Impact of Electric Vehicle Charging on the Portuguese Electricity Demand Curve

Tiago Meintjes

tiago.f.meintjes@tecnico.ulisboa.pt

Instituto Superior Técnico, Universidade de Lisboa, Portugal

January 2021

Abstract:

This study aims to explore the impact of light-duty passenger (LP) electric vehicle (EV) charging on the Portuguese national load diagram (LD) in 2030. The goal is to identify EV charging strategies that enable a sustainable configuration of the Portuguese LD under different potential levels of LP EV penetration in 2030. The research offers information for Portuguese utilities and policy makers regarding potential threats and solutions of distinct EV charging strategies on the national power system in 2030. Furthermore, it proposes a methodology which can also be adopted by other countries to analyse similar problems. The three predicted scenarios of EV penetration were designated as: *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. Moreover, morning charging sessions must also be 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 patterns; Charging patterns; Charging strategies

1.Introduction

Several predictions foresee electric vehicles (EVs) making up a considerable portion of national vehicle fleets. If charging activities are performed in an uncontrolled (UC) manner, EVs capable of connecting to the grid, *i.e.* plug-in EVs and plug-in hybrid EVs [1], which from this moment forth will be designated collectively as EVs, will pose as a threat to future power systems, due to the significant loads induced on national grids [2].

One of the main research fields that addresses the aforementioned problem is based on analysing the impacts of EV charging on national LDs, with the purpose of identifying and quantifying the peak loads associated with UC charging. Additionally, authors propose numerous EV controlled charging strategies that attempt to promote LDs with sustainable configurations. Within this field, research is typically divided into three categories: *i.) UC Charging and Non-Optimised Controlled Charging Solutions*; *ii.) Optimised Controlled Charging Solutions*; and *iii.) Vehicle-to-Grid* (V2G) *and Additional UC Charging Operations.*

In *i.)*, studies identify the most common patterns of UC EV charging and subsequently portray those findings on LDs to locate the most prominent threats. Additionally, authors propose non-optimised controlled charging solutions.

Within the scope of *i.)*, studies indicate that UC charging will mostly affect peaking units in the evening, due to the considerable number of users charging their vehicles simultaneously upon arriving home from work [3, 4, 5]. This conclusion was drawn under the assumption that the most significant EV loads will be registered when the highest number of vehicle arrivals is observed, which according to travel surveys, such as the *National Household Travel Survey*, will take place within the aforementioned evening period [6, 7]. Furthermore, authors have identified that the distribution which most resembles the pattern associated with the arrival of a fleet of vehicles in the evening is the Gaussian distribution. As such, the same studies have used this function to mathematically model the distribution of UC EV charging within the respective period [8, 9]. Research has also analysed the outcomes of using distinct levels of power in EV charging activities.

The results obtained from these studies suggest that charging with lower levels of power induces less threatening LD configurations than charging with higher levels of power, as the latter provoke sudden peaks of considerable load and the former merely extend the period in which secure levels of EV demand is registered [6, 7, 9]. Lastly, studies have typically identified that shifting charging events to the valley period, via time-of-use (TOU) tariffs or utility-based scheduling, for example, can reduce the impact of EV charging on the LD [6, 9].

Within the second category, *ii.) Optimised Controlled Charging Solutions*, research aims to obtain optimised controlled charging solutions based on the constraints and proposals defined in *i.)*. The solutions are obtained through algorithms which incorporate the economical/technical needs of EV users, grid/utilities and energy producers via centralised or decentralised (distributed) programmes. *Masoum, et al.* [10] state that decentralised programmes, with the aid of real time information, enable EV users to decide under what power and time their vehicles are to be charged, while centralised coordination charging is scheduled through an EV aggregator that acts as a middleman between utilities and users. As such, the same study concludes that centralised programmes are intend to guarantee higher levels of optimal grid usage by forfeiting user ownership, while decentralised programmes look to prioritise the desires of each individual.

Quadratic programming (QP) stands out as one of the main forms used to achieve optimal EV charging scheduling within centralised coordination [2, 8, 11]. In decentralised programmes, research has primarily focused on developing multi-agent solutions (MAS) [2, 12, 13]. Within the research associated with scheduling EV charging through MAS, studies typically associate each agent to a smart charging controller (SCC), which has the ability to calculate and update each charging schedule by monitoring the real-time price (RTP) of electricity and the battery status of the respective EV [12, 14]. Furthermore, decentralised algorithms predominately operate in two distinct stages, which firstly determine the optimal conditions of EV charging according to the benefits obtained by each user, and secondly, analyse if those conditions enable a safe operation of the grid through a verification stage [14, 15, 16]. Additional studies have developed optimised controlled charging scheduling through Particle Swarm Optimization algorithms [17], innovative pricing measures applied on heuristic algorithms [18] and interactive decision making via a Nash equilibrium point [19].

In the third category, *iii.) Vehicle-to-Grid* (V2G) *and additional UC charging operations*, studies have analysed how the operation of V2G can further aid coordinated charging strategies in improving the configuration of LDs. Within *iii.)*, research typically follows a standard pattern, which consists of initially applying charging strategies proposed in *ii.)* to successfully shift EV charging to off-peak periods, and subsequently, activating V2G operation during peaks of consumption [20, 21].

A significant portion of the aforementioned studies attribute more focus to the impacts of UC charging within evening peak hours, assuming that EV charging will mostly take place within the vicinity of the user's home [3, 5, 6, 7]. However, research has shown that as EVs become more financially accessible, large portions of future EV charging will not only take place at home, but also within the workplace, in the morning, and commercial settings in the afternoon [22, 23]. These studies describe distinct results for the weekends, whereby LDs present less distinctive configurations that typically vary throughout the entire afternoon. These *additional UC charging operations* do not display the flexibility of evening charging sessions, as they are unable to be postponed to periods of low demand, such as the valley period. Thus, authors have proposed models in which V2G is applied to aid the national grid with said charging operations [24, 25].

Bearing the aforementioned in mind, this paper attempts to account for both evening and *additional UC charging operations*, to establish if future EV charging raises potential threats within other periods. Furthermore, this work also analyses the EV penetration levels for which discussed charging coordination strategies are actually required. This analysis can be useful for national policy makers and utilities for planning the upgrade process of national grids according to the growth rate of their respective EV fleet, as accommodating optimised controlled charging strategies, through smart grids (SG), will be a timely and costly process that will have to be implemented in a progressive and thoughtful manner.

