TECHNICAL UNIVERSITY OF CRETE
SCHOOL OF ELECTRICAL AND
COMPUTER ENGINEERING

**Diploma Thesis**

# Electric Power Demand Estimation of Plug-in Electric Vehicles

PALIALEXIS KONSTANTINOS

**Thesis Committee**

**Kanellos Fotios (supervisor)**
**Kalaitzakis Konstantinos**
**Stavrakakis Georgios**

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## ABSTRACT

In recent years there has been a rapid increase in sales of electric cars around the world. This is mainly due to the environmental benefits of electrified transportation. At low penetration rates, electric cars do not constitute a load capable of causing problems in the country-wide electric power system. However, as their use becomes more widespread, their uncontrolled charging can lead to system overloading or inability to meet energy demands, while at the same time it can be a flexible load, which can help the system at the necessary time periods.

In this work we use real driver behavior data to model not only the charging needs of their vehicles during the day but also the ability to supply energy as long as they are parked and the energy they have stored is sufficient. We propose a modeling method for calculating the load of a large number of electric cars in a short run time. Also, time series of the daily price of electricity in Greece are used as well as the corresponding daily load in order to approach the effects that the penetration scenarios will have on the system but also on the price of electricity and how they would respond to electricity price variations.

We study three different penetration scenarios of plug-in electric vehicles. The charging techniques applied are simple direct charging and smart charging, with or without the ability to supply energy to the system. Finally, the obtained results are compared and general conclusions are drawn.

# Περιληψη


Τα τελευταία χρόνια έχει παρατηρηθεί μια ραγδαία αύξηση των πωλήσεων των ηλεκτρικών αυτοκινήτων σε όλο τον κόσμο. Αυτό οφείλεται κυρίως στα οφέλη της ηλεκτροκίνησης ως προς το περιβάλλον. Σε μικρά ποσοστά εισχώρησης τα ηλεκτρικά αυτοκίνητα δεν αποτελούν φορτίο ικανό να προκαλέσει προβλήματα στο δίκτυο μεταφοράς ενέργειας σε επίπεδο χώρας. Όσο όμως η χρήση τους γίνεται πιο διαδεδομένη, η ανεξέλεγκτη φόρτιση τους μπορεί να οδηγήσει σε υπερφορτώσεις μετασχηματιστών ή σε αδυναμία κάλυψης των ενεργειακών αναγκών ενώ παράλληλα αρχίζει να αποτελεί ενα ευέλικτο φορτίο, το οποίο μπορεί να προσφέρει βοήθεια στο σύστημα τις απαραίτητες χρονικές στιγμές που η ζήτηση ενέργειας είναι υψηλή .

Σε αυτή την εργασία χρησιμοποιούμε πραγματικά δεδομένα συμπεριφοράς των οδηγών για να μοντελοποιήσουμε όχι μόνο τις ανάγκες φόρτισης των οχημάτων τους μέσα στην μέρα αλλά και την δυνατότητα προσφοράς ενέργειας όσο είναι σταθμευμένα και η ενέργεια που έχουν αποθηκευμένη είναι επαρκής. Προτείνουμε μια μέθοδο μοντελοποίσης για τον υπολογισμό του φορτίου μεγάλου αριθμού ηλεκτρικών αυτοκινήτων σε μικρό χρονο εκτέλεσης. Επίσης, χρησιμοποιούνται χρονοσειρές της ημερίσιας τιμής ηλεκτρικής ενέργειας της Ελλάδας καθώς και το αντίστοιχο ημερίσιο φορτίο ώστε να προσεγγίσουμε τις επιπτώσεις που θα έχουν τα σενάρια διείσδυσης στο σύστημα αλλά και στην τιμή της ηλεκτρικής ενέργειας.

Μελετάμε τρία διαφορετικά σενάρια διείσδυσης σύμφωνα με το πόσο αισιόδοξη θα είναι η προσαρμογή στην ηλεκτροκίνηση.Οι τεχνικές φόρτισης που εφαρμόζονται είναι η απλή άμεση φόρτιση και η έξυπνη φόρτιση, με ή χωρίς την δυνατότηα προσφοράς ενέργειας στο σύστημα, ώστε να συγκριθούν τα αποτελέσματα τους.

# Table of Contents

# Table of Figures

# CHAPTER 1

## Introduction

### 1.1 General

It is widely known that unless some measures are taken to mitigate global warming, its effects will be devastating to our planet and everyday life. Due to the uncertain future of fossil fuels and the huge amount of emissions they produce, the whole world is moving towards a more energy secured future planning.

Europe in particular, has made a rather ambitious plan in order to limit the global warming to 2 degrees Celsius [1]. The objectives for 2030 are to reduce the greenhouse gasses at least 40% compared to 1990 as well as reaching 27% energy production from renewable resources. This entails the transformation of Europe's energy market and economy, making it more secure and sustainable.

As part of this transformation, special consideration has been given to the transportation sector [2]. Regarding private cars, the goal is to limit the use of conventionally fueled vehicles in urban areas by 2030 and phase them out by 2050. This way the air pollution in cities can be limited to healthy levels.

It has to be noted that, although electrical vehicles have zero direct emissions, there are still some emissions from battery manufacturing as well as from electricity generation [3]. If the vehicle is fueled by energy provided from renewable resources, then it is truly a clean means of transport.

Analyses have shown that battery electric vehicles (EV) on average emit less CO2 than their conventional counterparts over their lifetimes. Even with electricity produced by fossil fuel, EVs produce about half CO2 emissions than an average EU conventional vehicle. In addition, even if the energy generation is based on fossil fuel, the emissions are shifted from denser populated urban places to rural power generation sites.

Some countries have made aggressive policy decisions so they can achieve the aforementioned goals. Norway is planning to ban sales of internal combustion engine cars by 2025 followed by France and UK (2040)[4]. This will lead to electric vehicle penetration rate to drastically increase. As a result, a large number of battery electric vehicles will simultaneously connect to the grid so they can satisfy their charging needs. From the power system operator's side, this will create not only new challenges to overcome but also new opportunities to take advantage of.

## 1.2 Aims and Objectives

The main objective of this thesis is to develop an electric vehicle aggregator model that can realistically simulate the charging behavior of a large number of battery electric vehicles and therefore evaluate the impact of the excess power demand in large electric power systems.

