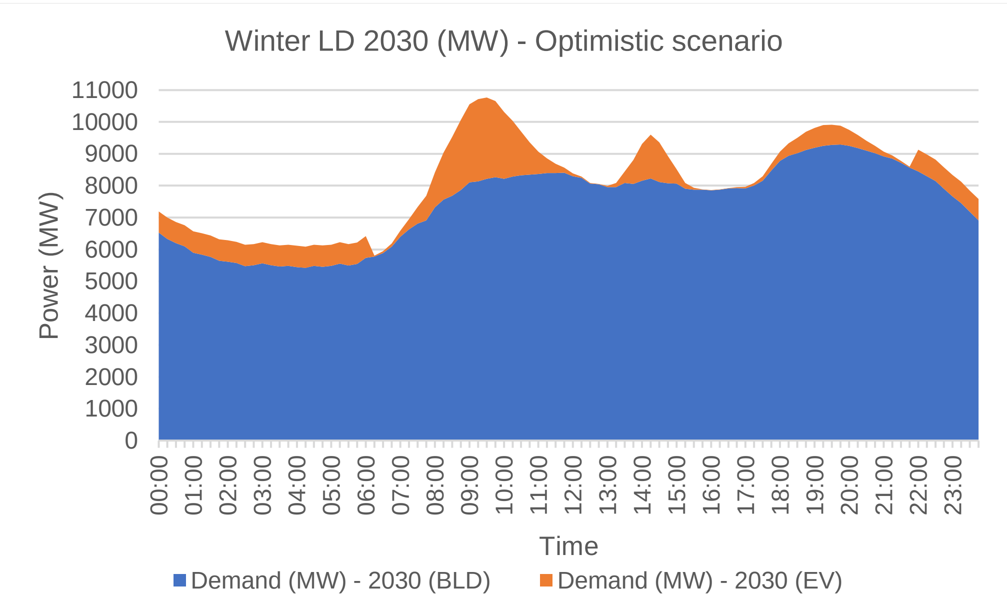

Figure 29. Load Diagram corresponding to the Weekdays of Winter Season in 2030, under the Optimistic EV Penetration Level following the Smart Grid Charging Strategy.

Studying figure 29, it is clear that out of all the strategies proposed in the *optimistic* scenario, the SG charging strategy produces the most positive results. Firstly, comparing the UC and SG charging strategies, one notices that the evening peak load is reduced from 13,094MW to 9,917MW, respectively. Furthermore, with regard to the charging activities which are shifted to a later time, not only are new peaks of consumption avoided, but visible levels of valley-filling are also achieved, promoting a more levelled configuration to the LD.

A further analysis of the LD presented in figure 29 leads to interesting conclusions regarding the use of SG charging in the *optimistic* scenario. In what is an unprecedented configuration, the maximum peak load occurs during the morning charging session, at 09:30, with a value of 10,768MW. This result leads to the conclusion that by charging under an SG strategy, the evening peak load, at a certain level of EV penetration, will cease to be the biggest threat to utilities. Instead, as the size of the EV fleet gradually increases, the morning hours may start to present the highest values of demanded power, and therefore, present bigger problems for utilities than the evening hours. As mentioned, EV charging in the evening is generally more flexible than in the morning, as vehicles are connected to the grid until the early hours of the following day, and as such, are able to make use of the valley hours. On the contrary, although EVs that begin charging in the morning slot may be connected to the grid for an extensive time, their connection does not take place during a timeslot in which delaying or slowing the rate of charging can improve the LDs, as the valley hours do for evening charging events. Moreover, the possibility of controlling or shifting the morning charging session is further complicated by the presence of the afternoon charging session.

In light of the above, it must be acknowledged that morning peaks, which will possibly require more complex controlled charging solutions than those associated with the evening load, may well cause problems for the power system in the future. As such, to prevent oversized peak loads during the morning, and to succeed in further flattening the daily LD, solutions to this problem must be carefully studied.

As most of the charging activities in the morning occur as a result of users' lack of access to charging facilities in the vicinity of their residential settlement, a potentially simple way to avoid this new peak of consumption from occurring is to install a higher number of public charging points in residential areas. This would need to be followed by creating incentives for users to replace their morning charging activities (private and public), during working hours, with public charging in the evening, prior to arriving home. The outcome of such regulation would not only reduce the morning load induced by EV charging, but it would also promote further levels of valley-filling, through the use of the SG charging strategy. Figure 30 illustrates the LD obtained from applying the set of abovementioned measures within the *optimistic* scenario, in which *Normal charging* activities in the morning are shifted to the off-peak period.

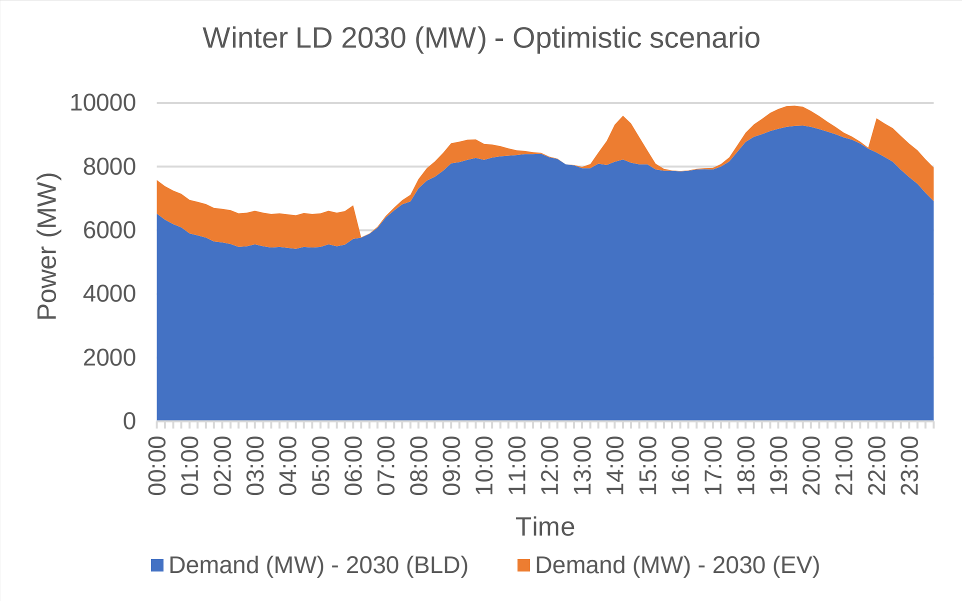

Figure 30. Load Diagram corresponding to the Weekdays of Winter Season in 2030, under the Optimistic EV Penetration Level following the Additional Measures of Smart Grid Charging Strategy.

By comparing figures 29 and 30, one notices that the above-described measures result in further benefits for the configuration of the LD, as the morning peak is reduced from 10,768MW to 8,720MW, and higher levels of valley-filling are achieved. Moreover, the new measures allow for a maximum daily load of 9,917MW, which is a small increase from the 9,293MW registered in the BLD. This is noteworthy considering the overall amount of daily energy demanded from EV charging, which is 8,208MWh.

As already discussed, the Autumn and Spring BLDs present a similar configuration to that which is observed in Winter. However, the Summer BLD, presented in figure 30, is distinguishable from the other seasons and reveals interesting results in the *optimistic* scenario.

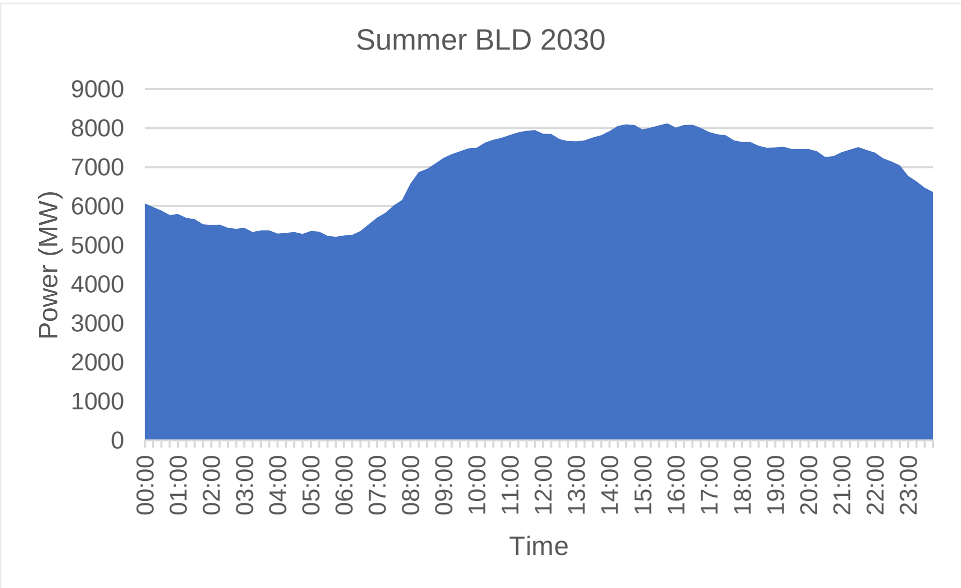

Figure 31. Baseline Load Diagram corresponding to the Weekdays of Summer Season in 2030.

Figure 31 suggests that, similarly to the Winter season, Summer also presents valley hours during dawn. However, the load during the daytime assumes a more flattened format, with no evident peaks of consumption associated with different times of the day.

While the main results and conclusions associated with the UC and TOU charging strategies in the *optimistic* scenario are the same for Winter and Summer, the LD resulting from the SG charging strategy during a weekday in Summer does present interesting details which differ from the Winter season. Figure 32 presents the results of said simulation conditions.

By analysing figure 32, one can observe that, similarly to figure 29, the morning hours present the biggest threat to the national power grid. However, the transfer of private and public *normal charging* events from the evening period to the beginning of the valley hours results in improved configurations for the LD during the evening and dawn, when compared to Winter. As figure 32 suggests, the charging activities carried out during the evening fill a small valley existent in the LD during that specific period, which flattens the LD. Furthermore, the charging activities transferred to the beginning of the valley hours induce satisfying levels of valley-filling within the off-peak period.

Given these results, although morning and afternoon peaks of consumption are evident, it is clear that the SG charging strategy under the *optimistic* EV penetration level during the Summer season presents a more flattened LD than the one in figure 29.

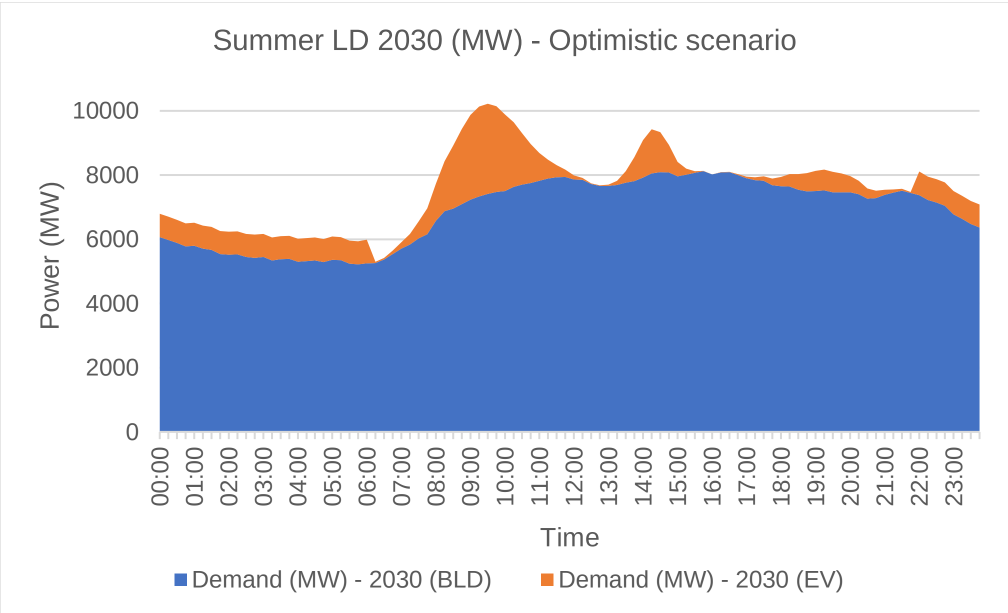

Figure 32. Load Diagram corresponding to the Weekdays of Summer Season in 2030, under the Optimistic EV Penetration Level following the Smart Grid Charging Strategy.