As such, the objective of this study is to identify charging strategies discussed within the literature that guarantee sustainable configurations of the Portuguese LD under different potential levels of EV penetration in 2030. This research has been carried out for week and weekend days within all seasons of the year, and is based on a theoretical analysis developed within the scope of this research. Specifically, the theoretical analysis has the objective of 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. This methodology can be adapted to the conditions of other countries to study similar problems.

The remainder of this paper is organised as follows: Section 2 – *Methodology and Simulation Conditions*, presents the conception and application of the methodology for gathering the simulation conditions required for this research. Section 3 – *Results and Discussion* describes relevant results obtained from the simulations, and answers the main research question. Finally, section 4 – *Conclusions* presents some final remarks regarding the overall conclusions of this work.

2. Methodology and Simulation Conditions

2.1. Prediction of the Portuguese baseline load diagram (BLD) for 2030

Until 2050, the consumption of electric energy in Portugal will grow due to the presence of EVs and the increasing demand from traditional electric energy consuming sectors [26, 27]. As such, to predict the impact of EV charging on the configuration of future Portuguese LDs, it is necessary to obtain a baseline load diagram (BLD) for 2030 that accounts for the growth in electric energy consumption of activities other than EV charging.

To obtain the BLDs belonging to the different seasons of the 2030, a growth rate (GR) associated with the increase in yearly electrical consumption between a reference year and 2030 was applied to the LDs of the respective reference year, designated as reference load diagrams (RLDs). The RLDs used within this research belong to the year of 2017 and correspond to the week and weekend days in which the highest value of daily electric energy consumption was registered within each season [28].

The calculation of GR depended on the registered and predicted values of Portuguese annual electric energy consumption within the years of 2017 and 2030, which within the scope of this research correspond 49,383 GWh and 52,319 GWh, respectively [26]. Accordingly, the GR between 2017-2030 is 5.95%. Figure 1 illustrates the RLD and the BLD obtained for the weekday of Winter in 2017 and 2030, respectively.

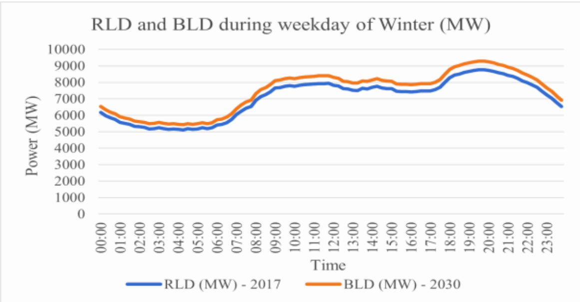

Figure 1. RLD (2017) and BLD (2030) for Winter weekday in MW

2.2. Prediction of LP EV penetration in Portugal for 2030

Regarding the prediction of the light-duty passenger (LP) EV fleet in Portugal for 2030, three different scenarios were considered: *pessimistic*; *base*; and *optimistic*, in which the size of the EV fleet increases from the *pessimistic* to the *optimistic* scenario.

2.2.1. Pessimistic Scenario

The *pessimistic* scenario assumes the predictions carried out by the *Direção-Geral de Energia e Geologia* (DGEG), *i.e.* Ministry of Environment and Energy, which predicts that the size of the LP EV fleet by 2030 will correspond to 85,925 vehicles [26].

2.2.2. Base Scenario

The size of the LP EV fleet within the *base* scenario was based on a European Union (EU) directive that establishes minimum procurement levels for share of clean LP vehicles between 2nd August 2021 and 31st of December 2030 for each member-state [29]. In the case of Portugal, that target is set at 29.7%. As the aforementioned target is established as a percentage of the entire Portuguese LP vehicle fleet, a prediction of the size of said vehicle fleet for 2030 was initially required. To obtain the respective prediction, a linear regression associated with the development of the Portuguese LP vehicle fleet from 1991-2018 [30] was performed, with the intent of obtaining a trend line depicting its annual development. Illustrations of the linear regression, performed from 1991-2030, as well as the development of the respective LP vehicle fleet from 1991-2018 are depicted in figure 2.

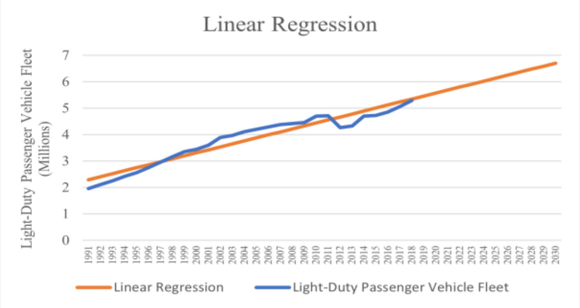

Figure 1. Linear Regression of LP vehicle fleet from 1991-2018.

The linear regression model indicates that Portugal will register an annual increment of 113,008 LP vehicles from 2018 to 2030. Given the 29.7% procurement level established for Portugal, the annual increment of LP EVs corresponds to 33,563. Thus, in addition to the 19,689 LP EVs existent in Portugal as of 2018 [31], the number LP EVs in Portugal by 2030, within the *base* scenario, is 422,445.

2.2.3. Optimistic Scenario

The size of the *optimistic* EV fleet considers targets set by the Portuguese government regarding desired levels of EV penetration for 2030 [27]. According to the aforementioned reference, the national government has targeted at securing 30% of its mobility through electrified sources. As such, considering the linear regression's prediction of the size of the LP vehicle fleet in 2030, the number of LP EVs within the *optimistic* scenario is 2,008,717. Table 1 presents the sizes of the EV fleet within each scenario.

Table 1. Size of the LP EV fleet per scenario.

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

2.3. Mobility Patterns of Portuguese drivers and EV consumption rates

2.3.1.1. Mobility Patterns – Metropolitan Areas of Porto and Lisbon

The Portuguese mobility patterns built for this study were based on information retrieved from a document published by the Portuguese National Institute for Statistics (INE) [32], which presents organised statistical data on the mobility patterns associated with the main forms of transport within the Metropolitan Areas of Porto (MAP) and Lisbon (MAL). Regarding the mobility of vehicles, the document categorises the daily recorded trips according to the travel motive (TM) of each journey, *e.g.* work and study. Subsequently, the report identifies the most common *travelled distance*, in *km*, and *portion of fleet*, in percentage, associated with the different TMs of each metropolitan area.

As the mobility patterns (*i.e. travelled distance* and *portion of fleet* corresponding to each TM) of MAP and MAL were established separately, it was necessary to create a single set of data which merged the mobility patterns of both regions. Within the scope of this research, the aforementioned data was designated *combined mobility pattern of MAP and MAL* (MAP+MAL). MAP+MAL was obtained through a weighted arithmetic average, whereby the weights, used to express the contribution of MAP and MAL within the calculation of the mobility patterns of each TM, were established according to the number of journeys registered within the respective TM of each metropolitan area.