The sub-objectives that are derived from the main are the following:

- The development of a method to generate daily trips containing different purposes and various mileage that each driver will follow during the day.
- Estimate the ability of the vehicle to inject power into the power system when it is under heavy load
- Provide a fast method to calculate the load of an aggregated fleet of EVs
- Evaluate the impact that the load from the EVs will have on the national price of the electricity and vice versa.

## 1.3 Related Work

In the last decade many studies have been made in order to evaluate the impact of plug-in electric vehicle (PEV) load. A wide range of methods are used to model the estimation of the final fleet load, each with different advantages and accuracy.

One of the most commonly used methods is agent based modelling [5] , [6] where agents are responsible for the decision making resulting in fair load distribution. There are also studies like [7], [8] where authors choose to use reinforcement learning to model driving patterns and optimal charging policies. Another modelling method is statistical representation of driving characteristics, where both real world driving data [9] and arbitrary probability density functions based on experience have been used [10].

In many studies it is assumed that drivers only charge their vehicles at their homes during the night[11][12] but as the PEV penetration increases and public charging stations become commonly available, the charging load will have a different profile so a multipurpose daily tour method must be implemented. This is referred in the literature as activity based modelling

[13]. Furthermore, despite G2V having an important role in the PEV integration, it is not always included in the relative works [10], [14], [15].

In [10] real driving cycles in urban setting were used and fuzzy logic system was implemented to emulate the charging decision probability of drivers. In our methodology, fuzzy logic is used to quantify the desirable target energy at the time of departure, as when the electricity price is higher a driver may opt to charge his vehicle enough to return home and not at full capacity. Also the V2G option is added through the fuzzy system.

In [9], all parameters like mileage and all electric range, were formulated as random variables in order to incorporate all possible future EVs. An extensive database of travel characteristics was used to model the behavior of drivers. The same database will be used in this study but with a new way to generate daily trips.

While many studies discuss the importance of electricity price for the charging scheduling, the fact that the introduction of a large PEV fleet will affect the price is usually ignored. Hence there is also the need to assess the impact that the new total load (including PEV load) will eventually have to the electricity price

In Greece, not many studies have been made as PEV penetration is still in early stage. A recent study is focused only in the autonomous system of Crete [17], so in our study the load of the whole country is investigated.

In order to be able to process the large number of PEVs that an entire country will have, an aggregated dynamic battery model is introduced, that emulates an entity like an aggregator [18] and enables smaller simulation time.

## 1.4 Document Structure

In chapter 2, some background information is presented regarding the electrical vehicle state of art technology, as well as some current regulations about the charging modes.

In chapter 3, the driving characteristics of conventional vehicles are analyzed and an algorithm is presented to generate daily trips with different starting times and mileage for each vehicle.

In chapter 4, the load estimation algorithms for the two charging strategies are presented with the necessary mathematical modelling, as well as the price iteration model to simulate the load-price interaction.

In chapter 5, the case study with all the necessary input parameters is presented. The respective results for each charging strategy and for each penetration scenario are given and general conclusions are drawn.

# CHAPTER 2

## Background

### 2.1 Electric Vehicles

EV can be any vehicle that has a battery and runs at least partly on an electric drive train. Despite their fame lately, EVs are not a new concept The first practical electric vehicles were produced back in 1880s but advances in conventional internal combustion engine vehicles led them out of the global market. Recent improvements of battery technology and environmental concern have elicited the use of electro-mobility.

*Figure 2-1: First practical electric vehicle [19]*

### 2.2 EV types

Depending on the degree that electricity is used as propulsion energy EVs are classed by three main types [20][22].

### 2.2.1 Hybrid Electric Vehicles (HEV)

HEVs have both an internal combustion engine and an electric drive train with a small battery. When HEVs start, they use the electric motor but when they reach a certain speed or low state of charge, the gasoline engine assists the propulsion. Because HEVs cannot plug in to the electricity, they are able to recharge their batteries using the ICE and with their braking system as it can use the energy that otherwise converts to heat by the brakes.

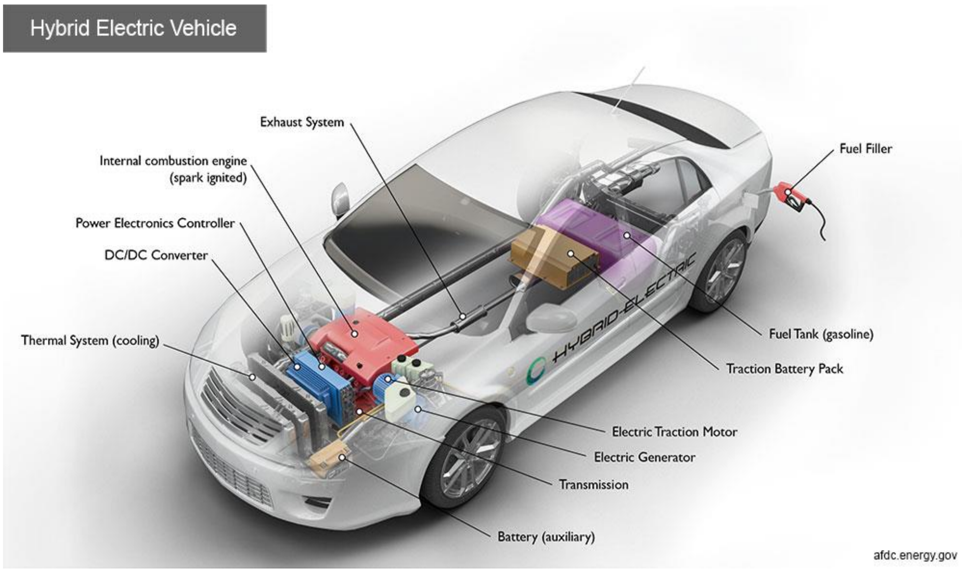


*Figure 2-2: Hybrid Electric Vehicle –HEV [20]*

### 2.2.2 Plug in Hybrid Electric Vehicle (PHEV)

PHEVs use batteries to power an electric motor and some fuel like gasoline or diesel to power an ICE. Like HEVs, those vehicles can recharge the battery through the braking system, but they also can connect to an external source of electrical power like a public charging station or the driver's home. They usually have bigger battery capacity than typical HEVs and their fuel economy depends on how often the grid is being used for battery charge.