Although the results obtained in figure 32 indicate that the SG strategy is an adequate charging strategy within the *optimistic* scenario, its morning load remains significant, and higher levels of valley-filling could still be achieved. As such, an even more flattened configuration of the Summer LD could be obtained if the additional measures presented for the SG charging strategy were to be applied. Figure 33 presents the results obtained from the simulation.

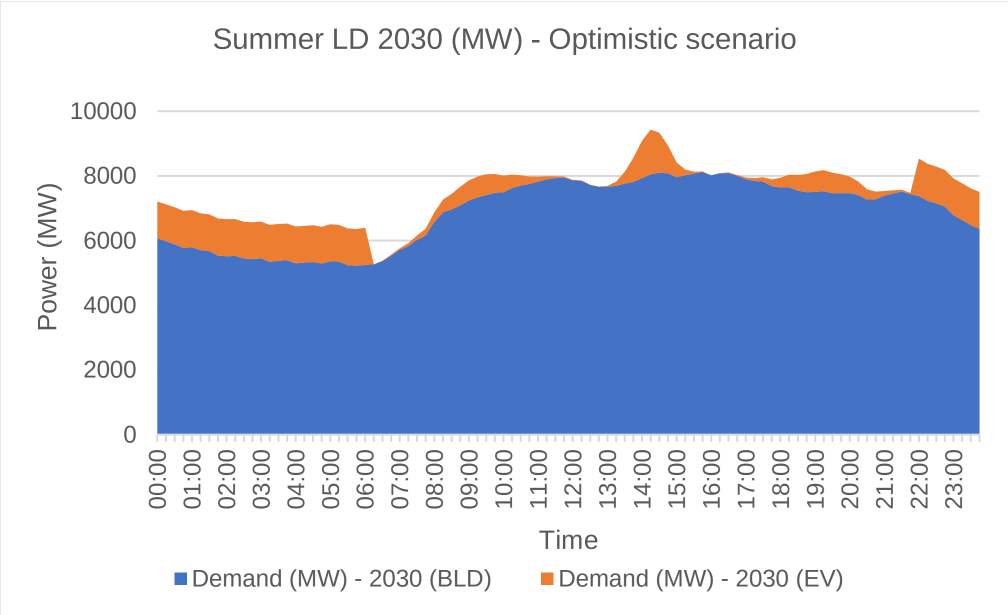

Figure 33. Load Diagram corresponding to the Weekdays of Summer Season in 2030, under the Optimistic EV Penetration Level following the Additional Measures of the Smart Grid Charging Strategy.

The above results indicate that the additional measures applied to the SG charging strategy are successful, as figure 33 presents the most flattened LD configuration of all the simulations, in which significant levels of valley-filling are achieved and the maximum daily load is reduced to 9,431MW.

4.3.2. Optimistic Scenario – Weekends

As is the case with the *base* EV penetration level, the conclusions drawn in respect of each charging strategy for the *optimistic* scenario are very similar for both weekdays and weekends. As such, this section will discard the LDs obtained for the *optimistic* EV penetration level during the weekend, and will rather be dedicated to briefly discussing its results. However, the LDs obtained from the simulations can be found in appendix E.

Similar to weekdays in the *optimistic* scenario, the UC charging strategy during the weekend induces significant additional EV charging loads when compared to the BLD, with the most considerable change taking place in the evening. As such, the substantial increase in the registered power level during the evening, induced by UC charging, must be avoided through controlled charging strategies.

Again, the results of the *original* TOU charging strategy present similar conclusions for both weekdays and weekends. The results indicate a significant reduction in the evening load. However, the transfer of evening private and public *normal charging* operations to the off-peak timetable introduces an unprecedented maximum daily power level, which is considerably larger than the one obtained with

UC charging. As such, this charging strategy is evidently unsuitable to address the problems caused by UC charging during weekends in the *optimistic* EV penetration scenario.

The application of the *alternative* TOU charging method to weekends presents improved results when compared to the *original* TOU strategy, although it results in a maximum daily registered power level larger than the one obtained under UC charging. Moreover, the new maximum daily registered power, induced by EVs charging simultaneously during off-peak hours, will only be further aggravated as the size of the EV fleet increases.

The set of results associated with TOU charging under the *optimistic* scenario provide further evidence that, once a certain EV fleet size has been reached, a user-controlled charging strategy through TOU price tariffs is no longer suitable to contain the impacts of EV charging.

As such, the results obtained from the weekday and weekend simulations indicate that, under the *optimistic* EV penetration level, an EV aggregator must be put in place to guarantee the safe use of the national power system. In this research, the aggregator is simulated by the SG charging strategy. With regard to the results obtained for the weekend, the SG strategy presents, by a considerable margin, the lowest daily maximum power level. Interestingly, within the SG strategy, the loads associated with the afternoon and evening charging sessions present similar values. However, it is predicted that as the size of the EV fleet increases, charging during the afternoon period may begin to create more problems than charging activities during the evening. This result corresponds to the same problem identified in respect of morning charging activities during weekdays under the *optimistic* EV scenario.

Finally, similar to the results obtained during weekdays, the season of the year that presents the most flattened LD when SG charging is applied is Summer. Moreover, the results from the Summer simulation further confirm the aforementioned conclusions, as the afternoon charging session clearly presents the highest power level during the day. As previously discussed, afternoon charging during the weekend presents less flexibility and susceptibility to being controlled, and therefore, requires more complex controlled charging solutions than in the evening. Furthermore, when compared to the morning charging sessions during the weekdays, users charging their EVs during the afternoon on the weekend are connected to the grid for a smaller period of time, which further complicates controlled charging during the mentioned period. This problem could be resolved by applying the same solution presented for weekdays, where users are incentivised to charge their EVs in public charging stations in the evening, under the SG charging strategy, rather than the afternoon period. Once again, these results can be consulted in appendix E.

5. Conclusions

This chapter is first dedicated to summarising the theoretical objectives of this thesis, namely, designing a methodology to conceive, develop and test the various electric vehicle (EV) charging models considered in this research. Thereafter, it summarises and analyses the main findings obtained from the simulations of the charging models. Finally, a brief section is devoted to discussing future work.

5.1. Methodology

The objective of this section is to define the methodology used to develop the EV charging models considered in this research. As such, the structure of this section is based on the main theoretical investigations conducted within this thesis, which were: i.) prediction of the Portuguese baseline load diagram (BLD) for 2030; ii.) prediction of the light-duty passenger (LP) EV penetration in Portugal for 2030; iii.) mobility patterns of Portuguese drivers and EV consumption rates; iv.) EV charging patterns; and v.) EV charging strategies.

5.1.1. Prediction of the Portuguese BLD for 2030

The purpose of the first stage of this research was to obtain a set of Portuguese load diagrams (LDs) for 2030 which accounted for the growth in electrical energy demand within traditional energy consuming sectors, *i.e.* excluding EV charging. The resulting LDs, referred to as BLDs, were subsequently overlapped with the daily EV power demands predicted in this research.

Presently, the impacts of EV charging are barely registered in daily LDs due to the small number of EVs in the Portuguese vehicle fleet. Thus, for the purposes of this research, it was assumed that the patterns of daily energy consumption of traditional energy consuming sectors in 2030 would be similar to the demand patterns reflected in LDs for the period when this thesis was written. As such, the BLDs were obtained by applying a growth rate, related to the increase in energy demand of the aforementioned sectors, to LDs associated with a reference period, which was 2017.

5.1.2. Prediction of the LP EV Penetration in Portugal for 2030

Within this research, three predictions of the Portuguese LP EV fleet for 2030 were used, which were identified as the *pessimistic*; *base*; and *optimistic* scenarios. The sizes of the fleet associated with these scenarios were 85,925; 422,445 and 2,008,717 EVs, respectively.

The size of the LP EV fleet under the *pessimistic* scenario was based on predictions by *Direção-Geral da Energia e Geologia* (DGEG). The EV fleet sizes of the *base* and *optimistic* scenarios were based on the target EV penetration levels established by the European Union (EU) and the Portuguese government for 2030, respectively. However, as both of the aforementioned EV penetration levels are reflected only as a percentage of the total vehicle fleet in 2030, it was necessary to obtain a prediction of the numerical size of the Portuguese vehicle fleet for said year. To make this prediction, a linear regression was applied to the annual sizes of the Portuguese vehicle fleet from 1991-2018, in order to obtain a mathematical model which could estimate the size of the national vehicle fleet in a random year, including 2030. The sizes of the *base* and *optimistic* EV penetration levels were subsequently obtained by applying the percentage targets established by the EU and Portuguese government to the prediction obtained through the linear regression.

5.1.3. Mobility Patterns of Portuguese Drivers and EV Consumption Rates

The Portuguese driving patterns developed in this research were based on information acquired from the study *IMOB 2017*, which identified the travelled distances and portion of fleet associated with the most common travel motives (TM(s)) within the Metropolitan Area of Porto (MAP) and Lisbon (MAL), which were: *Work; Study; Friend/Family Accompanying; Leisure; Shopping; Personal Affairs;* and *Other Activities*. The driving patterns of the remaining Portuguese locations (Intermunicipal Communities (ICs)) were extrapolated from the data established for MAP and MAL according to the difference between the geographical areas of the ICs, on the one hand, and MAP and MAL, on the other. A single set of data expressing the driving patterns of the entire Portuguese population was then obtained through a weighted arithmetic average of the driving patterns established in all the locations, according to their respective population sizes.

As the electrical consumption rate of EVs varies with temperature, distinct EV consumption rates were considered within each season of the year. Each rate was obtained through a previously developed mathematical model which computes the electrical consumption of an EV as function of the ambient temperature. The input temperatures used in the mathematical model were the average temperatures recorded for each season of 2017, which corresponds to the reference year used to build the BLDs.

By combining the specific EV consumption rates of each season and the travelled distances associated with each of the TMs, it was possible to determine the daily charging needs linked to each of the EV penetration levels identified for the Portuguese EV fleet in 2030.

The results indicated that the majority of charging events are linked to journeys associated with the TMs of *Work* during the weekdays and *Shopping* during the weekends.

5.1.4. EV Charging Patterns

This section was dedicated to analysing the most common EV charging patterns presently practiced in Portugal. Specifically, the charging variables analysed were: time, location, portion of fleet and power level associated with different EV charging sessions.

With regard to the time and location of charging activities during weekdays, it is possible to observe that they typically take place in three distinct periods – in the morning, afternoon and evening. The vast majority of the abovementioned charging events occur during the morning and evening periods, which predominantly take place in the workplaces and households of users, respectively. The number of afternoon charging events are significantly lower and are mostly carried out within commercial settings. The weekend registers a lower overall number of charging events and only two charging sessions are identified, which take place during the afternoon, in commercial settings, and in the evening when users arrive at their respective households.

For the three distinct periods of EV charging identified throughout the whole week, users initiate EV charging as soon as they arrive at their respective destinations, *i.e.* workplace, commercial setting or household. As such, the impact of EV charging on daily LDs depends on how users' arrivals at their respective destinations are distributed. According to the literature, users' arrivals typically follow a Normal distribution.

The morning charging sessions during weekdays, and evening charging activities during both weekdays and weekends, are predominantly carried out using private charging points. However, depending on whether the user has access to a dedicated charging point within their workplace or household, these charging activities also take place, to a lesser extent, in public charging stations. The weekday and weekend afternoon charging activities all use public charging points, as they are carried out in commercial spaces.

Regarding their influence on the LD, the main difference between public and private charging lies on the power level used to charge the EVs. Private charging is carried out with a lower value of rated power, as it is typically assumed that the EVs associated with these charging events are parked, and therefore connected to the grid, for longer periods. As public charging activities use higher levels of power, they register greater levels of demand on the LD, and therefore pose a greater threat to the national power system.

With regard to the duration of EV charging, the charging events are divided into *Normal charging* and *Fast charging* activities. *Normal charging* encompasses all the charging events that are carried out with a rated power which is lower than or equal to 22kW. These charging events account for all private and most of the public charging activities. *Fast charging* corresponds with a small portion of the daily charging events and uses a rated power greater than 22kW.