2.3.1.2. Mobility patterns – Portugal

The Portuguese mobility patterns were established according to the NUTS III geographical classification, which subdivides the Portuguese territory into metropolitan areas and intermunicipal communities (ICs) due to the functional similarity existent between both geographical classifications [33].

To combine the driving behaviours of the ICs and MAP+MAL, it was initially necessary to establish the mobility patterns of each IC in accordance with the data of MAP+MAL. The aforementioned requirement was achieved via a linear extrapolation of the MAP+MAL data, according to the proportional difference existent between the geographical areas of MAP+MAL and the respective ICs [34]. Thus, ICs with the same geographical area of MAP+MAL possess *travelled distances* equal to the ones of MAP+MAL within every TM. For simplicity, the *portion of fleet* linked to the TMs of each IC were assumed to be equal to the ones registered in MAP+MAL. Moreover, the single area of MAP+MAL, used to perform the linear extrapolation, was calculated via a weighted arithmetic average, whereby the contribution of both areas was based on their proportional difference.

Once the mobility patterns of each IC were established in accordance with MAP+MAL, the statistical data associated with each location was combined into a single representation of the driving behaviours of the entire Portuguese population. Again, this unique set of data was obtained via a weighted arithmetic average, in which the contribution of each location was established according to the size of the population existent within each region [34]. Thus, locations with larger populations have greater impact on the calculation of the *travelled distance* of each TM. Likewise, the *portion of fleet* of each TM are equal to the ones obtained in the calculation of MAP+MAL. Table 2 presents the mobility patterns of the Portuguese population during weekdays.

Table 2. TM characteristics for Portuguese population during weekdays.

TM	Travelled Distance (km)	Portion of Fleet (%)
Work	33.3	36.06
Study	16.7	13.53
Friend/Family Accompanying	16.6	18.85
Leisure	35.9	6.9
Shopping	14.5	13.44
Personal Affairs	34.1	10.89
Other Activities	30.2	0.61

2.3.2. EV consumption rates:

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 [35]. Further studies categorise EV consumption ratings according to the size of the vehicle, which range from 11kWh/100km to 23kWh/100km in *mini* sized and *large* sized EVs, respectively [36, 37]. Additionally, studies conducted by *Darabi et al.* [6], *Wu et al.* [38] and *Chen et al.* [39] consider consumption rates of 0.22 kWh/km, 0.15 kWh/km and 0.19 kWh/km, respectively.

According to *Yuksel et al.* [40], the consumption rating of an EV varies according to the ambient temperature. Thus, the authors developed a mathematical model, exhibited in equation 1, which determines the electrical consumption rating (c_i) of the Nissan Leaf, a common mid-sized EV within the Portuguese fleet [36, 41], according to the temperature (T_i) in which it is being driven in. As the present study analyses EV charging within different seasons of the year, the consumption ratings were obtained according to the aforementioned model, which was manipulated in order to accommodate values of temperature and distance in ºC and km, rather than the original ºF and miles. The input temperature used to determine the electrical consumption for each season was assumed as the average temperature registered in each season of 2017 [42], which corresponds to the same year of the RLDs. Table 3 indicates the consumption ratings obtained.

$$c_i(T_i) = 0.62 * \left[\sum_{n=0}^{5} a_n (1.8T_i + 32)^n\right] \quad (1)$$

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

Table 3. EV energy consumption ratings per season.

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

2.4. Charging infrastructure, patterns and strategies

2.4.1. Charging infrastructure

The charging infrastructure assumed within the simulations of this research is the one associated with the European Standard [43]. Thus, the charging power rates follow three different categories: *i.) Slow charging*, in which charging is carried out in a domestic or long-time parking environment with a rated power ≤3.7kW in AC current; *ii.) Normal charging*, where charging is performed in private and semi-public locations with a rated power between 3.7kW to 22kW in AC current; and *iii.) Fast charging*, in which charging is undergone in public areas with a rated power >22kW in AC or DC current.

2.4.2. Charging patterns

2.4.2.1. Charging patterns – Selected charging modes

Currently, charging in private outlets plays an important role in certifying the energetic needs of EVs, however, as EVs become more financially accessible, governments recognise the need to assure public charging points. In particular, the EU has begun to create targets directed at establishing minimum levels of available public charging outlets within each of its member-states [44]. As such, the present research takes into consideration different charging power rates according to the environment in which the charging operation is being undergone. Specifically, private charging is carried out under *Normal charging* at home or work, with a rated power of 7.4kW, while public charging can either be performed in: *i.)* the vicinity of home or work under *Normal charging* via a rated power of 22kW; or *ii.)* commercial settings in AC *Fast charging* or DC *Fast charging*, with a rated power of 50kW [44].

2.4.2.2. Charging patterns – Time and location of charging events

Private charging operations typically take place upon the user's arrival at work during weekdays, or following the arrival of the EV user at home during weekdays and weekends. Alternatively, public charging events are carried out under two distinct situations, which are: *i.)* EV users who do not have access to a private charging outlet, and therefore carry out charging in a public station upon their arrival at work during weekdays, or at home during weekdays and weekends; and *ii.)* in commercial spaces, where EVs are parked for a considerable amount of time due to leisure, shopping, sports facilities or other activities during both weekdays and weekends [22, 45].

Two dominant distribution of arrivals are noticed within journeys carried out during weekdays, which take place in the morning and evening when drivers arrive at their workplaces and households. As such, these events correspond to charging activities which are carried out in both public and private settings. Additionally, a more modest cluster of arrivals is also identified during the afternoon, which correspond to journeys that have commercial spaces as their destination, and therefore, correspond to charging events carried out in public outlets. The time at which the peak of arrivals is registered in the morning, afternoon and evening is 9AM, 2PM and 7PM, respectively [22, 23, 32].

During the weekend, there is an absence of journeys in the morning, due to users not driving into work. As such, weekend charging is mostly undergone between early afternoon and evening hours, however, its distribution is less obvious, as some authors consider it to be undergone continuously within the abovementioned timespan [22], while others identify two peaks of arrivals in the early afternoon and evening [23, 32]. Within the scope of this research, the latter charging distribution was considered, as it closely resembles the charging distribution of journeys performed in Lisbon [32]. Specifically, afternoon charging activities are assumed to be undergone in commercial spaces via public outlets, while evening charging events are carried out upon the user's arrival at home, and therefore take place in both private and public charging points. The time at which the peak of weekend arrivals is registered within the afternoon and evening is at 12PM and 7PM, respectively. Information regarding the arrivals of EVs can be found in table 4.