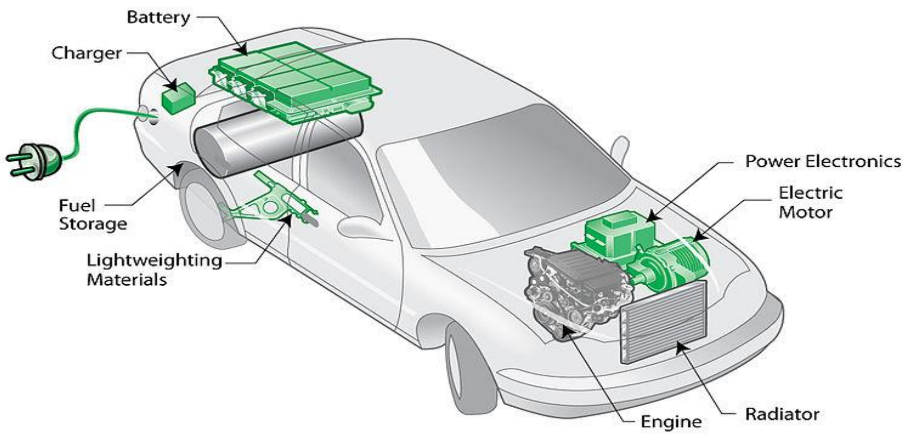


*Figure 2-3: Plug in Hybrid Electric Vehicle- PHEV [21]*

### 2.2.3 Battery Electric Vehicles (BEV)

BEVs don't have an ICE so they are fully electric. They use high capacity batteries that can provide large autonomy of mileage. This driving range can be affected by the driving conditions such as extreme outside temperatures and rapid acceleration. They have special chargers that support very fast dc charging so they can be fully charge in the time span of minutes.

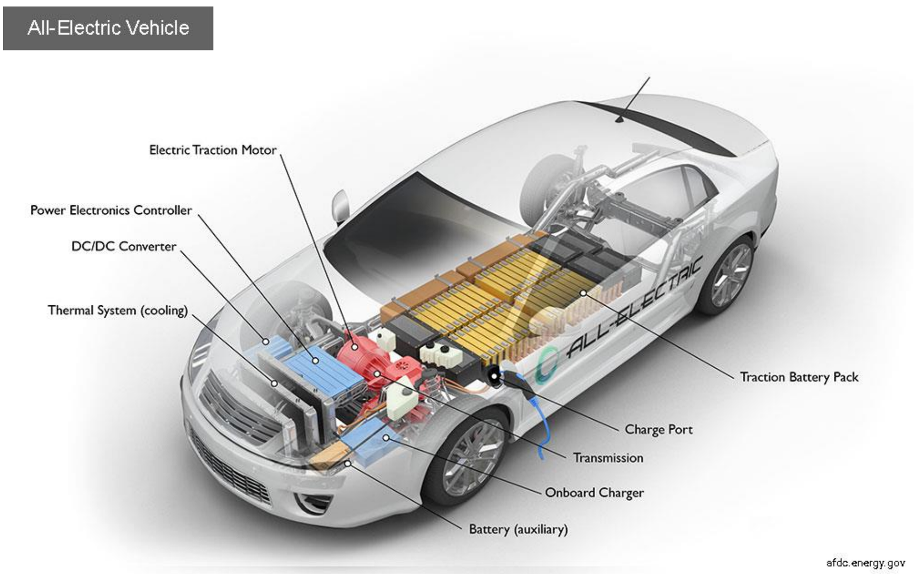


*Figure 2-4: Battery Electric Vehicle-BEV[20]*

## 2.3 Benefits and Disadvantages of Electric Vehicles

The most important advantages of EVs are the following [23]:

- They are eco-friendly as they do not directly emit toxic greenhouse gases. If the energy that is used for the charge of their batteries comes from renewable resources, then they are truly green. Even if the electricity used is produces by oil fuels, the air pollution is limited to electricity generation sites rather than the cities.
- Their maintenance cost is lower because tasks related to ICE such as lubrication of the engines is not needed
- Limited noise pollution as electric motors are much quieter. This is especially significant in urban setting because of the substantial number of vehicles.
- Their driving is easier. Commercial electric vehicles are automatic and include a transmission that has one long gear. Thus, there is no need for a clutch mechanism and the driver only uses the brake and acceleration pedal enabling him to focus his attention on his surroundings
- They can be cost-effective as there are many government policies that significantly reduce car registration taxes. BEVs also do not depend on fuel prices. They only recharge at special recharge points or at the driver's home from the electricity grid

Despite the benefits described above, there are many problems that are delaying the establishment of EVs as the main car type choice:

- The driving range of EVs is being limited by their battery capacity although this problem is addressed by latest research and technology. As of now the most recent EVs have a range of 80-160 km and some models can reach up to 300 km range
- They still have a higher price than conventional vehicles even on the more affordable brands. This is due to the equipment used and mostly to the batteries. As EV penetration rate rises, the technology used will become mainstream and their price will gradually fall.
- Their batteries need replacement because of the limited life cycle. Depending on the type and usage, they have to be changed every 3 to 10 years. Most recent models try to tackle this problem
- They have longer recharge time than the refueling of an ICE vehicle. It can take 4 to 6 hours or even more to fully charge an EV, depending on the battery. With special charging station it can reduced to a few minutes

## 2.4 PEV Charging Strategies

There are three main charging strategies that allow the driver to have varied control of the timing that the charging process starts:

- Uncontrolled or Dumb charging: This is currently the most used strategy because of the low EV penetration. PEVs are charged with steady power until the target SOC is reached. The charging process begins immediately when the PEV is connected and as so it can overlap with load peaks through the day. So there is no option to minimize impact on the distribution network and on large penetration number this can be devastating for the system.
- Time of use tariff: in this strategy the day is divided in 2-3 time periods and a different price is allocated in each period. For peak load hours the price is higher and the driver prefers to charge on off-peak cheaper hours. TOU tariff can be useful in low penetration of PEVs but with higher penetration where the PEV load is substantial, it can cause overload problems just like the dumb charging strategy.
- Smart charging: It is the most efficient strategy. The charging rate of every PEV is actively controlled in order to ensure that the distribution network is not overloaded and the charging cost for the driver is as low as possible for the target SOC that he decided.

V2G: The ability of the PEV to inject energy into the grid on periods of the day where the load is maximum. In the context of smart grid, V2G with smart charging can provide great technical and economic benefits.