As such, charging events within the scope of this research were divided into *Normal charging* and *Fast charging* activities. *Normal charging* events were subsequently divided into private and public *Normal charging* events, which assumed EVs charge at a rate of 7.4kW and 22kW, respectively. Further, *Fast charging* activities were carried out using a rated power of 50kW and were assumed to take place at public charging points.

5.1.5. EV Charging Strategies

For the purposes of this research, the three main charging strategies considered were the *uncontrolled* (UC); *time-of-use* (TOU) and *smart grid* (SG) charging strategies.

The UC charging strategy followed the charging patterns described in section 5.1.4 above.

The TOU charging strategy aims to shave the EV load registered in the evening – the most significant period of EV charging – by making use of TOU price tariffs offered by utilities. TOU price tariffs offer lower electricity price rates during the off-peak hours of national demand (also known as the valley period) which typically begin at night and last until the following morning. As such, users charging in the evening are incentivised to shift their EV charging operations to a period when the national load registers lower levels of demanded power, with the purpose of reducing the overall power registered on the LD.

The SG charging strategy follows a similar logic to the TOU strategy, as users are also incentivised to shift evening charging events to off-peak hours through the use of lower electricity price rates. However, by scheduling charging events using a smart system, which ensures batteries are fully re-charged by the following morning under the lowest possible power rate, the SG charging strategy simultaneously satisfies the needs of both grid and users. Furthermore, not only does this strategy result in a lower impact on the LD by carrying out EV charging slowly throughout the whole night, but it also induces significant levels of valley-filling by shifting charging operations to the valley hours. This ultimately enables a more levelled configuration of the LD.

5.2. Main Findings

This section is devoted to discussing the findings obtained from the practical implementation of the EV charging models established in this thesis. Ultimately, the discussion aims to highlight the solutions associated with the principal objective of this research, which was to identify the charging strategies that guarantee sustainable configurations of the Portuguese LD for each of the potential levels of EV penetration identified for 2030.

As such, the structure of this section 5.2 is divided according to the three levels of EV penetration considered in the research – *pessimistic*; *base*; and *optimistic*.

5.2.1. Main Findings – Pessimistic EV Penetration Level

The simulations carried out for the *pessimistic* scenario revealed that this level of EV penetration did not induce significant changes to the levels of demanded power registered on the Portuguese daily BLD. It was found that even the UC charging strategy failed to noticeably distort the BLD from its original form. This result was obtained for all the seasons of the year and days of the week. As such, allowing users to charge in a UC manner is acceptable for the *pessimistic* EV penetration level.

5.2.2. Main Findings – Base EV Penetration Level

As expected, under the UC charging strategy, the *base* EV penetration level induced a higher value of maximum daily demanded power on the LD than the *pessimistic* scenario. However, the aforementioned increase in recorded power, registered in the evening, still does not represent a substantial threat to the power system, as the resulting LD is not significantly different from its original form. This result indicates that the UC charging strategy is still practicable within the *base* scenario. Nevertheless, although UC charging does not noticeably disturb the LD for the *base* EV penetration level, it should not be seen as the preferable charging strategy, as UC charging entails an element of uncertainty, and therefore, could result in unpredicted consequences for the *base* scenario.

By analysing the results of the proposed TOU charging strategy within the *base* EV penetration level, an unexpected result will be observed. The shifting of evening charging events to the off-peak electric demand hours generates a significant spike in EV load, which is caused by a considerable number of vehicles initiating their charging operations simultaneously. Interestingly, this sudden demand in power, caused by EV charging, induces a maximum daily power level which is greater than the one registered in the UC charging strategy. This outcome suggests that the UC charging strategy is preferable to the TOU strategy within the *base* EV penetration level. However, by varying the initially proposed TOU charging strategy to create the *alternative* TOU charging strategy, in which a lower number of evening charging operations are shifted to a later off-peak period, satisfactory results were achieved. Within the *base* EV penetration level, the *alternative* TOU charging strategy presented lower levels of maximum daily recorded power when compared to the UC charging strategy and the initially proposed TOU strategy (referred to as *original* TOU charging strategy).

The aforementioned finding led to the conclusion that the TOU charging strategy has its limitations, as, once the EV fleet reaches a certain size, it can produce results that are worse than the UC strategy. However, the results obtained from the *alternative* TOU charging strategy suggest that, depending on the size of the EV fleet, adaptations of the TOU method can still present positive results when compared to the UC charging strategy. This finding is important, because it indicates that the implementation of a more advanced charging strategy, such as SG charging, under the *base* scenario or similar levels of EV penetration is not necessary. This is because variations to existing strategies can still produce satisfying results which contain the threats imposed by the *original* TOU and UC charging strategies in a simple, user voluntary manner. Yet again, these conclusions were obtained for all the seasons of the year and days of the week.

5.2.3. Main Findings – Optimistic EV Penetration Level

The simulations carried out within the *optimistic* scenario suggest that only the SG charging strategy is practicable within said EV penetration level, as the UC, *original* TOU and *alternative* TOU charging strategies all generate disproportionate and unsustainable levels of demanded power.

The results for the SG charging strategy also reveal an interesting phenomenon regarding the time when the maximum daily power level is recorded on the LD, as the evening ceased to be the period in which the highest levels of power were registered. The reason for this relates to the fact that SG charging merely controls charging events taking place in the evening, and does not change the scheduling of charging activities taking place during the remainder of the day. This fact, together with the considerable size of the EV fleet within the *optimistic* scenario, resulted in the morning session becoming the period in which the daily LD registered its highest levels of demanded power under the SG charging strategy.

It is important to note that, despite being the maximum daily level of registered power, the aforementioned peak load registered in the morning under the SG strategy did not present dangerous levels of demanded power within the simulations. However, if these morning charging events are to be continuously carried out in a UC manner, the progressive growth of the EV fleet will induce a further rise in the level of power registered during the morning. This will eventually raise significant concerns for utilities. As such, within an EV penetration level similar or greater to the one identified in the *optimistic* scenario, careful solutions are required to ensure that morning charging activities are carried out in a sustainable manner. Again, this conclusion was obtained for all the seasons of the year and days of the week.

A possible simple solution to the above problem could be to install more public charging points in residential areas, and incentivise users through the use of off-peak tariffs to progressively shift their charging operations from the morning to the evening, where charging events can be carried out using SG charging. This initiative would also promote a more levelled configuration of the LD, as the reduction in the morning EV load would be accompanied by further levels of valley-filling. The aforementioned measures were simulated in this research and revealed positive results, whereby during Winter a new maximum daily load of 9,917MW was achieved, which is a small increase from the 9,293MW registered in the BLD. This is noteworthy considering the overall amount of daily energy demanded from EV charging, which is 8,208MWh.

5.3. Future Work

To develop a more in-depth understanding of the levels of energy demanded by EVs in Portugal, further research into the travel patterns of Portuguese drivers must be conducted. Although travel pattern statistics for the MAP and MAL are well-documented, a significant amount of information regarding the rest of Portugal is still missing. Moreover, a more detailed analysis of driving patterns over the weekend must be carried out. Further research in this area would allow for more accurate results.

As mentioned, the SG charging strategy will inevitably become necessary in the future to allow for a sustainable relationship between national grids and EVs. In light of the increasing importance of the SG strategy, a considerable amount of research concerning the development of algorithms directed at its implementation has already been carried out. However, these models must be tested and adapted to the conditions of the national grids of each country. This will not only allow for healthy levels of demanded power within their respective daily LDs, but will also ensure that equipment linked to national power systems operates within the particular established limits of each country.

Furthermore, in the context of the SG charging strategy, the main body of research is focused on methods for controlling evening charging operations. As the results of this thesis demonstrate, morning charging sessions will soon begin to pose serious concerns for utilities too. If sufficient measures to shift morning charging events to the evening period are not put in place, algorithms to control morning charging activities must be developed to ensure that the morning EV load does not induce the same threats that were initially associated with evening charging activities.

EVs are at the forefront of the wave of revolutionary technologies responsible for re-building our economy and society in the cleanest possible way. However, as the past has clearly taught us, pioneering innovation, if not studied and monitored properly, can present new and unexpected challenges for our society. As such, the creation of new forms of technology must be accompanied by research which analyses their interaction with the environment into which they are integrated. This work has offered a small contribution to the field with these important objectives in mind.

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Appendix

List of Figures - Appendix

Figure 34. DC/AC CCS – Combo 2 [88]. I

Figure 35. AC Type 2 – Mennekes [88]. I

Figure 36. AC household outlet [88]. I

Figure 37. Cumulative Normal Distribution [83]. ..... J

Figure 71. Base, UC, Winter, weekend ..... K

Figure 72. Base, original TOU, Winter, weekend and Figure 73. Base, alternative TOU, Winter, weekend ..... K

Figure 74. Base, SG, Winter, weekend and Figure 75. Base, UC, Spring, weekday K

Figure 76. Base, UC, Spring, weekend and Figure 77. Base, original TOU, Spring, weekday L

Figure 78. Base, original TOU, Spring, weekend and Figure 79. Base, alternative TOU, Spring, weekday L

Figure 80. Base, alternative TOU, Spring, weekend and Figure 81. Base, SG, Spring, weekday L

Figure 82. Base, SG, Spring, weekend and Figure 83. Base, UC, Summer, weekday L

Figure 84. Base, UC, Summer, weekend and Figure 85. Base, original TOU, Summer, weekday ..... M

Figure 86. Base, original TOU, Summer, weekend and Figure 87. Base, alternative TOU, Summer, weekday ..... M

Figure 88. Base, alternative TOU, Summer, weekend and Figure 89. Base, SG, Summer, weekday ..... M

Figure 90. Base, SG, Summer, weekend and Figure 91. Base, UC, Autumn, weekday M

Figure 92. Base, UC, Autumn, weekend and Figure 93. Base, original TOU, Autumn, weekday N

Figure 94. Base, original TOU, Autumn, weekend and Figure 95. Base, alternative TOU, Autumn, weekday ..... N

Figure 96. Base, alternative TOU, Autumn, weekend and Figure 97. Base, SG, Autumn, weekday ..... N

Figure 98. Base, SG, Autumn, weekend and Figure 99. Optimistic, UC, Winter, weekend ..N

Figure 100. Optimistic, original TOU, Winter, weekend and Figure 101. Optimistic, alternative TOU, Winter, weekend ..... O
Figure 102. Optimistic, SG, Winter, weekend and Figure 103. Optimistic, add.m.SG, Winter, weekend ..... O
Figure 104. Optimistic, UC, Spring, weekday and Figure 105. Optimistic, UC, Spring, weekend ..... O
Figure 106. Optimistic, original TOU, Spring, weekday and Figure 107. Optimistic, original TOU, Spring, weekend ..... O
Figure 108. Optimistic, alternative TOU, Spring, weekday and Figure 109. Optimistic, alternative TOU, Spring, weekend ..... P
Figure 110. Optimistic, SG, Spring, weekday and Figure 111. Optimistic, SG, Spring, weekend ..... P
Figure 112. Optimistic, add.m.SG, Spring, weekday and Figure 113. Optimistic, add.m.SG, Spring, weekend ..... P
Figure 114. Optimistic, UC, Summer, weekday and Figure 115. Optimistic, UC, Summer, weekend ..... P
Figure 116. Optimistic, original TOU, Summer, weekday and Figure 117. Optimistic, original TOU, Summer, weekend ..... Q
Figure 118. Optimistic, alternative TOU, Summer, weekday and Figure 119. Optimistic, alternative TOU, Summer, weekend ..... Q
Figure 120. Optimistic, SG, Summer, weekend and Figure 121. Optimistic, add.m.SG, Summer, weekend ..... Q
Figure 122. Optimistic, UC, Autumn, weekday and Figure 123. Optimistic, UC, Autumn, weekend ..... Q
Figure 124. Optimistic, original TOU, Autumn, weekday and Figure 125. Optimistic, original TOU, Autumn, weekend ..... R
Figure 126. Optimistic, alternative TOU, Autumn, weekday and Figure 127. Optimistic, alternative TOU, Autumn, weekend ..... R
Figure 128. Optimistic, SG, Autumn, weekday and Figure 129. Optimistic, SG, Autumn, weekday ..... R

Figure 130. Optimistic, add.m.SG, Autumn, weekday and Figure 131. Optimistic, add.m.SG, Autumn, weekend ....R

Appendix A

Linear Regression

Equation 13 presents the regression model used to generate estimated values of the light-duty vehicle fleet in each year according to the least squares estimation [87].

$$\hat{Y}_i = b_0 + b_1 X_i \tag{13}$$

Where:

$\hat{Y}_i$: Estimated value of light-duty vehicle fleet in year i

b_0 : y – intercept of linear regression

b_1 : Slope of linear regression

X_i : Year of estimated values

As the time-series associated to the sample begins in 1991, X_i takes the form of equation 14.

$$X_i = i - 1990, where\ i = (1990, 1991, \dots, 2030) \tag{14}$$

To obtain a regression line through the least squares error estimation, equation 13 must be rewritten in the form of equation 15 with the purpose of creating a variable that represents the error between the real values and the regression line values.

$$Y_i = b_0 + b_1 X_i + \epsilon_i \tag{15}$$

Where ϵ_i is the error measured between $\hat{Y}_i$ and Y_i.