Table 4. Charging pattern characteristics for weekdays and weekends.

Day	Peaks	Charging Point	Location
Weekday	Morning – 9AM	Private + Public	Work + Commercial
	Afternoon – 2PM	Public	Commercial
	Evening – 7PM	Private + Public	Home + Commercial
Weekend	Afternoon – 12PM	Public	Commercial
	Evening – 7PM	Private + Public	Home + Commercial

Similarly to the articles discussed in the introductory chapter, the distribution of EV arrivals considered in the simulations of this work were mathematically modelled according to normal probability density function. Table 5 displays the normal distribution parameters for each charging session. Figure 3 depicts the distribution of EV arrivals in the evening during weekdays.

Table 5. Normal distribution parameters of weekday and weekend charging sessions.

Day	Mean	tandard Deviation
Weekday	Morning – 9AM	1 Hour
	Afternoon – 2PM	40 Minutes
	Evening – 7PM	1 Hour
Weekend	Afternoon – 12PM	1 Hour
	Evening – 7PM	1 Hour

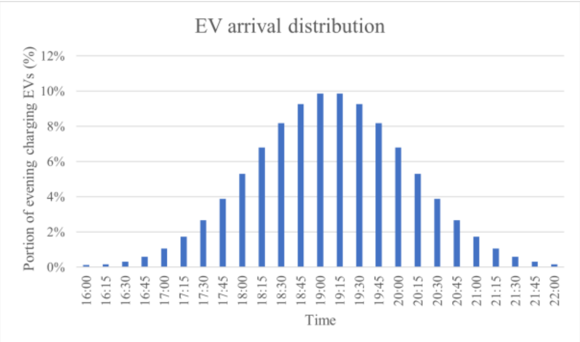

Figure 3. Distribution of EV arrivals during evening weekdays.

2.4.2.3. Charging patterns – Quantification of charging events

As Portugal is a member-state of the EU, the information regarding the share of fleet associated with private and public charging was obtained from the study *Recharge EU*, performed by *Transport and Environment* (T&E) [45]. Table 6 indicates the referenced values, in which public charging events are registered according to their rated power.

Table 6. Share of EV fleet charging under private/public charging points.

Charging Point	Location	Portion of EV fleet (%)
Private	Home	45
	Work	24
Public	Commercial – Fast	9
	Commercial – Normal	22

To quantify the amount of public *Normal* and *Fast charging* events taking place under each weekday charging period, information from the study by *Helmus, et al.* [46] was considered, where the amount of *charging sessions/hour* are divided into two distinct categories: public charging with less than 6 hours (<6h) and with more than 6 hours (>6h). Moreover, the study classifies these charging events according to the type of charging point used, *i.e.* demand driven or strategic. However, these classifications are disregarded within this research, as they are merely intended at distinguishing charging points which are regularly frequented by dedicated consumers (demand driven) from those that are used by a wider range of drivers (strategic). Thus, the amount of *charging sessions/hour* within the <6h and >6h categories are to be interpreted as a sum of both demand driven and strategic classifications.

The results of the aforementioned study [46] identify charging events with similar patterns to the ones already discussed, with three distinct peaks of charging events occurring within the <6h category – morning, afternoon and evening – and two peaks occurring in the >6h category – morning and evening. As such, within the scope of this research, the >6h category is carried out by users who do not possess a private charging outlet, and therefore, charge publicly in the vicinity of their workplace, in the morning, or household in the evening, via *Normal charging* – 22kW. Alternatively, the <6h category is assumed to be undergone by charging events that present short connection times and are therefore undergone through *Fast charging* – 50kW. The aforementioned information is specified in table 7 where the column identified as *portion of EV fleet* resembles the corresponding information of table 6 according to the proportions indicated in *Charging sessions/hour*.

Table 7. Share of EV fleet associated with public charging stations during weekdays [46].

Charging duration	Time	Charging sessions/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

The partition of public charging during weekends was established according to the T&E document, which indicates that commercial areas should equip 50% of their public or semi-public parking lots with charging infrastructure by 2030. As such, this study considers that, during the weekend, half of the public charging events are carried out during the afternoon, while the other half in the evening. Furthermore, this logic is extended to EVs that charge privately during weekdays in the morning, as users do not travel to work in the weekend. Private charging at home is undergone in the same fashion as during weekdays. Table 8 identifies the share of public EV charging during the weekend more clearly [45].

Table 8. 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

According to INE [32], MAL registers an approximated 16.7% reduction of its mobility level during the weekend. As MAL accounts for a considerable number of journeys executed in Portugal, the size of the EV fleet during the weekend is considered be 83.3% of its original value within each penetration scenario.

Lastly, *Morrissey, et al.* [47] indicate that *Fast charging* stations register a higher quantity of demanded energy per vehicle than *Normal charging* points. As such, for the present research, the demand of *Fast charging* events adopts a distribution which was obtained via an arithmetic average of the energy demanded, per *Fast charging* event, within petrol stations and car parks [47]. (See figure 4).

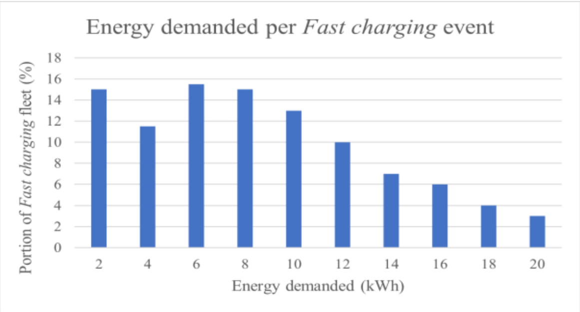

Figure 4. Energy demanded from EVs in Fast charging stations (kWh).

2.4.3. Charging strategies

This research analyses the effect of EV charging on the LD according to three distinct charging strategies: *i.) Uncontrolled (UC) charging*; *ii.) Time-of-Use (TOU) charging*; and *iii.) Smart grid (SG) charging.*

UC charging is characterised by EV owners that charge their vehicles immediately after their arrival at a certain destination. Thus, this EV charging strategy is characterised by all the steps described in the previous subsection – 2.4.2.

The TOU charging strategy adopts the patterns of UC charging, with the difference that *Normal* private and public EV charging in the evening is shifted to the beginning of the off-peak hours, which according to the daily cycle of the TOU price tariff established by *Energias de Portugal* (EDP), the biggest utility in Portugal, begins at 22:00 [48]. Additionally, evening *Fast charging* operations continue to be undergone in an UC manner, as users are generally seeking to charge their vehicle on demand.