## 2.5 PEV charging modes

There are 4 charging modes for the PEVs defined by standard IEC 61851-1 [24][26]

### 2.5.1 Mode 1: slow charging (AC)

The rated values of voltage and current must not surpass 250V and 16 A in single-phase and about 400 V in three-phase. The vehicle is connected directly to a home type socket and there is no protection or safety system like a residual current device.


*Figure 2-5: Mode 1 charging [26]*

### 2.5.2 Mode 2: slow charging (AC) with safety

The rated values of voltage are the same with the previous mode but the rated value of the current must not exceed 32A. A safety system is placed in the charging cable called Control Box. It is mostly found in portable chargers.

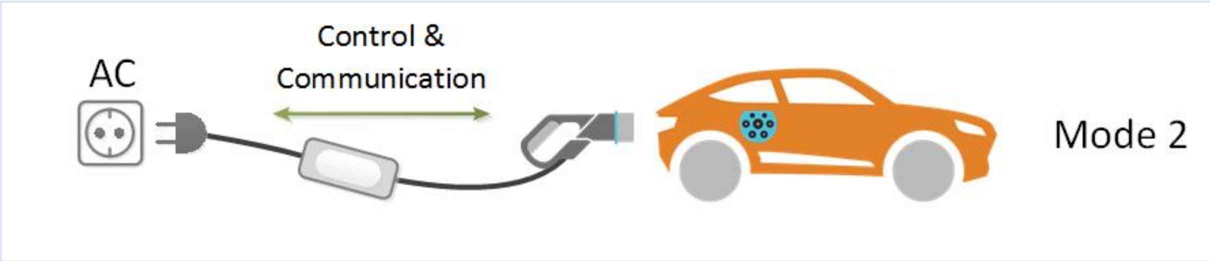


*Figure 2-6: Mode 2 charging [26]*

### 2.5.3 Mode 3: slow to semi-fast charging (AC)

In this mode a specific power system supply is required which is permanently connected to the electricity grid. The Control Box is integrated to the supply system. The maximum voltage and current values are the same with mode 2 but charging is a bit faster because of the communication between the charger and the vehicle.

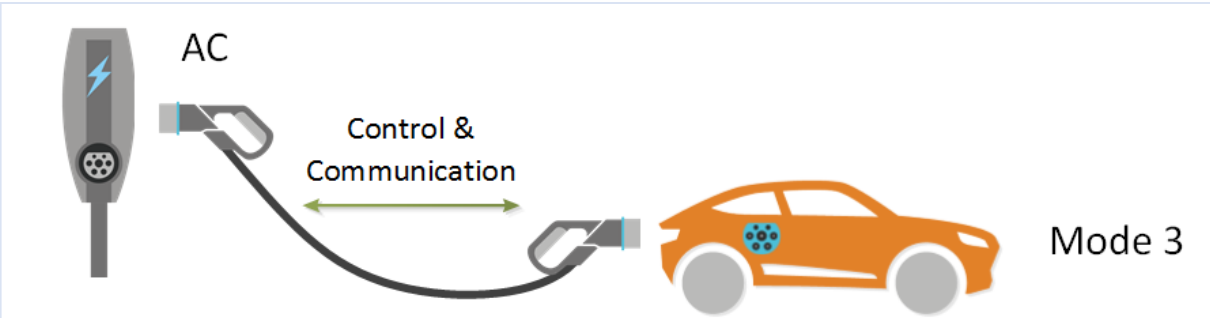


*Figure 2-7: Mode 3 charging [26]*

### 2.5.4 Mode 4: Fast charging (DC)

In this mode the charging time can be minimized as the electrical power can vary from 40kW to 350 kW. An external current converter is required that transforms the current from AC to DC before passing through the charging cable. The safety system is integrated in the external charger and there is continuous communication with the vehicle for optimal charging.

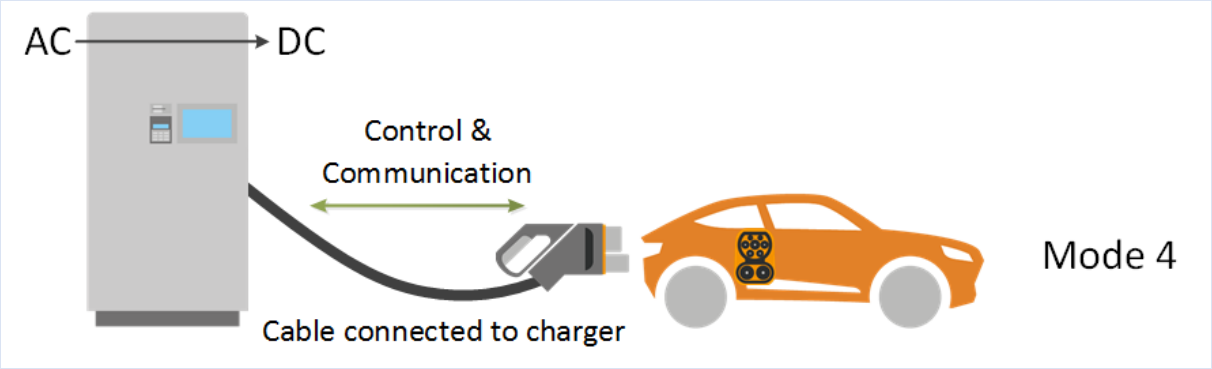


*Figure 2-8: Mode 4 charging [26]*

### 2.5.5 Wireless charging

The battery is charged using an electromagnetic field to transfer energy from an induction coil to the vehicle. High frequencies are used to overcome the air gap and usually the coils from the two sides are tuned to the same resonance frequency for optimal results. The electric power output is about 20 kW and the efficiency close to 70%. Some recent research is focusing on integrating wireless chargers on the roads so the vehicle can recharge its battery while moving