To obtain the regression line values of b_o and b_1 that minimize the error between the estimated and real values of the light-duty vehicle fleet, one must differentiate the *sum of square function* (16), S, with respect to both b_o and b_1, represented in equation 17.

$$S = \sum_{i=1}^{n} \epsilon_i^2 = \sum_{i=1}^{n} (Y_i - b_0 - b_1 X_i)^2 \tag{16}$$

$$\begin{cases} \dfrac{dS}{db_0} = -2 \sum_{i=1}^{n} (Y_i - b_0 - b_1 X_i) = 0 \\ \dfrac{dS}{db_1} = -2 \sum_{i=1}^{n} X_i (Y_i - b_0 - b_1 X_i) = 0 \end{cases} \tag{17}$$

Resolving the pair of equations 17 with respect to b_0 and b_1, one obtains the following expressions:

$$\begin{cases} b_1 = \dfrac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sum_{i=1}^{n}(X_i - \bar{X})^2} \\ b_0 = \bar{Y} - b_1\bar{X} \end{cases} \tag{18}$$

Where:

$\bar{X}$: average of values associated to X_i

$\bar{Y}$: average of values associated to Y_i

Which can be described as:

$$\begin{bmatrix} \bar{X} \\ \\ \bar{Y} \end{bmatrix} = \begin{bmatrix} \dfrac{(X_1 + X_2 + \cdots + X_n)}{n} \\ \dfrac{(Y_1 + Y_2 + \cdots + Y)}{n} \end{bmatrix} = \begin{bmatrix} \dfrac{\sum_{i=1}^{n} X_i}{n} \\ \dfrac{\sum_{i=1}^{n} Y_i}{n} \end{bmatrix} \tag{19}$$

The values of b_0 and b_1 are obtained by resolving equations 18 and 19. Which result in a y-intercept and slope values of, approximately, $b_0 = 2{,}175{,}421$ and $b_1 = 113{,}008$, respectively.

Appendix B

B.1. Weighted Arithmetic Average of Portions of Fleet

$$\bar{z}_i = \frac{\sum_{j=1}^{n} w_{ij} z_{ij}}{\sum_{j=1}^{n} w_{ij}} \qquad (20)$$

Where:

$\bar{z}_i$: weighted arithmetic average of *Portion of Fleet* associated to TM i of MAP + MAL

z_{ij} : *Portion of Fleet* for TM i in metropolitan area j

B.2. Weighted Arithmetic Average of MAP + MAL Areas

$$x_1 = \frac{\sum_{j=1}^{n} w_j A_j}{\sum_{j=1}^{n} w_j} \qquad (21)$$

Where:

w_j : weight of area associated to metropolitan area j (%)

A_j : Area of metropolitan area j (km^2)

As the abovementioned weights are calculated based on the values of the area associated to MAP and MAL, the computation of said weights was carried out according to the following equation 22.

$$w_j = \frac{A_j}{\sum_{j=1}^{n} A_j} \qquad (22)$$

B.3. Weighted Arithmetic Average of Travelled Distances

$$d_i = \frac{\sum_{k=1}^{m} W_k y_{ik}}{\sum_{k=1}^{m} W_k} \qquad (23)$$

Where:

W_k : weight associated to *Travelled Distance* y_{ik} of IE k

d_i : *Travelled Distance* of Portuguese population for TM i

The weights W_i were calculated according to equation 18.

$$W_k = \frac{P_k}{\sum_{k=1}^{m} P_k} \qquad (24)$$

Where:

P_k : Population size of IE k

Appendix C

C.1. Charging Modes

Bearing in mind the aforementioned details related to different EV charging conditions in Europe, the IEC established, in *IEC 61851 – 1*, four different charging modes – three in AC and one in DC, which are [38]:

AC CHARGING MODES

Mode 1:

Charging is carried out through conventional household sockets or monophasic or triphasic industrial plug sockets. In this charging mode, sockets in use must be equipped with Residual Current protective Device (RCD) – which protects people from the threats of touching electrical contacts by automatically disconnecting when an electric current leakage is detected. Regarding the information stated in table 14, charging mode 1 can be used as a *Low Power* or a *Medium Power* charging method. Although available for usage, this mode demonstrates a lack of safety compared to the others and should, therefore, be avoided.

Mode 2:

In this mode charging is also carried out via a conventional household socket or monophasic or triphasic industrial plug socket. However, in this case, an In-Cable Control and Protection Device (IC-CPD), commonly known as an in-cable control box, is incorporated into the charging cable. The IC-CPD communicates through a pilot signal with the vehicle and includes an RCD. Bearing in mind the information located in table 14, charging mode 2 can be operated as *Low Power* or *Medium Power*.

Mode 3:

Charging is carried out via a dedicated EV charging socket set in a charging station or a wallbox, which are permanently connected to the electric grid. The vehicle and the charging facility communicate through a pilot signal. This mode presents increased advantages to the previous ones as it provides a greater level of safety for people, protection from overloads and presents the possibility to perform controlled charging, which takes into account constraints from the grid side. According to table 14, charging mode 3 can be operated as a *Medium Power* or *AC High Power* charging method.

DC CHARGING MODES

Mode 4:

Charging operation is executed via an external charging device which is permanently connected to the electricity grid. As in modes 2 and 3, mode 4 communicates with the charging facility via a pilot signal. However, in this mode the charging cable is permanently connected to the charging facility. Regarding the information illustrated in table 14, mode 4 is operated as a *DC High Power* charging method.

C.2. Charging Plugs

As stated above, modes 1 and 2 are typically carried out via conventional household outlets. However, charging operations in modes 3 and 4 are performed through dedicated EV charging cables. There are three types of plugs/connectors used for charging in mode 3, one type used in mode 4 and a unique plug that enables charging in both mode 3 and 4 [72, 38]:

MODE 3 CHARGING PLUGS:

IEC 62196-2 “Type 1” – Yazaki connector

These connectors are favoured by the Japanese and American markets. It reflects the SAE J1772/2009 automotive plug specifications. The connector only supports monophasic power with maximum power capacity of 8kW – 250V and 32A. Having been developed by the Japanese company Yazaki, this connector is commonly known as *Yazaki connector*,

IEC 62196-2 “Type 2” – Mennekes connector

Reflecting the VDE-AR-E 2623-2-2 plug specifications, it supports monophasic as well as triphasic power flow. The plug supports 250V monophasic power at 13, 20, 32, 63 or 70A, and 380 to 480V triphasic power at 13, 20, 32 and 63A, which configure a maximum power capacity of 17.5kW and 52.4kW, respectively. The plug enables bi-directional power flow, as well as communication between the EV and charging facility. Developed by the German company *Mennekes*, they are more commonly known as *Mennekes connector*.

IEC 62196-2 “Type 3” – SCAME

A shutter incorporates the connector, which impedes people touching the socket outlet. The connector reflects the *EV Plug Alliance* proposal standard and presents three variations: i.) *Type 3a* supports a maximum monophasic power of 4kW (250V, 16A); ii.) *Type 3b* supports a maximum monophasic power of 8kW (250V, 32A); and iii.) *Type 3c* which supports a maximum triphasic power of 52.4kW (480V, 63A). The connector is more commonly referred to as *Scame connector.*

MODE 4 CHARGING PLUGS:

CHAdeMO

The CHAdeMO supports fast DC charging. The power level associated to the connector is not fixed, although it is usually set at 50kW. The charger allows for bi-directional power flow and is therefore adequate for V2G and Vehicle-to-Home applications.

MODE 3+4 CHARGING PLUGS:

Combined AC/DC Charging System (CCS – Combo 2)

The CCS system enables, with a single CCS inlet, to charge the EV with both AC and DC power. In Europe, the inlet, located in the EV, is suited for both a unique CCS DC connector, designated Combo 2, while simultaneously being compatible with Type 2 AC connectors.

According to regulation established in *Annex 2* of the EU *Directive 2014/94/EU of European Parliament and of the Council of 22 October 2014 – on the deployment of alternative fuels infrastructure* [78] on *Technical Specifications for recharging points*:

***Normal power recharging points for motor vehicles*:**

"AC normal power recharging points for EVs shall be equipped, for interoperability purposes, at least with socket outlets or vehicles connectors of Type 2 as described in standard EN 62196-2…"

***High power recharging points for motor vehicles*:**

"AC high power recharging points for electric vehicles shall be equipped, for interoperability purposes, at least with connectors of Type 2 as described in standard EN 62196-2.

DC high power recharging points for electric vehicles shall be equipped, for interoperability purposes, at least with connectors of the combined charging system 'Combo 2' as described in standard EN 62196-3."

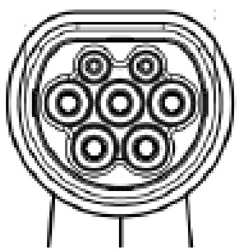


Figure 35. AC Type 2 – Mennekes [88].

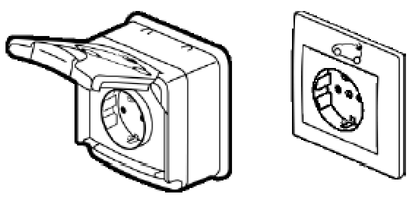


Figure 36. AC household outlet [88].

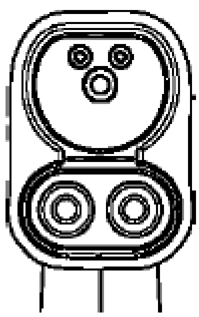
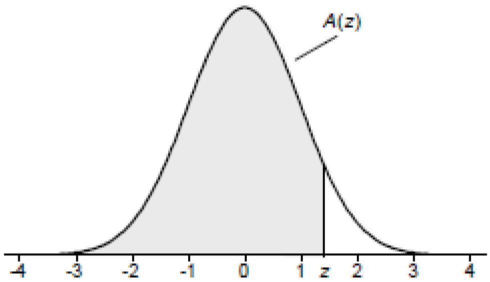


Figure 34. DC/AC CCS – Combo 2 [88].