The SG charging strategy is similar to the TOU strategy, as all evening public and private *Normal charging* events are also shifted to off-peak hours via the monetary incentive offered by the TOU price tariff. However, in this case, by interacting in real time with a central aggregator, each EV is charged with the minimum power level required to fulfil its respective energy needs until 6 AM – when users begin travelling to work.

3. Results and Discussion

This section is devoted to discussing the set of results obtained from the simulations, with the purpose of identifying the most adequate charging strategy within each of the three predicted levels of EV penetration. Due to the extensive number of results obtained from the simulations, only the results which present relevant or unexpected information will be depicted.

3.1. Results and Discussion – Pessimistic Scenario

Within the *pessimistic* EV penetration level, the highest rise in demanded power takes place under the UC charging strategy during the evening. However, as the size of the EV fleet is small, the rise in demand is of no major concern, as the load induced by UC EV charging during said period presents itself in a relatively flattened manner. As such, within the *base* scenario, EV charging can be performed in an UC manner. This result was equally obtained within the weekdays and weekends of every season.

3.2. Results and Discussion – Base Scenario

EV charging under the *base* scenario does induce a greater difference in the LDs when compared to the *pessimistic* scenario. Nevertheless, the most significant change induced by UC charging on the configuration of the BLD is a 9% increase in demanded power during the evening, due to the combination of a relatively low sized EV fleet with charging events that are adequately spread out in time. However, one should attempt to apply the TOU charging strategy to avoid this unnecessary burden of evening EV charging.

To discuss these results, the simulations associated with weekdays of Winter will be presented, as they correspond to the time of year in which the Portuguese LDs register their highest levels of daily consumption. The results obtained for the UC and TOU charging strategies within the *base* EV penetration level are depicted in figures 5 and 6, respectively.

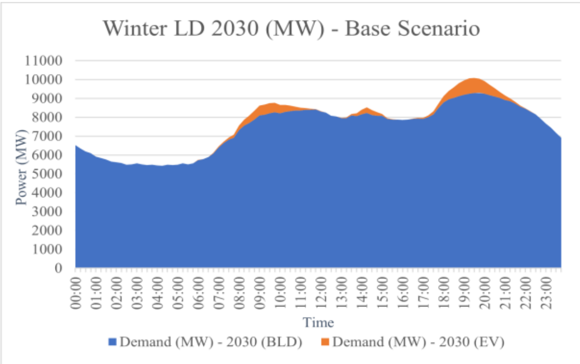

Figure 5. LD of Winter weekdays in 2030, under the base EV penetration level following the UC charging strategy.

Figure 6 clearly suggests that TOU charging does successfully allow for a reduction of the EV demand in the evening, as a considerable number of charging events within that period are shifted to the off-peak hours. However, by shifting most evening charging events to a later period, and by initiating the respective charging activities simultaneously, a significantly sharp difference in power is induced within the LD that gives way to a new maximum daily load of 11,016MW, which surpasses the 10,082MW registered within the UC charging strategy in the evening. As such, it is possible to state that number of EVs that can charge under the TOU strategy and produce results that contribute to a better working power system is limited.

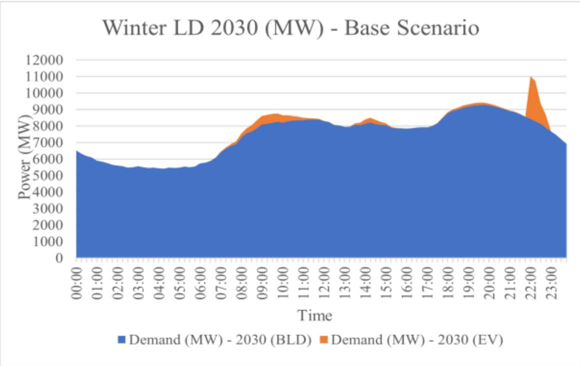

Figure 6. LD of Winter weekdays in 2030, under the base EV penetration level following the original TOU charging strategy.

Although the aforementioned results present a limitation towards the application of the TOU charging strategy, they should not mislead the reader into thinking that, under this level of EV penetration, the UC strategy is always more beneficial. Firstly, UC charging is not regulated, and therefore presents a greater level of uncertainty. Secondly, modifications to the TOU strategy, such as shifting a smaller amount of charging events to an even later off-peak period, can produce more satisfying results, depending on the size of the EV fleet. Within the scope of this research, the charging strategy associated with the latter indicated TOU measures is designated *alternative* TOU charging strategy, whereby only private *Normal charging* events are shifted 00:00 (see results in figure 7). Meanwhile, from here forth, the TOU strategy depicted in figure 6 will be named *original* TOU charging strategy.

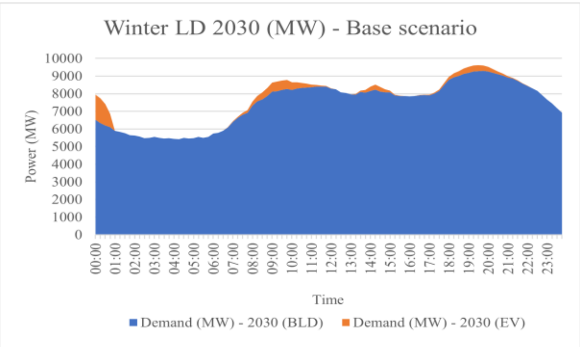

Figure 7. LD of Winter weekdays in 2030, under the base EV penetration level following the alternative TOU charging strategy.

By analysing figure 7, it is evident that the *alternative* TOU charging strategy induces a higher evening load than the *original* TOU strategy, given the larger amount of charging events taking place at that time. However, shifting a lower amount of evening charging events to an even later period produced enhanced results, as the maximum daily load of 9,622MW, registered within the *alternative* TOU charging strategy, is lower than one observed in the UC and *original* TOU strategies, which are 10,082MW and 11,016MW, respectively. This result confirms that while the *original* TOU charging strategy may present adversities to certain EV penetration levels, it does not necessarily have to be discarded immediately, as adaptations of said method, according to the EV penetration level in which it is being used, can still help to contain the complexities induced by UC charging in a simple, and user voluntary manner.

The SG charging strategy produces the most attractive results within the *base* scenario. However, as figure 7 suggests, it is not imperative for this specific EV penetration level, as the *alternative* TOU charging strategy guarantees a safe enough use of the national power system. This conclusion is simultaneously obtained for the weekdays and weekends of the remaining seasons.