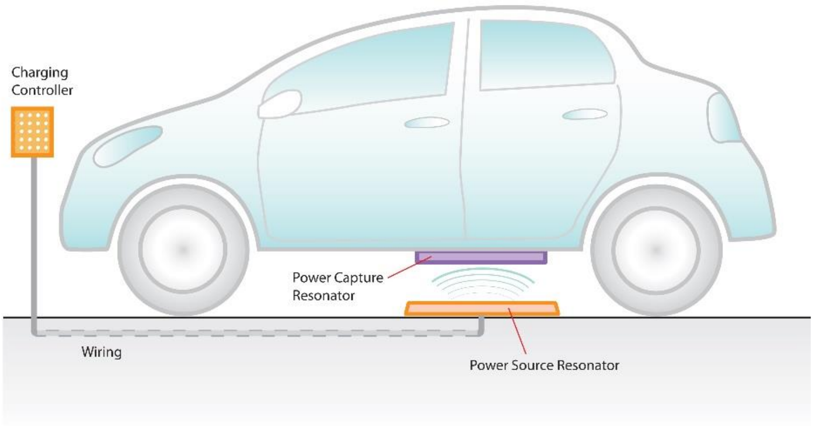


*Figure 2-9: Wireless charging [27]*

## 2.6 Charging station infrastructure

The charging infrastructure of a Country is perhaps the most important factor to ensure that the transition from conventional to electrical vehicles is smooth and that it is sufficient to support the needs of everyday mileage. As the penetration rate rises, the availability of public chargers will also increase to compensate for the increased numbers of PEVs on the streets.
While simple chargers may be available in every single family home, workplace and public stations are becoming the norm with different levels of

charging. There is also the option of public chargers near on the streets as well as wireless charging at stopping lights or on a road lane while moving

The current state of Greece's infrastructure can be seen in the following figure:

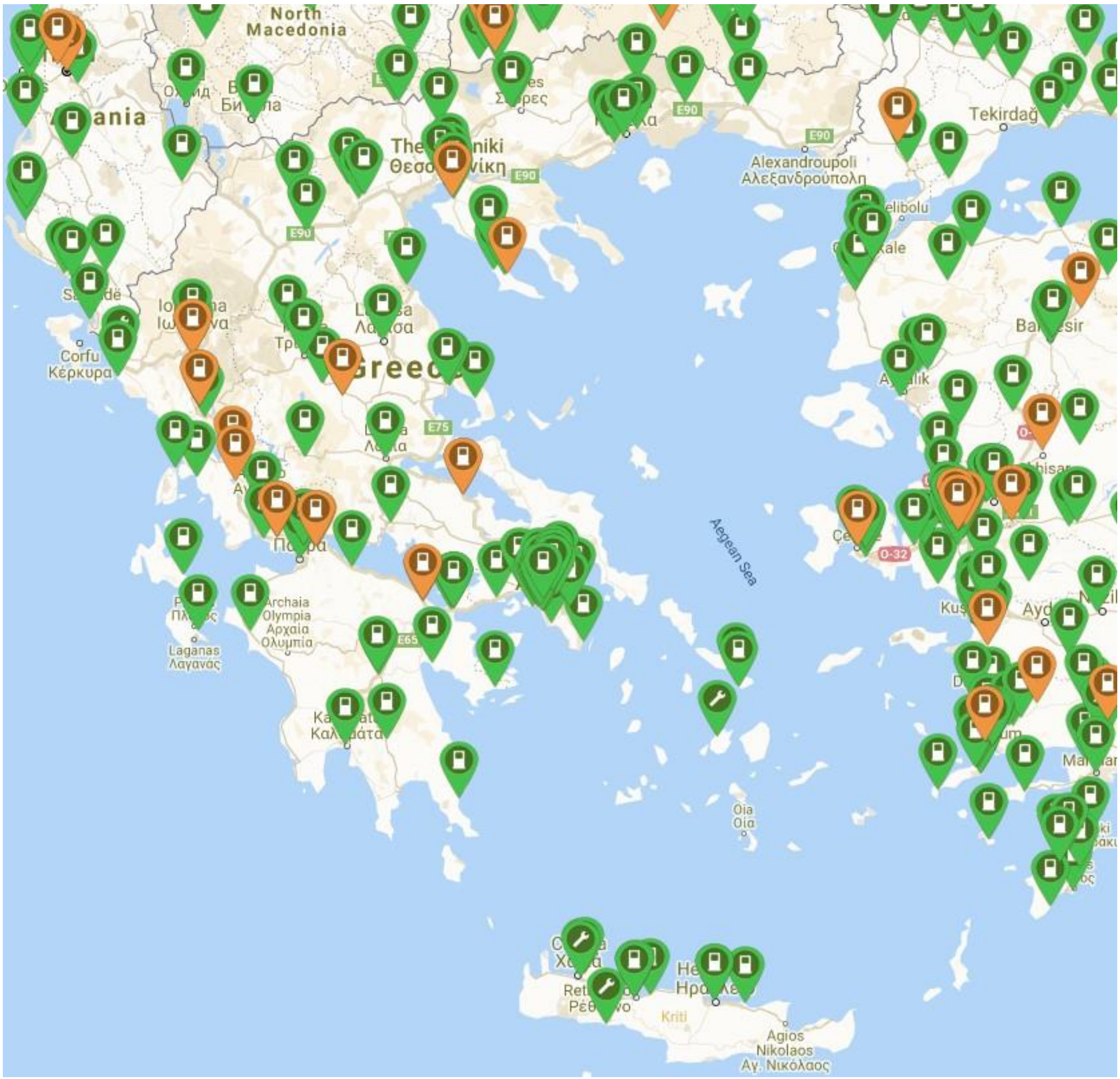


*Figure 2-10:Charging stations in Greece (green=Public, orange=High power) [28]*

# CHAPTER 3

## Travel Pattern Model

In order to estimate the daily load of PEVs, it is essential to define some realistic mobility characteristics of the vehicles. In the literature, there are many studies that assume that PEVs only charge during the night when they return home. Some of them use home arrival times extracted from real data, while others use probability functions based on reasonable assumptions.
In this study, a large database [29] will be utilized that contains real world driving data and an opportunity charging scenario will be adopted, which enables vehicles to charge on all locations (home, work, shopping and social activities). As EVs become more dominant in the market, in comparison to ICE vehicles, more public or private charging stations will be constructed in strategic locations to ensure the mobility of EVs. That is why opportunity charging resembles a realistic future scenario.

### 3.1 NATIONAL HOUSEHOLD TRAVEL SURVEY (NHTS)

NHTS [29] is widely used in transportation studies as it provides assistance to transportation planners and policymakers who need extensive data of travel patterns. It is a source of North America's travel patterns and contains information about various trips that household drivers participate during the day. The trips included comprise all modes of travel and for different purposes but in this study only those made by private cars were included. While the vehicles in this study are not PEVs, it can be assumed that as the electric car market penetration rises (and public charge stations become widely available), the habits of the drivers will match those of conventional vehicles. From the NHTS website, the corresponding csv file (named trippub.csv) that contains the information necessary in this study can be downloaded. The columns that were used are: HOUSEID, PERSONID, TDTRPNUM, STRTTIME, ENDTIME, TRVLCMIN, TRPMILES, DWELTIME, TDWKND, WHYTRP1S, URBRUR.
Using information from those columns, realistic trips that the vehicles have to do during the day can be produced.