Appendix D



$A(z)$ is the integral of the standardized normal distribution from $-\infty$ to z (in other words, the area under the curve to the left of z). It gives the probability of a normal random variable not being more than z standard deviations above its mean. Values of z of particular importance:

z	$A(z)$	
1.645	0.9500	Lower limit of right 5% tail
1.960	0.9750	Lower limit of right 2.5% tail
2.326	0.9900	Lower limit of right 1% tail
2.576	0.9950	Lower limit of right 0.5% tail
3.090	0.9990	Lower limit of right 0.1% tail
3.291	0.9995	Lower limit of right 0.05% tail

z	0.00	0.01	0.02	0.03	0.04	0.05	0.06	0.07	0.08	0.09
0.0	0.5000	0.5040	0.5080	0.5120	0.5160	0.5199	0.5239	0.5279	0.5319	0.5359
0.1	0.5398	0.5438	0.5478	0.5517	0.5557	0.5596	0.5636	0.5675	0.5714	0.5753
0.2	0.5793	0.5832	0.5871	0.5910	0.5948	0.5987	0.6026	0.6064	0.6103	0.6141
0.3	0.6179	0.6217	0.6255	0.6293	0.6331	0.6368	0.6406	0.6443	0.6480	0.6517
0.4	0.6554	0.6591	0.6628	0.6664	0.6700	0.6736	0.6772	0.6808	0.6844	0.6879
0.5	0.6915	0.6950	0.6985	0.7019	0.7054	0.7088	0.7123	0.7157	0.7190	0.7224
0.6	0.7257	0.7291	0.7324	0.7357	0.7389	0.7422	0.7454	0.7486	0.7517	0.7549
0.7	0.7580	0.7611	0.7642	0.7673	0.7704	0.7734	0.7764	0.7794	0.7823	0.7852
0.8	0.7881	0.7910	0.7939	0.7967	0.7995	0.8023	0.8051	0.8078	0.8106	0.8133
0.9	0.8159	0.8186	0.8212	0.8238	0.8264	0.8289	0.8315	0.8340	0.8365	0.8389
1.0	0.8413	0.8438	0.8461	0.8485	0.8508	0.8531	0.8554	0.8577	0.8599	0.8621
1.1	0.8643	0.8665	0.8686	0.8708	0.8729	0.8749	0.8770	0.8790	0.8810	0.8830
1.2	0.8849	0.8869	0.8888	0.8907	0.8925	0.8944	0.8962	0.8980	0.8997	0.9015
1.3	0.9032	0.9049	0.9066	0.9082	0.9099	0.9115	0.9131	0.9147	0.9162	0.9177
1.4	0.9192	0.9207	0.9222	0.9236	0.9251	0.9265	0.9279	0.9292	0.9306	0.9319
1.5	0.9332	0.9345	0.9357	0.9370	0.9382	0.9394	0.9406	0.9418	0.9429	0.9441
1.6	0.9452	0.9463	0.9474	0.9484	0.9495	0.9505	0.9515	0.9525	0.9535	0.9545
1.7	0.9554	0.9564	0.9573	0.9582	0.9591	0.9599	0.9608	0.9616	0.9625	0.9633
1.8	0.9641	0.9649	0.9656	0.9664	0.9671	0.9678	0.9686	0.9693	0.9699	0.9706
1.9	0.9713	0.9719	0.9726	0.9732	0.9738	0.9744	0.9750	0.9756	0.9761	0.9767
2.0	0.9772	0.9778	0.9783	0.9788	0.9793	0.9798	0.9803	0.9808	0.9812	0.9817
2.1	0.9821	0.9826	0.9830	0.9834	0.9838	0.9842	0.9846	0.9850	0.9854	0.9857
2.2	0.9861	0.9864	0.9868	0.9871	0.9875	0.9878	0.9881	0.9884	0.9887	0.9890
2.3	0.9893	0.9896	0.9898	0.9901	0.9904	0.9906	0.9909	0.9911	0.9913	0.9916
2.4	0.9918	0.9920	0.9922	0.9925	0.9927	0.9929	0.9931	0.9932	0.9934	0.9936
2.5	0.9938	0.9940	0.9941	0.9943	0.9945	0.9946	0.9948	0.9949	0.9951	0.9952
2.6	0.9953	0.9955	0.9956	0.9957	0.9959	0.9960	0.9961	0.9962	0.9963	0.9964
2.7	0.9965	0.9966	0.9967	0.9968	0.9969	0.9970	0.9971	0.9972	0.9973	0.9974
2.8	0.9974	0.9975	0.9976	0.9977	0.9977	0.9978	0.9979	0.9979	0.9980	0.9981
2.9	0.9981	0.9982	0.9982	0.9983	0.9984	0.9984	0.9985	0.9985	0.9986	0.9986
3.0	0.9987	0.9987	0.9987	0.9988	0.9988	0.9989	0.9989	0.9989	0.9990	0.9990
3.1	0.9990	0.9991	0.9991	0.9991	0.9992	0.9992	0.9992	0.9992	0.9993	0.9993
3.2	0.9993	0.9993	0.9994	0.9994	0.9994	0.9994	0.9994	0.9995	0.9995	0.9995
3.3	0.9995	0.9995	0.9995	0.9996	0.9996	0.9996	0.9996	0.9996	0.9996	0.9997
3.4	0.9997	0.9997	0.9997	0.9997	0.9997	0.9997	0.9997	0.9997	0.9997	0.9998
3.5	0.9998	0.9998	0.9998	0.9998	0.9998	0.9998	0.9998	0.9998	0.9998	0.9998
3.6	0.9998	0.9998	0.9999							

Figure 37. Cumulative Normal Distribution [83].