3.3. Results and Discussion – Optimistic Scenario

For the reasons presented in the *base* scenario, the results illustrated in this subsection all correspond to weekdays of Winter. Figures 8 and 9 depict the results of the UC and *original* TOU charging strategies within the *optimistic* scenario, respectively. The results present alarming threats to the national power system, as the considerable size of the EV fleet induces significant levels of demanded power within both LDs. Moreover, the *optimistic* scenario further corroborates the observations made in the *base* scenario, as the difference between the maximum daily power recorded in the *original* TOU and UC strategies, which respectively correspond to 20,675MW and 13,094MW, is 7,581MW.

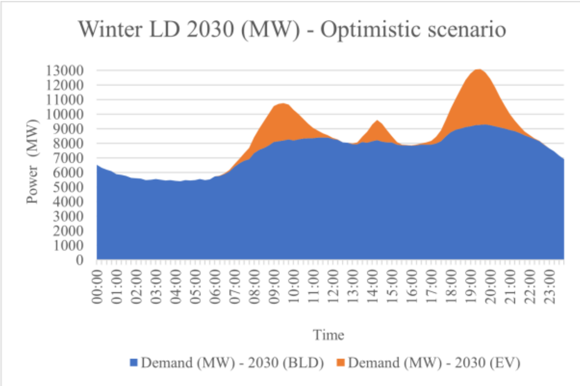

Figure 8. LD of Winter weekdays in 2030, under the optimistic EV penetration level following the UC charging strategy.

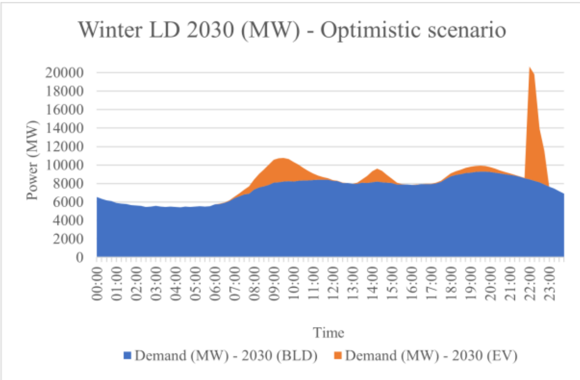

Figure 9. LD of Winter weekdays in 2030, under the optimistic EV penetration level following the original TOU charging strategy.

Given the above results, one must study the possibility of the *alternative* TOU strategy providing a safer platform to carry out EV charging within the *optimistic* scenario – depicted in figure 10. The results indicate that the evening peak load of the *alternative* TOU strategy is 17% lower than the one observed in UC charging. Moreover, the power registered at the beginning of its off-peak charging period is 36% lower than the one obtained in the *original* TOU strategy. However, the similar peak loads of 13,094MW and 13,216MW registered within the UC and *alternative* TOU strategies, respectively, suggest that the latter strategy is no longer a viable solution to contain the threats of EV charging within the *optimistic* scenario, as the level of power induced on the LD is already considerable and shows no improvement from the UC strategy.

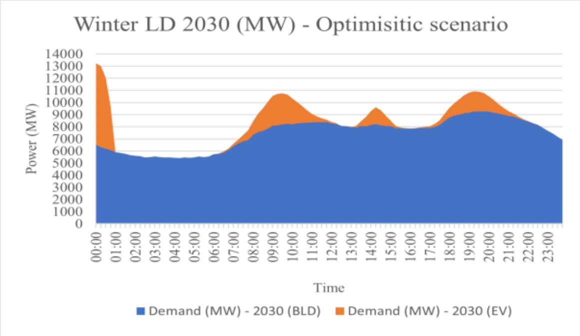

Figure 10. LD of Winter weekdays in 2030, under the optimistic EV penetration level following the alternative TOU charging strategy.

The above result suggests that, above a certain level of EV penetration, successive adjustments to the TOU charging strategy will not be sufficient to contain the threats of EV charging, and that ultimately, the SG charging strategy will be inevitable for countries who seek to promote clean mobility. Figure 11 depicts the simulation of the SG charging strategy within the *optimistic* scenario.

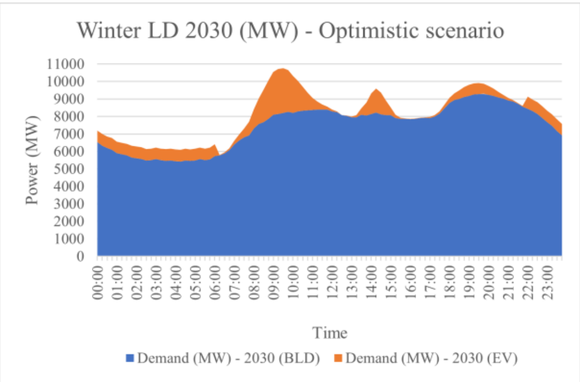

Figure 11. LD of Winter weekdays in 2030, under the optimistic EV penetration level following the SG charging strategy.

The results illustrated in figure 11 confirm that the SG charging strategy contains the dangers of EV charging under the *optimistic* scenario, as the maximum peak load of 10,768MW is considerably lower than the 13,094MW observed when EVs charge in an UC manner. Furthermore, carrying out private and public *Normal charging* events under a controlled power rate within the off-peak hours promotes valley-filling, which enables a LD with a more flattened format due to less power fluctuations. However, in an unprecedented manner, the daily peak of consumption occurs in the morning, indicating that the evening peak load could cease to be the biggest threat to utilities in the future, due to morning hours presenting higher values of demanded power.

As a solution, one could potentially apply the SG charging strategy for morning charging sessions also. However, applying the SG strategy to properly schedule morning charging is complex, as these connections do not present the opportunity of charging within a flexible off-peak period, like evening charges. Thus, a way of avoiding this new peak of consumption could be solved by possibly installing a higher number of public charging points in residential areas, for users to charge their EVs in the evening rather than the morning. This decision would have to be subsequently followed by creating incentives for users to shift their morning charging activities to the evening, which could be easily achieved through TOU price tariffs. The outcome of a regulation similar to this one would not only reduce the morning load induced by EV charging, as it would also promote further levels of valley-filling, through the use of the SG charging strategy. Figure 12 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.