## 3.2 NHTS database processing

Daily driving characteristics are one of the key factors that will affect both the charging load throughout the day, and as consequence, the final impact on the electricity grid.
By analyzing the NHTS data base, important information was extracted regarding the average daily mileage of a vehicle, the number of daily trips it does, starting times and dwelling times for different types of travels (work, social, shopping and home). Also this information is available for both rural and urban areas. Some preprocessing was needed in order to clean the data from invalid or incomplete rows or extreme values.
A brief review of the columns used and their data follows:

- HOUSEID and PERSONID: unique house and person identifier respectively
- TDTRPNUM: incrementing trip number starting at 1 for each person in the file
- STRTTIME: trip departure time
- ENDTIME: trip arrival time
- TRVLCMIN: trip duration in minutes
- TRPMILES: trip distance in miles. It was multiplied by 1.61 to be converted to km
- DWELTIME: time parked at the destination
- TDWKND: weekend trip (1=Yes, 2=No)
- WHYTRP1S: trip purpose
- URBRUR: Household in urban/rural area (1=Urban,2=Rural)

Departure and arrival times were in army hours so they had to be converted to minutes using:

$$minutes = floor\left(\frac{armyHour}{100}\right) * 60 + mod(armyHour, 100) \quad (3.1)$$

The end result of this chapter is to develop an algorithm that generates daily tours and ensures that they are as realistic as possible.

## 3.3 Driving characteristics

Each tour consists of different number of trips. First, a distribution of the number of daily trips is needed. Columns HOUSEID, PERSONID and TDTRPNUM were used with the matlab function grpstats, which provides statistics organized by group, in order to calculate in how many trips each person, of every different household, participates in.

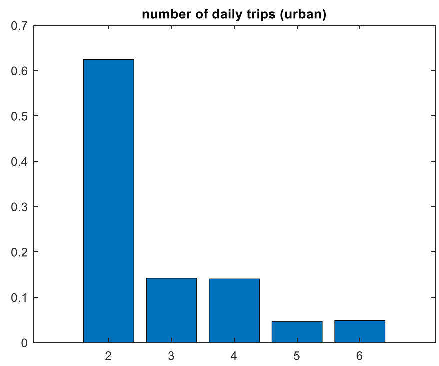


*Figure 3-1: Distribution of daily trips (urban)*

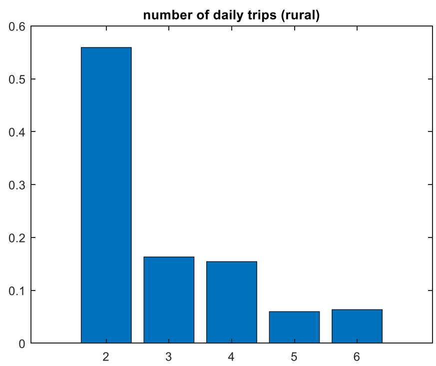


*Figure 3-2: Distribution of daily trips*

As it can be seen in this figure most drivers travel only 2 trips (e.g. from home to work and back home) while the numbers of 5 and 6+ trips are minimum. In this study tours that consist of 4 trips at most are considered.

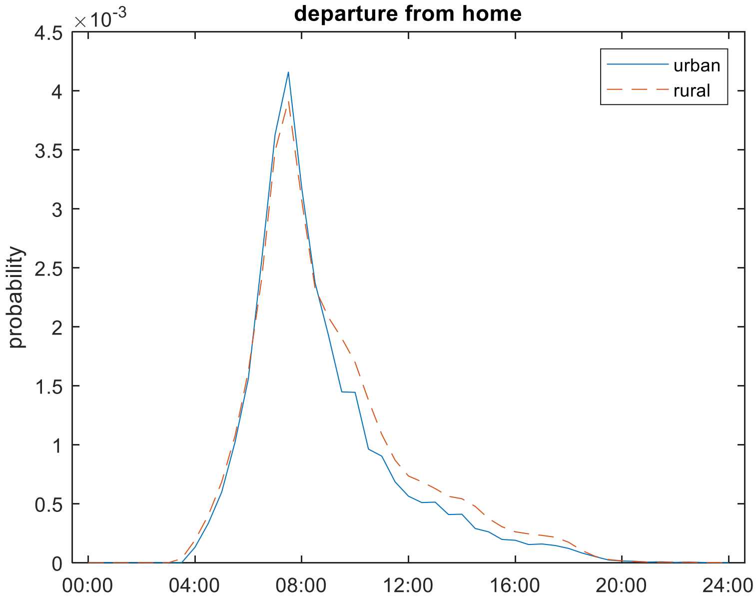


*Figure 3-3: time of departure from home at the start of the day*

### 3.3.1 Departure times for different purposes

The departure times for different travelling purposes that are necessary for this study can be obtained by columns STRTTIME and WHYTRP1S. The matlab function fitdist is used on the data.