Appendix E – Results

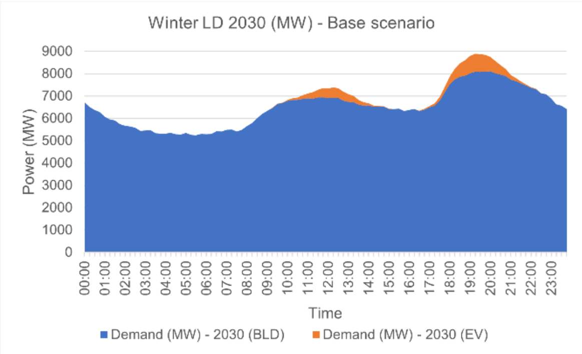


Figure 38. Base, UC, Winter, weekend

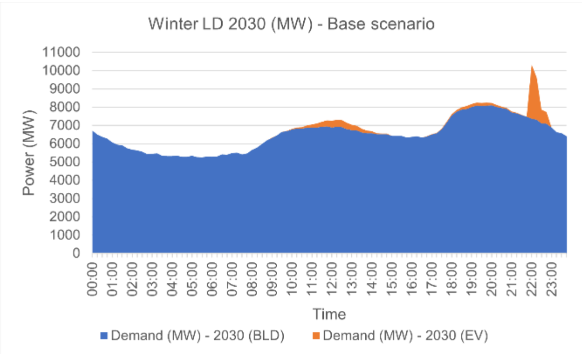


Figure 39. Base, original TOU, Winter, weekend

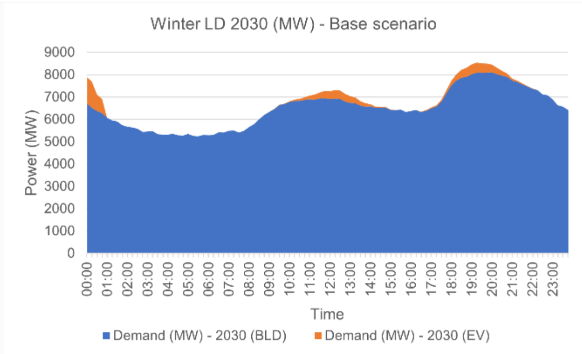


Figure 40. Base, alternative TOU, Winter, weekend

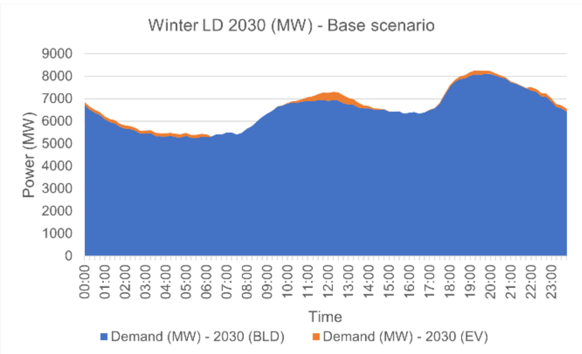


Figure 41. Base, SG, Winter, weekend

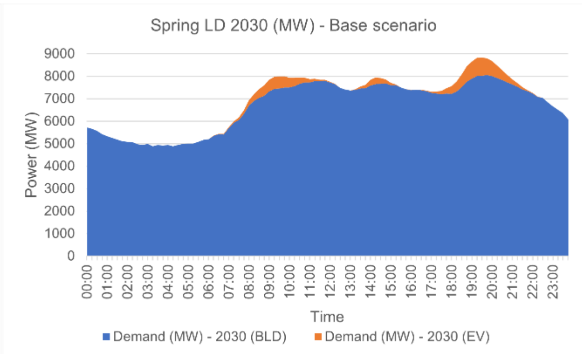


Figure 42. Base, UC, Spring, weekday

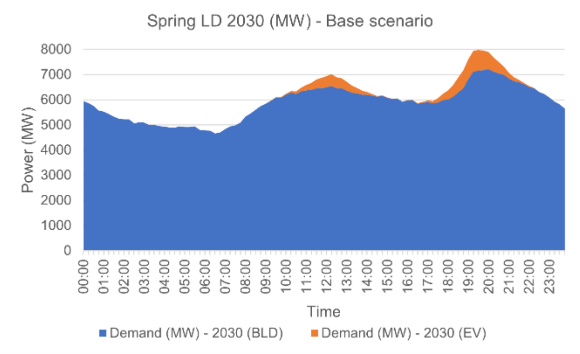


Figure 43. Base, UC, Spring, weekend

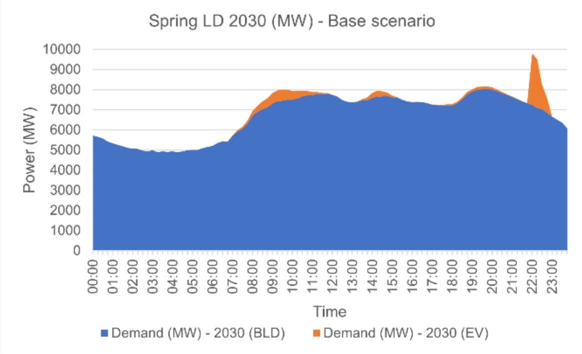


Figure 44. Base, original TOU, Spring, weekday

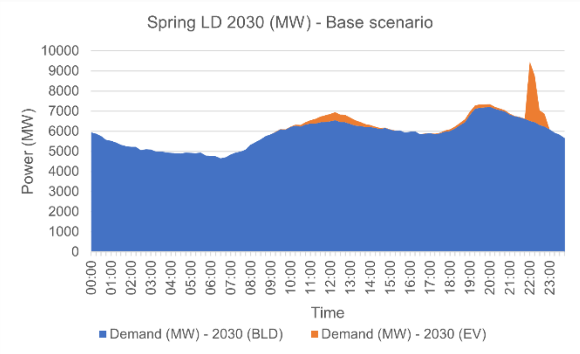


Figure 45. Base, original TOU, Spring, weekend

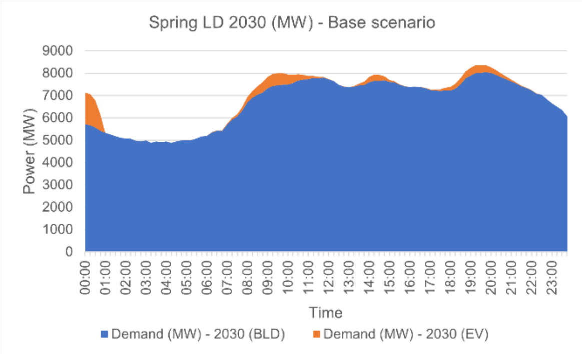


Figure 46. Base, alternative TOU, Spring, weekday

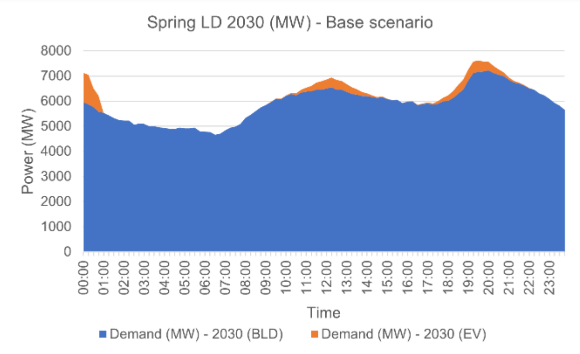


Figure 47. Base, alternative TOU, Spring, weekend

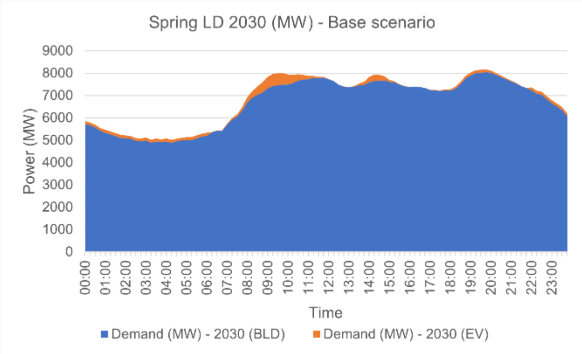


Figure 48. Base, SG, Spring, weekday

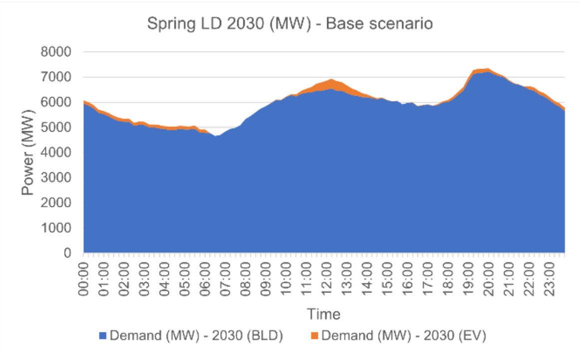


Figure 49. Base, SG, Spring, weekend

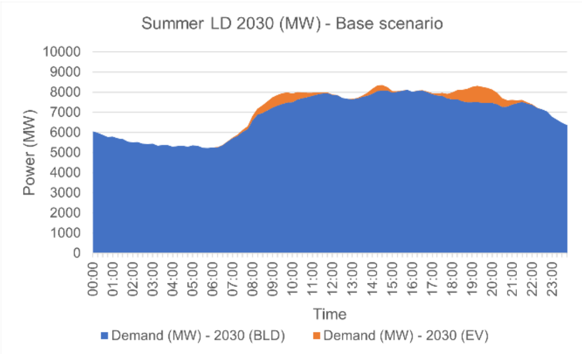


Figure 50. Base, UC, Summer, weekday

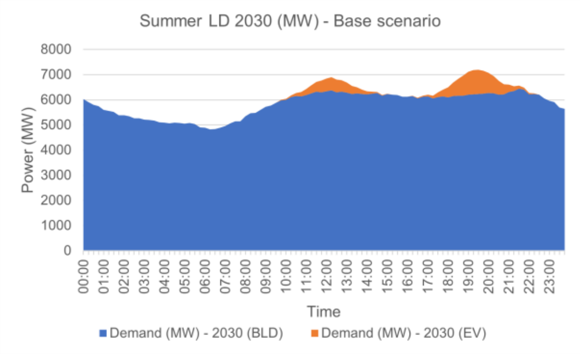


Figure 51. Base, UC, Summer, weekend

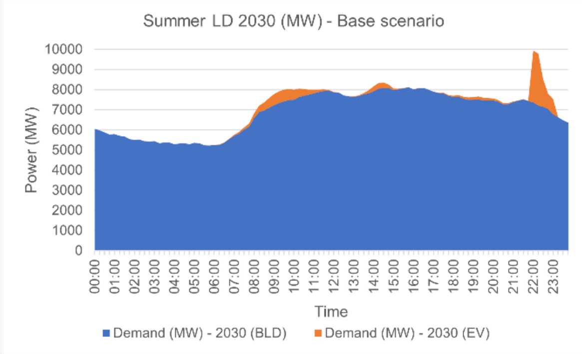


Figure 52. Base, original TOU, Summer, weekday

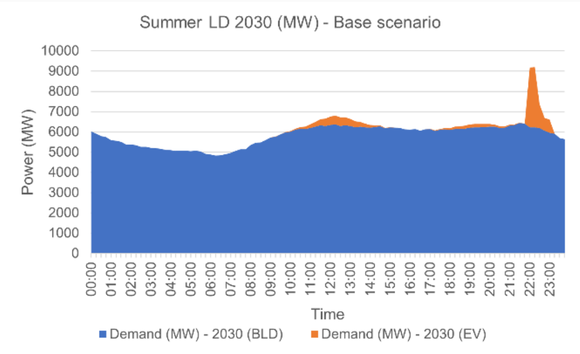


Figure 53. Base, original TOU, Summer, weekend

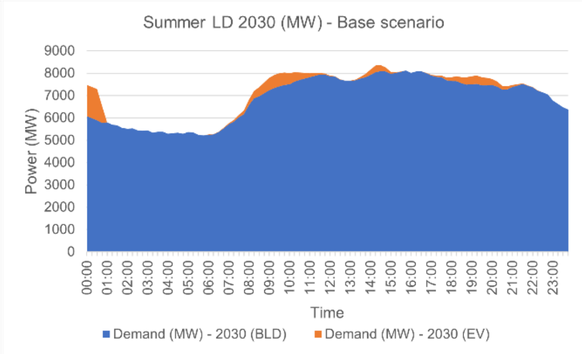


Figure 54. Base, alternative TOU, Summer, weekday

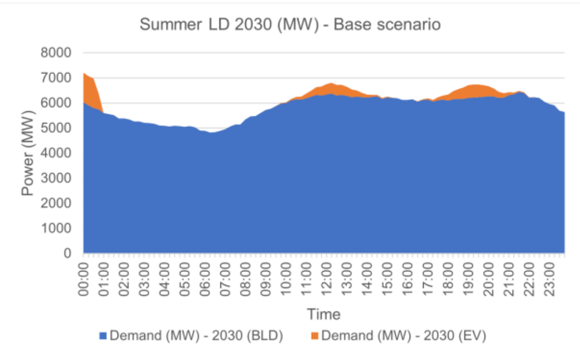


Figure 55. Base, alternative TOU, Summer, weekend

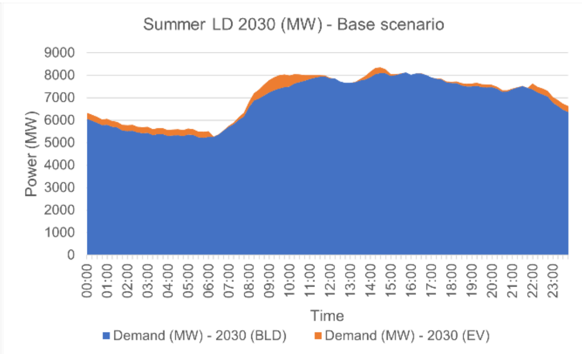


Figure 56. Base, SG, Summer, weekday

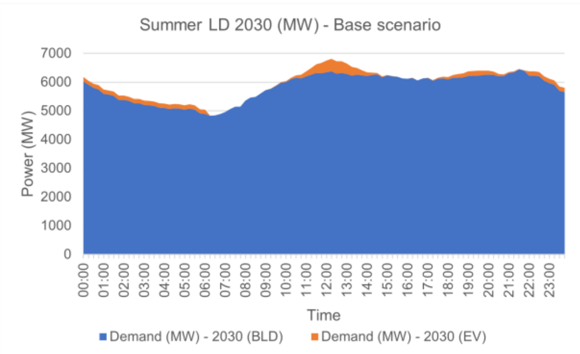


Figure 57. Base, SG, Summer, weekend

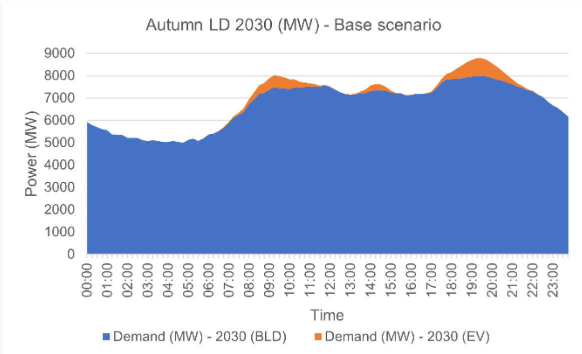


Figure 58. Base, UC, Autumn, weekday

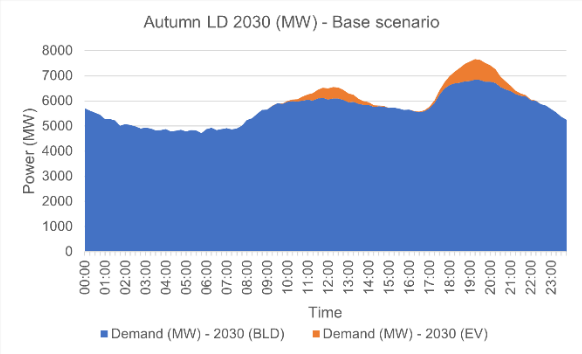