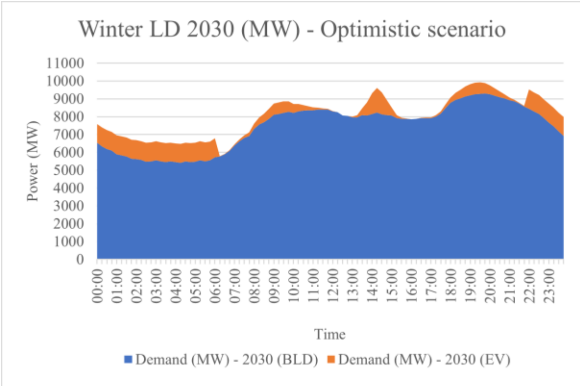

Figure 12. LD of Winter weekdays in 2030, under the optimistic EV penetration level following the additional measure of SG charging strategy.

By comparing figures 11 and 12, one notices that the respective morning peak is reduced from 10,768MW to 8,720MW, and that 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 considering the overall amount of daily energy demanded from EV charging, which corresponds to 8,208MWh. Likewise to the *base* scenario, the set of results and conclusions obtained for the *optimistic* EV penetration level were observed amongst all the days of the week and seasons of the year.

4. Conclusions

This paper offers a methodology that attempts to analyse the potential impacts of future EV charging on the configuration of a country's daily LD. Within the scope of this research, the aforementioned methodology was used to identify the charging strategies which enable sustainable configurations of the Portuguese LD under three potential levels of EV penetration for 2030. To do so, the aforementioned methodology was built via a theoretical analysis which was divided into four main areas of research: *i.) Prediction of the Portuguese BLD for 2030*; *ii.) Prediction of LP EV penetration in Portugal for 2030*; *iii.) Mobility Patterns of Portuguese drivers and EV consumption rates*; and *iv.) Charging infrastructure, patterns and strategies*.

The results indicate that an intelligent grid is not required to carry out charging activities within the *pessimistic* and *base* scenarios. Thus, within these EV penetration levels, charging may be carried out through the UC or TOU charging strategies, with the latter allowing further benefits. Within the *optimistic* scenario, Portugal's BLD can potentially increase from 9,293MW to 13,094MW in the evening if charging is performed in an UC manner. To avoid this situation, EV charging must be carried out through controlled charging strategies. However, the simulations indicate that the *original* and *alternative* TOU strategies do not guarantee a safe operation of the grid, as the former leads to an unprecedented 20,675MW, and the latter induces a maximum registered power of 13,216MW, which indicates no improvement in relation to the UC strategy. Thus, EV charging will need to be carried out through the SG charging strategy, which will enable an evening load of 9,917MW. However, by managing to control EV charging in the evening, the SG charging strategy will result in the morning load becoming the highest peak of daily consumption, as charging events will still be undergone in an UC manner in that period. As such, this paper suggests that more public EV stations be made available within residential areas for users to charge their EVs in the evening rather than the morning. Such measures could easily be incentivised by TOU price tariffs and are successful in reducing the morning peak from 10,768MW to 8,720MW. Moreover, higher levels of valley-filling are also achieved, as more users undergo SG charging.

References:

[1] N. Ding, K. Prasad and T. T. Lie, "The electric vehicle: a review," *Int. J. Electric and Hyrbid Vehicles*, 9:(1)49-66, 2017.

[2] S. Vandael, N. Bouké, T. Holvoet and G. Deconinck, "Decentralized demand side management of plug-in hybrid vehicles in a Smart Grid," in *Proceedings of the First International Workshop on Agent Technologies for Energy Systems*, 2010.

[3] G. A. Putrus, P. Suwanapingkarl, D. Johnston, E. C. Bentley and M. Narayana, "Impact of Electric Vehicles on Power Distribution Networks," in *2009 IEEE Vehicle Power and Propulsion Conference*, 2009.

[4] K. Parks, P. Denholm and T. Markel, "Costs and Emissions Associated with Plug-In Hybrid Electric Vehicle Charging in the Xcel Energy Colorado Service Territory," National Renewable Energy Laboratory, 2007.

[5] S. Shafiee, M. Fotuhi-Firuzabad and M. Rastegar, "Investigating the Impacts of Plug-in Hybrid Electric Vehicles on Power Distribution Systems," *IEEE Transactions on Smart Grid*, 4:(3)1351-1360, 2013.

[6] Z. Darabi and M. Ferdowsi, "Aggregated Impact of Plug-in Hybrid Electric Vehicles on Electricity Demand Profile," *IEEE Transactions on Sustainable Energy*, 2:(4)501-508, 2011.

[7] M. Sarker, M. Ortega-Vazquez and D. Kirschen, "Optimal Coordination and Scheduling of Demand Response via Monetary Incentives," *IEEE Transactions on Smart Grid*, 6:(3)1341-1352, 2015.

[8] A. Dogan, M. Kuzlu, M. Pipattanasomporn, S. Rahman and T. Yalcinoz, "Impact of EV Charging Strategies on Peak Demand Reduction and Load Factor Improvement," in *2015 9th International Conference on Electrical and Electronics Engineering*, 2015.

[9] S. Shao, T. Zhang, M. Pipattanasomporn and S. Rahman, "Impact of TOU Rates on Distribution Load Shapes in a Smart Grid with PHEV Penetration," in *IEEE PES T&D 2010*, 2010.

[10] A. S. Masoum, S. Deilami, A. Abu-Siada and M. Masoum, "Fuzzy Approach for Online Coordination of Plug-In Electric Vehicle Charging in Smart Grid," *IEEE Transactions on Sustainable Energy*, 6:(3)1112-1121, 2015.

[11] B. Sun , Z. Huang, X. Tan and D. Tsang, "Optimal Scheduling for Electric Vehicle Charging with Discrete Charging Levels in Distribution Grid," *IEEE Transactions on Smart Grid*, 9:(2)624-634, 2018.

[12] C. Li, E. Schaltz, J. C. Vasquez and J. M. Guerrero, "Distributed Coordination of Electric Vehicle Charging in a Community Microgrid Considering Real-Time Price," in *Proceedings of the 18th European Conference on Power Electronics and Applications*, 2016.

[13] C. Marmaras, E. Xydas and L. Cipcigan, "Simulation of electric vehicle driver behaviour in road transport and electric power networks," *Transportation Research Part C: Emerging Technologies*, 80:239-256, 2017.

[14] S. Martinenas, A. B. Pedersen, M. Marinelli, P. B. Andersen and C. Trreholt, "Electric vehicle smart charging using dynamic price signal," in *2014 IEEE International Electric Vehicle Conference*, 2014.

[15] R. Jiang, Z. Zhang, J. Li, Y. Zhang and Q. Huang, "A Coordinated Charging Strategy for Electric Vehicles Based on Multi-objective Optimization," in *2017 2nd International Conference on Power and Renewable Energy*, 2017.