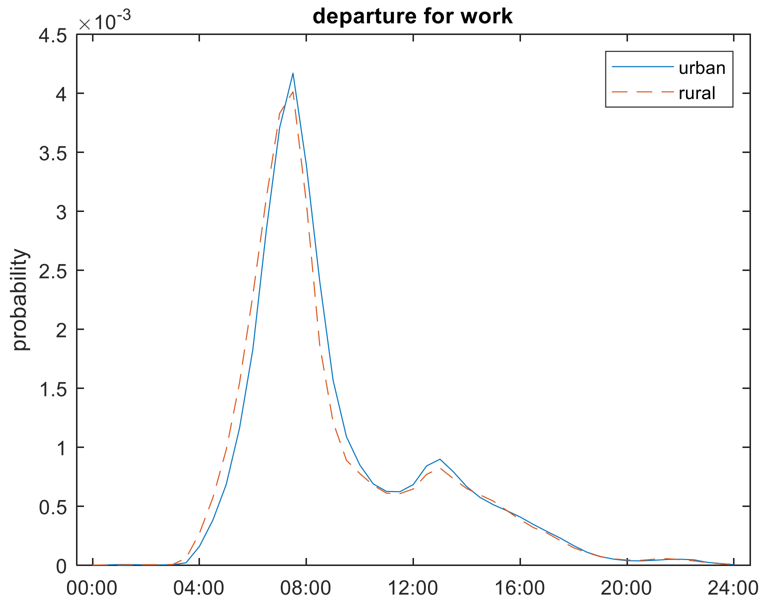


*Figure 3-4: Time of departure for work*

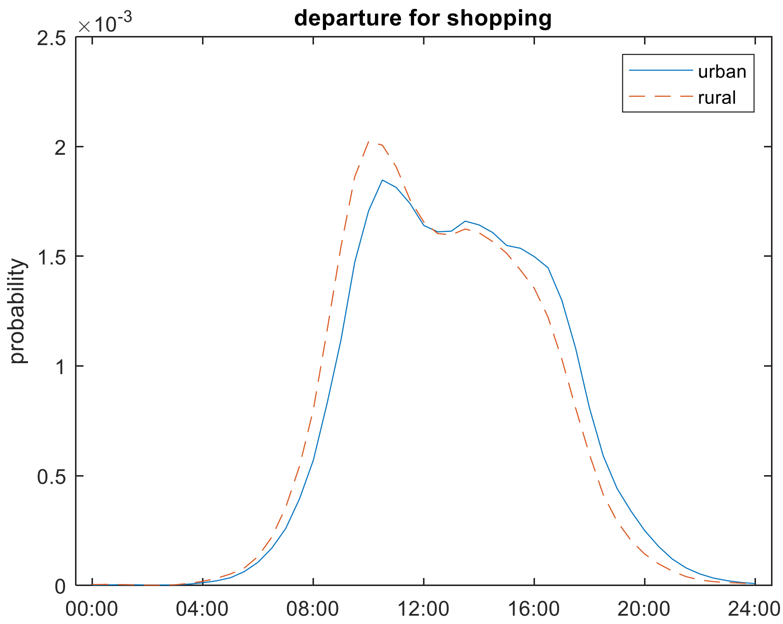


*Figure 3-5:Time of departure for shopping*

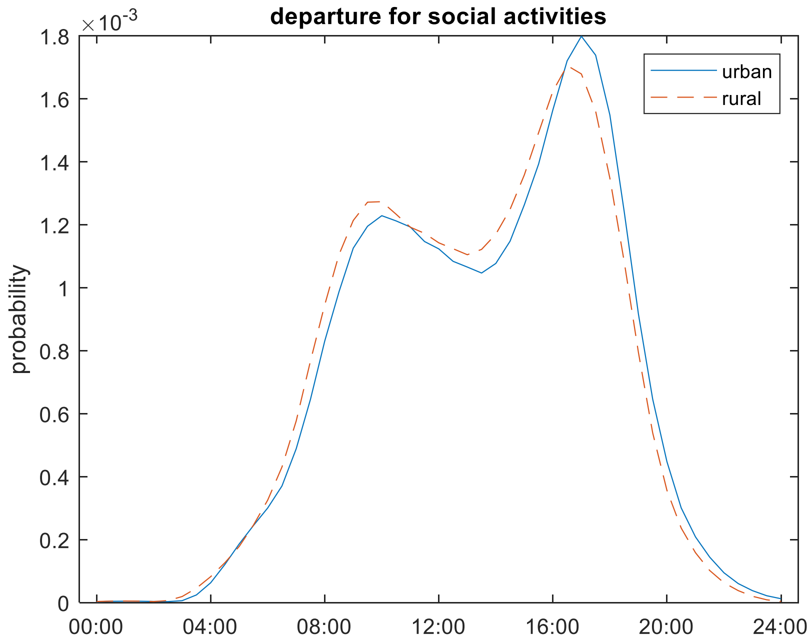


*Figure 3-6: Time of departure for social activities*

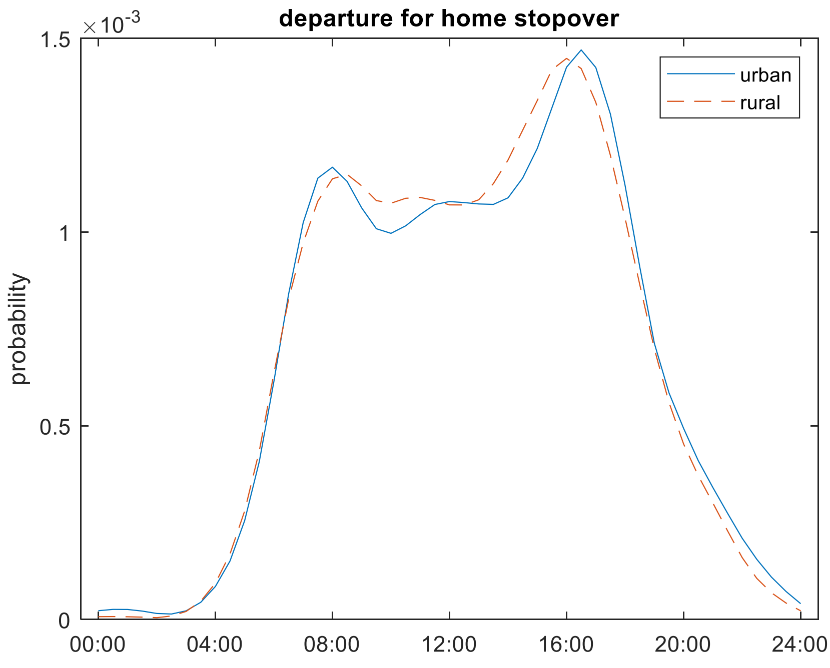


*Figure 3-7:Time of departure for home stopover*

The departure times for all the different purposes are similar for urban and rural locations. What mostly varies between those locations are the distance travelled for each trip and its travelling time.

### 3.3.2 Dwelling times at different locations

Dwelling times were extracted from column DWELTIME with the corresponding code on column WHYTRP1S for different purposes.