Figure 59. Base, UC, Autumn, weekend

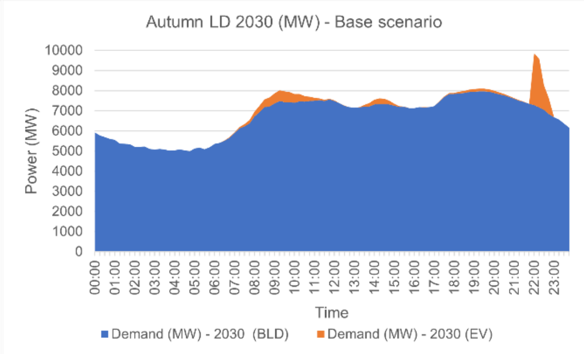


Figure 60. Base, original TOU, Autumn, weekday

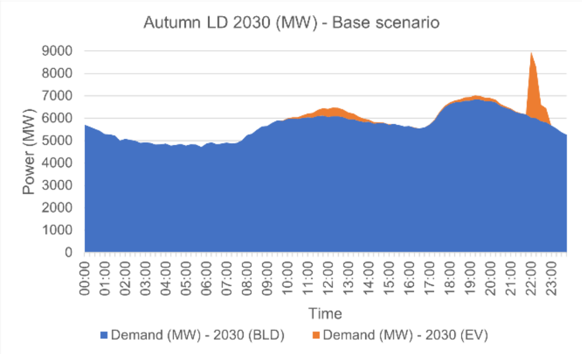


Figure 61. Base, original TOU, Autumn, weekend

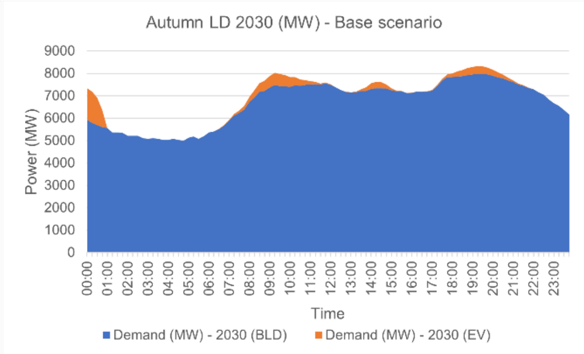


Figure 62. Base, alternative TOU, Autumn, weekday

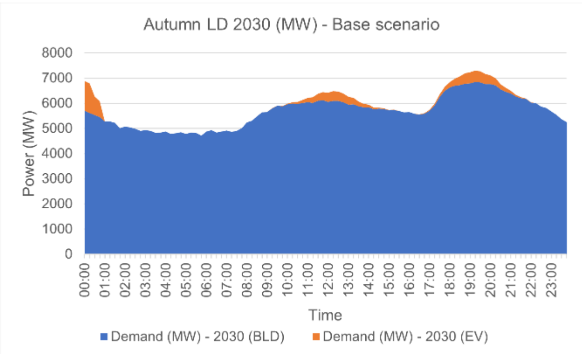


Figure 63. Base, alternative TOU, Autumn, weekend

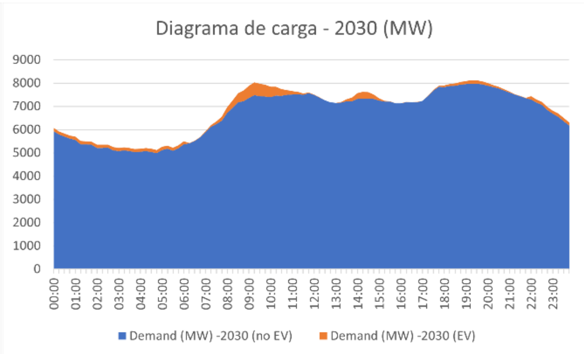


Figure 64. Base, SG, Autumn, weekday

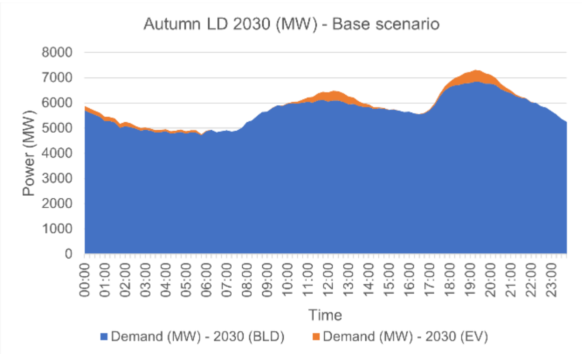


Figure 65. Base, SG, Autumn, weekend

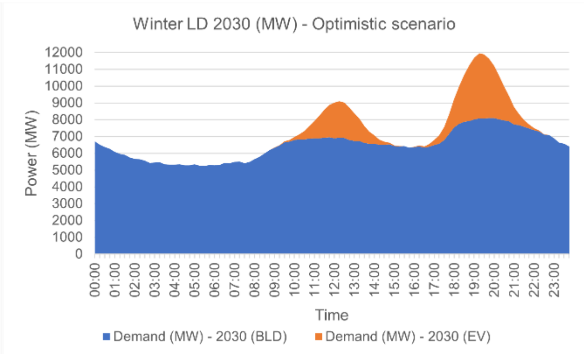


Figure 66. Optimistic, UC, Winter, weekend

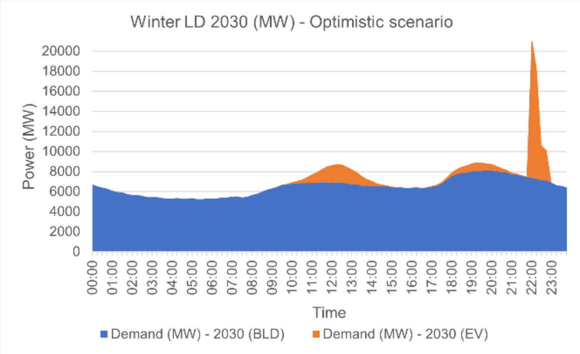


Figure 67. Optimistic, original TOU, Winter, weekend

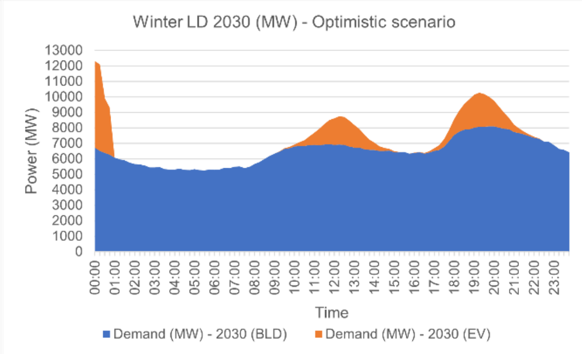


Figure 68. Optimistic, alternative TOU, Winter, weekend

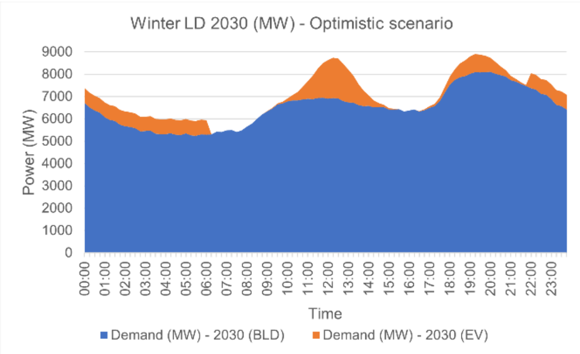


Figure 69. Optimistic, SG, Winter, weekend

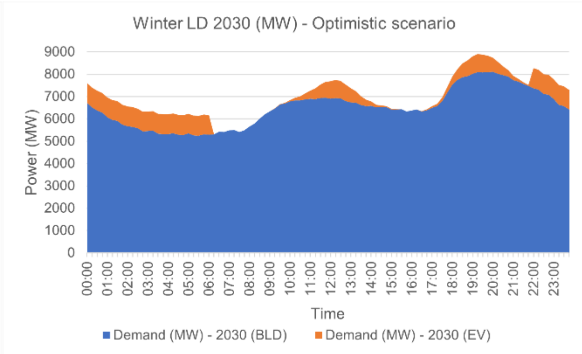


Figure 70. Optimistic, add.m.SG, Winter, weekend

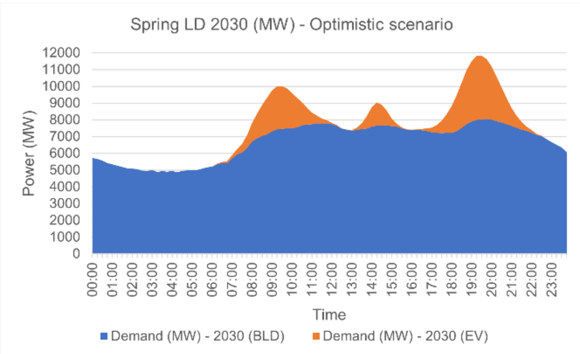


Figure 71. Optimistic, UC, Spring, weekday

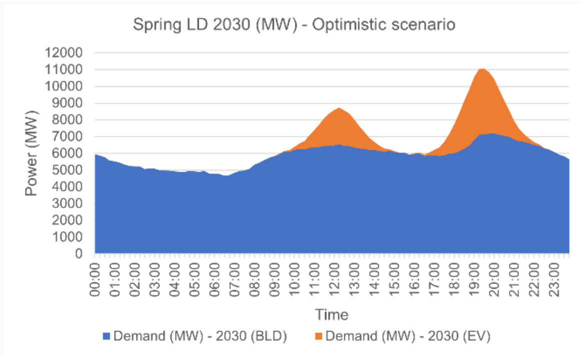


Figure 72. Optimistic, UC, Spring, weekend

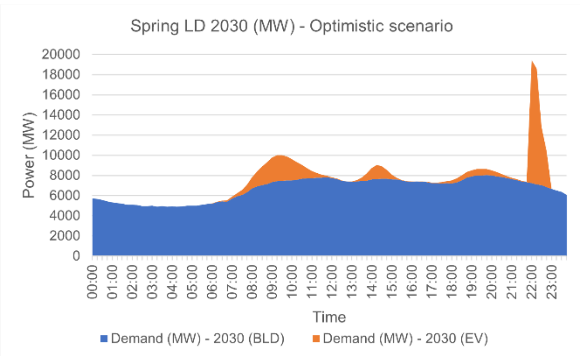


Figure 73. Optimistic, original TOU, Spring, weekday

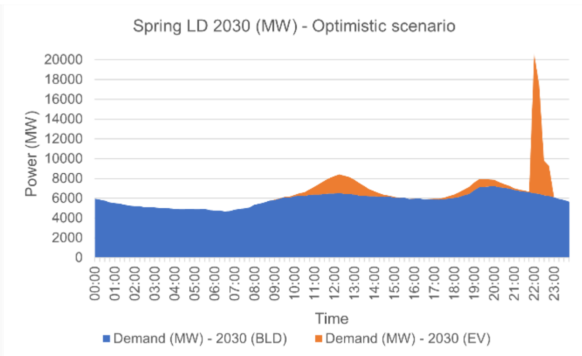
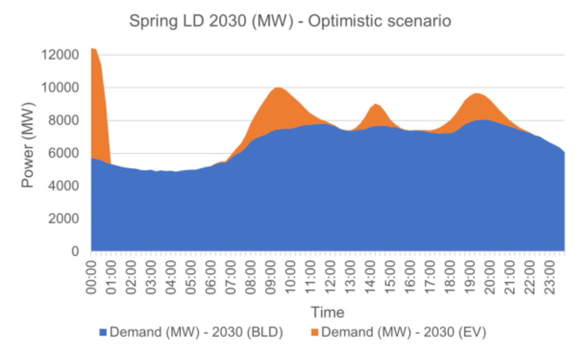


Figure 74. Optimistic, original TOU, Spring, weekend



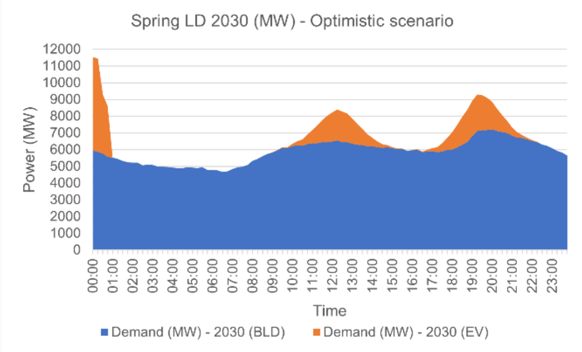
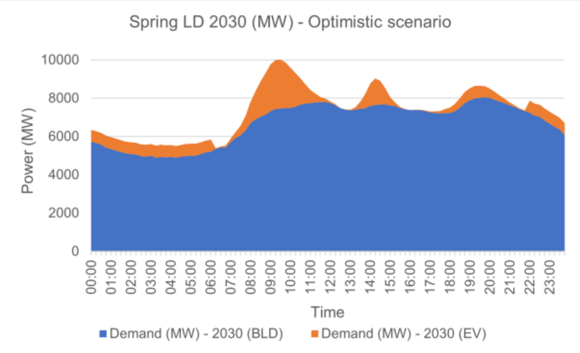


Figure 75. Optimistic, alternative TOU, Spring, weekday

Figure 76. Optimistic, alternative TOU, Spring, weekend



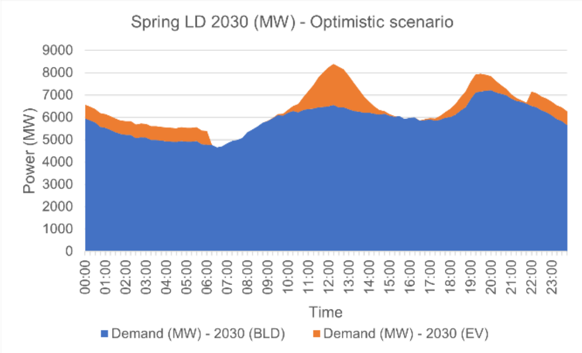
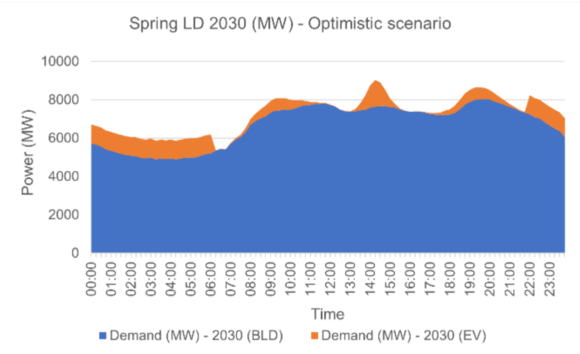


Figure 77. Optimistic, SG, Spring, weekday

Figure 78. Optimistic, SG, Spring, weekend



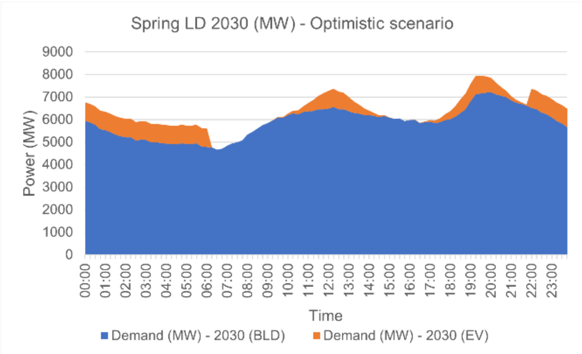
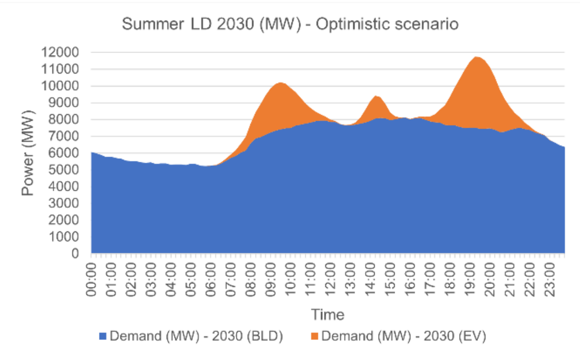