[16] P. Liu, J. Yu and E. Mohammed, "Decentralised PEV charging coordination to absorb surplus wind energy via stochastically staggered dual-tariff schemes considering feeder-level regulations," *IET Generation, Transmission & Distribution*, 12:(15)3655-3665, 2018.

[17] R. Shi, L. Xu and Y. Xue, "Research on Coordinated Charging Strategy of Electric Vehicles Based on PSO Algorithm," in *2018 Chinese Automation Congress*, 2018.

[18] Y. Zhao, H. Huang, X. Chen, B. Zhang, Y. Zhang, Y. Jin, Q. Zhang, L. Cheng and Y. Chen, "Charging Load Allocation Strategy of EV Charging Station Considering Charging Mode," *World Electric Vehicle Journal*, 10:(2), 2019.

[19] A. Sheiki, S. Bahrami, A. M. Ranjbar and H. Oraee, "Strategic charging method for plugged in hybrid electric vehicles in smart grids; a game theoretic approach," *International Journal of Electrical Power & Energy Systems*, 53:(1)499-506, 2013.

[20] M. A. López, S. de la Torre, S. Martín and J. A. Aguado, "Demand-side management in smart grid operation considering electric vehicles load shifting and vehicle-to-grid support," *International Journal of Electrical Power & Energy Systems*, 64:689-698, 2015.

[21] Y. Wang and D. Infield, "Optimal Demand Side Response to Real Time Price Signal Using Electric Vehicles," in *International Conference on Renewable Power Generation*, 2015.

[22] C. Weiller, "Plug-in hybrid electric vehicle impacts on hourly electricity demand in the United States," *Energy Policy*, 39:(6)3766-3778, 2011.

[23] E. Paffumi, M. De Gennaro and G. Martini, "European-wide study on big data for supporting road transport policy," *Case Studies on Transport Policy*, 6:(4)785-802, 2018.

[24] M. Sufyan, N. A. Rahim, M. A. Muhammad, C. K. Tan, S. Raihan and A. H. Bakar, "Charge coordination and battery lifecycle analysis of electric vehicles with V2G implementation," *Electric Power Systems Research*, 184, 2020.

[25] H. Liang, Y. Liu, F. Li and Y. Shen, "Dynamic Economic/Emission Dispatch Including PEVs for Peak Shaving and Valley Filling," *IEEE Transactions on Industrial Electronics*, 66:(4)2880-2890, 2019.

[26] DGEG, "Relatório de Monitorização da Segurança de Abastecimento do Sistema Elétrico Nacional 2017-2030," 2017.

[27] República Portuguesa, "Roteiro para a Neutralidade Carbónica 2050," 2019.

[28] REN, "Diagramas de Carga 2017," REN, 2017.

[29] EU, "Directive (EU) 2019/1161 of the European Parliament and of the Council of 20 June 2019 amending Directive 2009/33/EC on the promotion of clean and energy-efficient road transport vehicles," 2019.

[30] INE, Collection: "Estatística dos Transportes e Comunicações 1991-2018," INE, I.P., Lisbon, 1991-2018.

[31] IMT, "Anuário Estatístico da Mobilidade e dos Transportes," IMT, I.P., Lisbon, 2019.

[32] INE, "Mobilidade e funcionalidade do território nas Áreas Metropolitanas do Porto e de Lisboa 2017," INE, I.P., Lisbon, 2017.

[33] Assembleia da República, "Lei n.º 75/2013," 2013.

[34] INE, Collection: "Statistical Yearbook of Alentejo, Algarve, Centro, Norte Regions - 2018," INE, I.P., Lisbon, 2019.

[35] M. Fuller, "Wireless charging in California: Range, recharge, and vehicle electrification," *Transportation Research Part C: Emerging Technologies*, 67:343-356, 2016.

[36] A. Perujo and B. Ciuffo, "The introduction of electric vehicles in the private fleet: Potential impact on the electric supply system and on the environment. A case study for the Province of Milan, Italy," *Energy Policy*, 38:(8)4549-4561, 2010.

[37] R. Loisel, G. Pasaoglu and C. Thiel, "Large-scale deployment of electric vehicles in Germany by 2030: An analysis of grid-to-vehicle and vehicle-to-grid concepts," *Energy Policy*, 65:432-443, 2014.

[38] Q. Wu, A. H. Nielsen, J. Østergaard, S. T. Cha, F. Marra, Y. Chen and C. Træholt, "Driving Pattern Analysis for Electric Vehicle (EV) Grid Integration Study," in *2010 IEEE PES Innovative Smart Grid Technologies Conference Europe*, 2010.

[39] Z. Chen, F. He and Y. Yin, "Optimal deployment of charging lanes for electric vehicles in transportation networks," *Transportation Research Part B: Methodological*, 91:344-365, 2016.

[40] T. Yuksel and J. J. Michalek, "Effects of Regional Temperature on Electric Vehicle Efficiency, Range, and Emissions in the United States," *Environmental Science & Technology*, 49:(6)3974-3980, 2015.

[41] UVE, [Online]. Available: https://www.uve.pt/page/nissan-leaf-40-kwh-e-o-novo-campeao-de-vendas-em-2018/.

[42] IPMA, "Boletim Climatológico Anual: Portugal Continental 2017," IPMA, I.P., Lisbon, 2017.

[43] M. C. Falvo, D. Sbordone, I. S. Bayram and M. Devetsikiotis, "EV Charging Stations and Modes: International Standards," in *2014 International Symposium on Power Electronics, Electrical Drives, Automation and Motion*, 2014.

[44] J. Wirges, "Planning the Charging Infrastructure for Electric Vehicles in Cities and Regions," KIT Scientific Publishing, 2016.

[45] T&E, "Recharge EU: how many charge points will Europe and its Member States need in the 2020s," European Federation for Transport and Environment AISBL, 2020.

[46] J. R. Helmus, J. C. Spoelstra, N. Refa, M. Lees and R. van den Hoed, "Assessment of public charging infrastructure push and pull rollout strategies: The case of the Netherlands," *Energy Policy*, 121:35-47, 2018.

[47] P. Morrissey, P. Weldon and M. O'Mahony, "Future standard and fast charging infrastructure planning: An analysis of electric vehicle charging behaviour," *Energy Policy*, 89:257-270, 2016.

[48] EDP, [Online]. Available: https://www.edp.pt/particulares/apoio-cliente/perguntas-frequentes/pt/contratos/novo-contrato/o-que-e-a-opcao-horaria-e-qual-a-melhor-para-mim/faq-4823/.