Figure 79. Optimistic, add.m.SG, Spring, weekday

Figure 80. Optimistic, add.m.SG, Spring, weekend



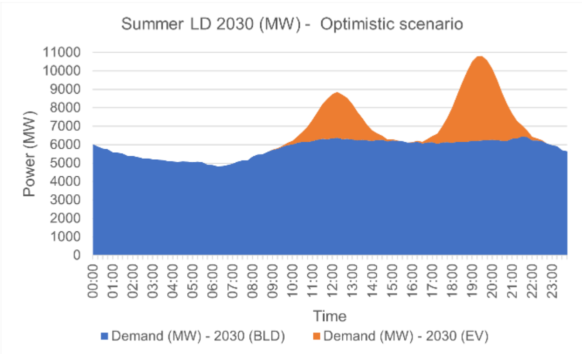


Figure 81. Optimistic, UC, Summer, weekday

Figure 82. Optimistic, UC, Summer, weekend

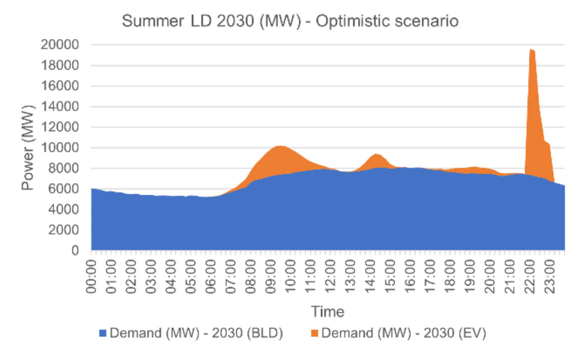


Figure 83. Optimistic, original TOU, Summer, weekday

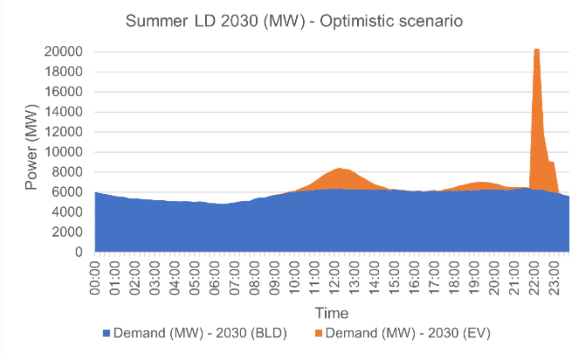


Figure 84. Optimistic, original TOU, Summer, weekend

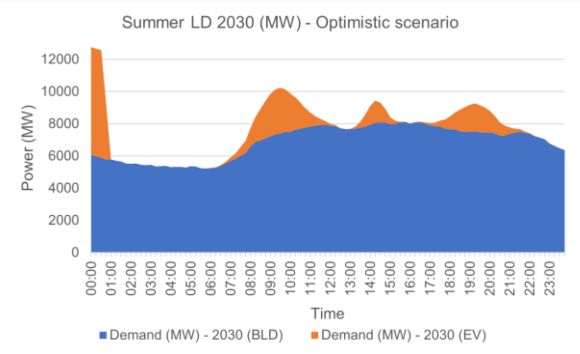


Figure 85. Optimistic, alternative TOU, Summer, weekday

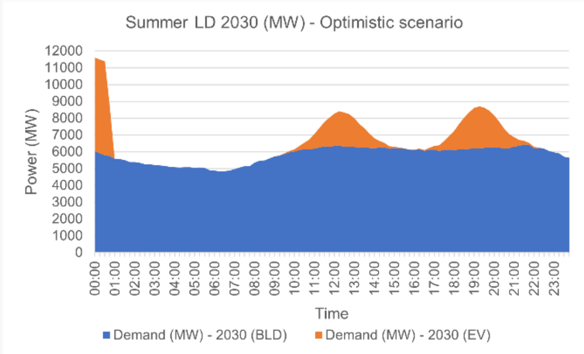


Figure 86. Optimistic, alternative TOU, Summer, weekend

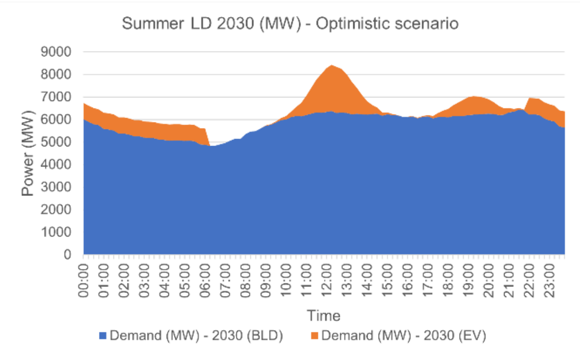


Figure 87. Optimistic, SG, Summer, weekend

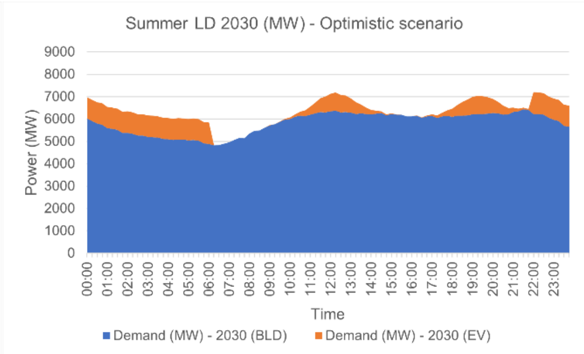


Figure 88. Optimistic, add.m.SG, Summer, weekend

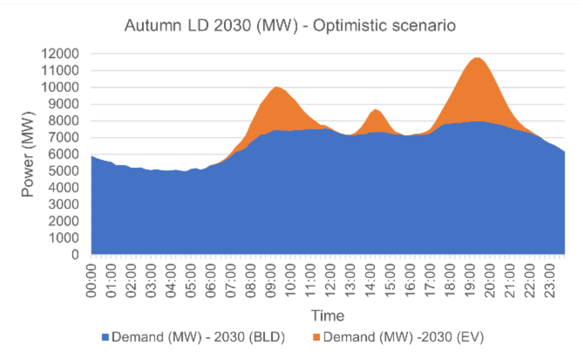


Figure 89. Optimistic, UC, Autumn, weekday

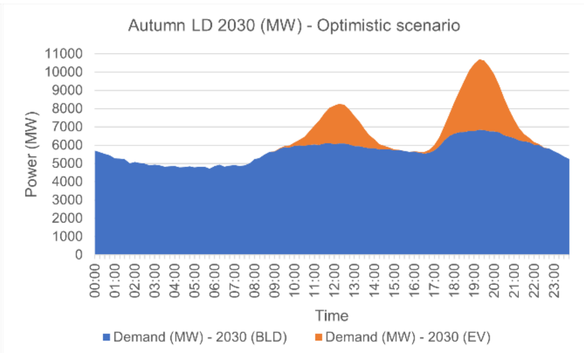


Figure 90. Optimistic, UC, Autumn, weekend

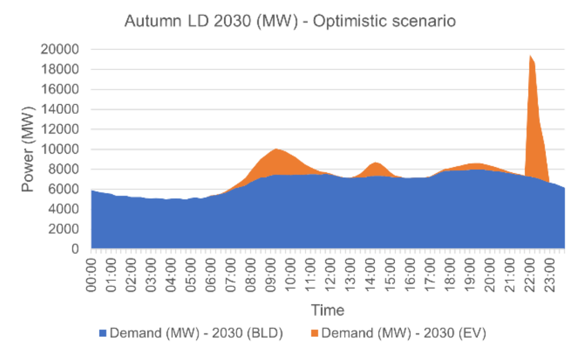


Figure 91. Optimistic, original TOU, Autumn, weekday

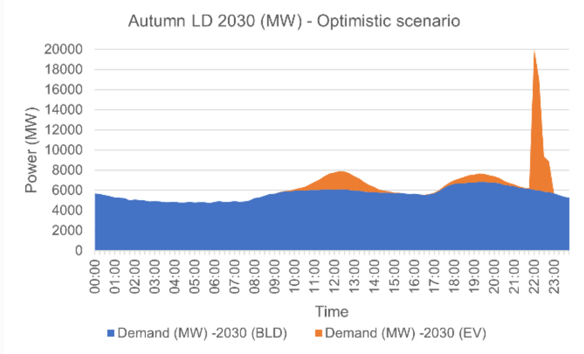


Figure 92. Optimistic, original TOU, Autumn, weekend

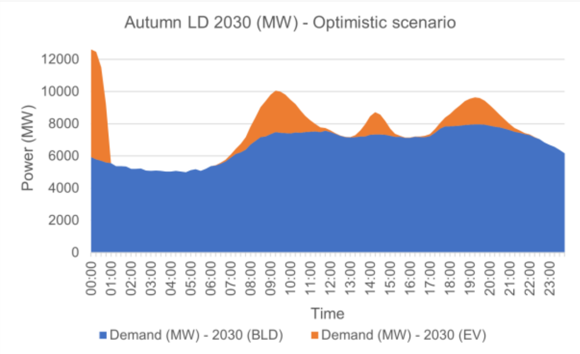


Figure 93. Optimistic, alternative TOU, Autumn, weekday

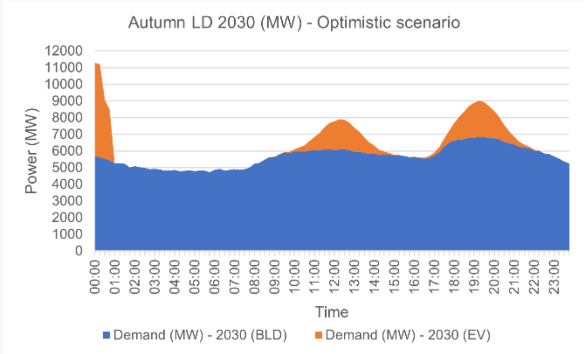


Figure 94. Optimistic, alternative TOU, Autumn, weekend

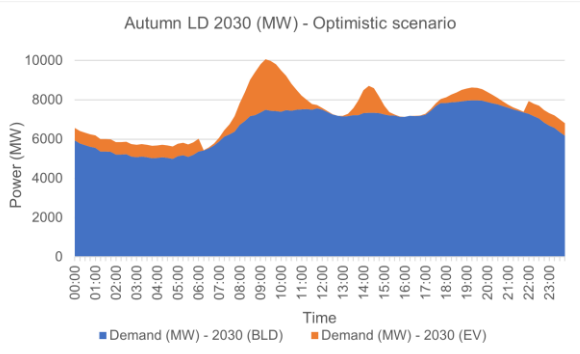


Figure 95. Optimistic, SG, Autumn, weekday

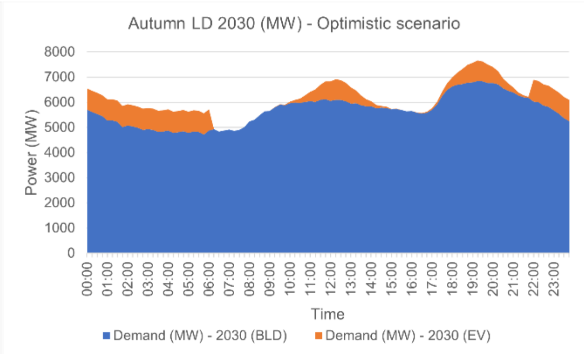


Figure 96. Optimistic, SG, Autumn, weekday

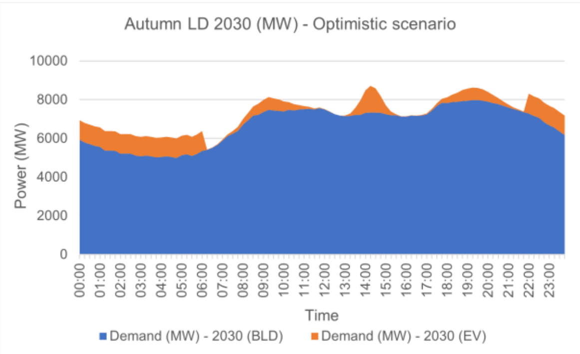


Figure 97. Optimistic, add.m.SG, Autumn, weekday

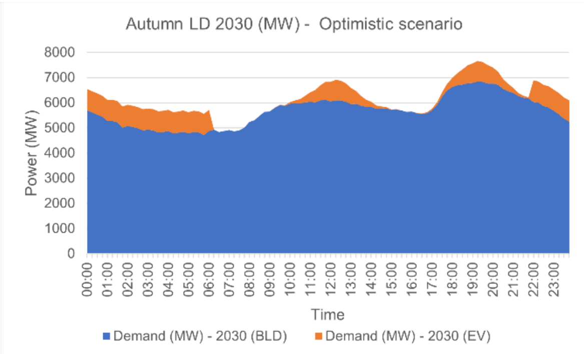


Figure 98. Optimistic, add.m.SG, Autumn, weekend