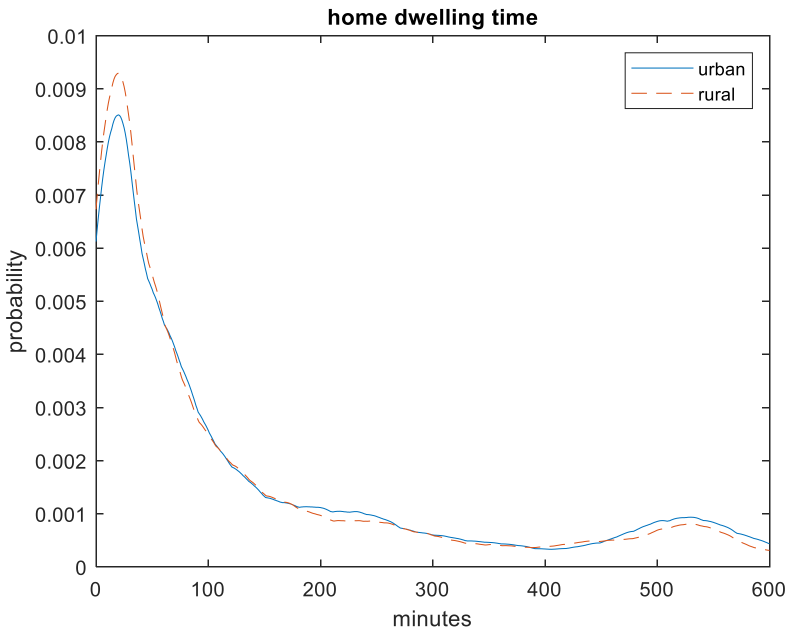


*Figure 3-8: Dwelling time at home*

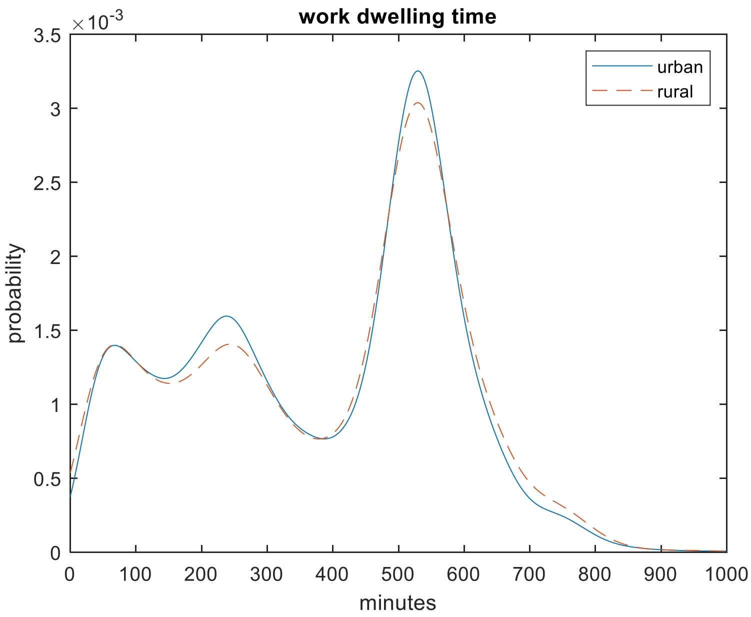


*Figure 3-9:Dwelling time at work*

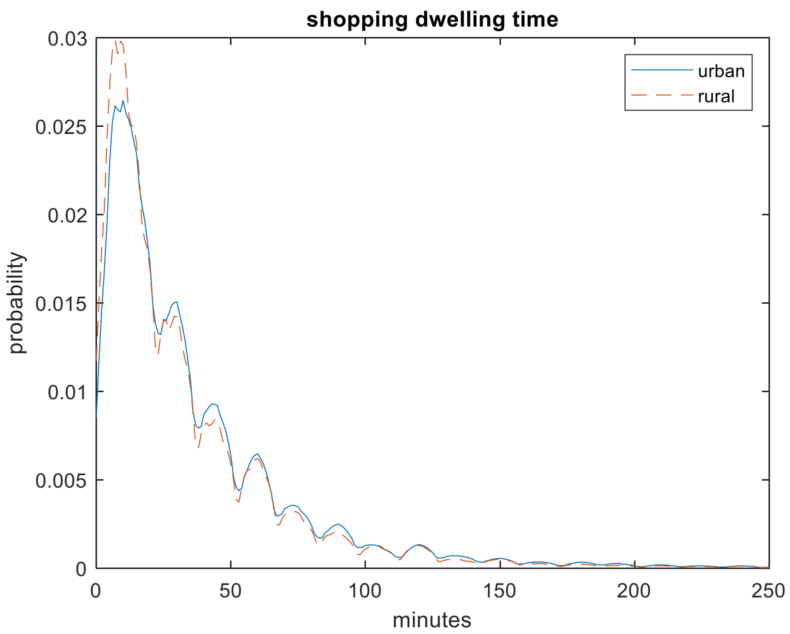


*Figure 3-10: Dwelling time for shopping*

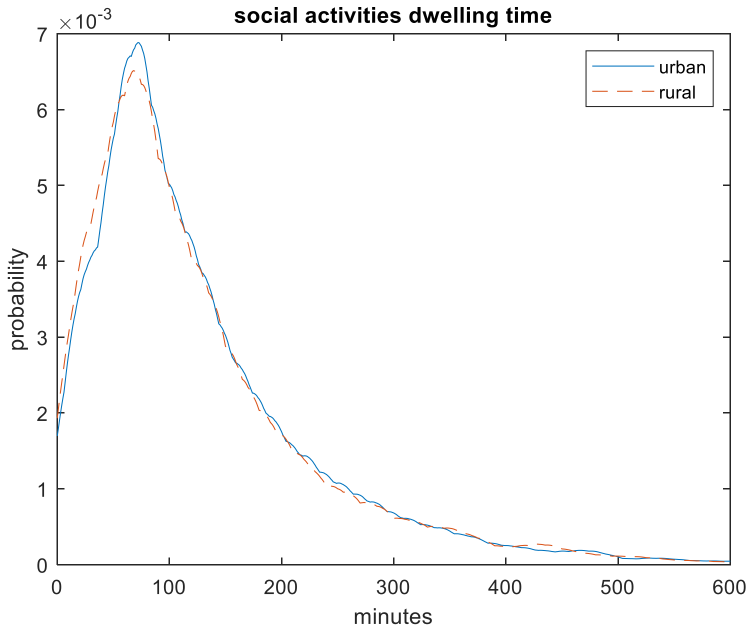


*Figure 3-11: Dwelling time for social activities*

It is observed that, like the departure times, the dwelling times are identical with minimum differences between the city and the countryside.

### 3.3.3 Travel distance and time

Daily distance travelled and total driving time were extracted from columns TRPMILES and TRVLCMIN by again using grpstats, with HOUSEID and

PERSONID, to estimate the total distance covered for the distinct trips that each person did during the day.

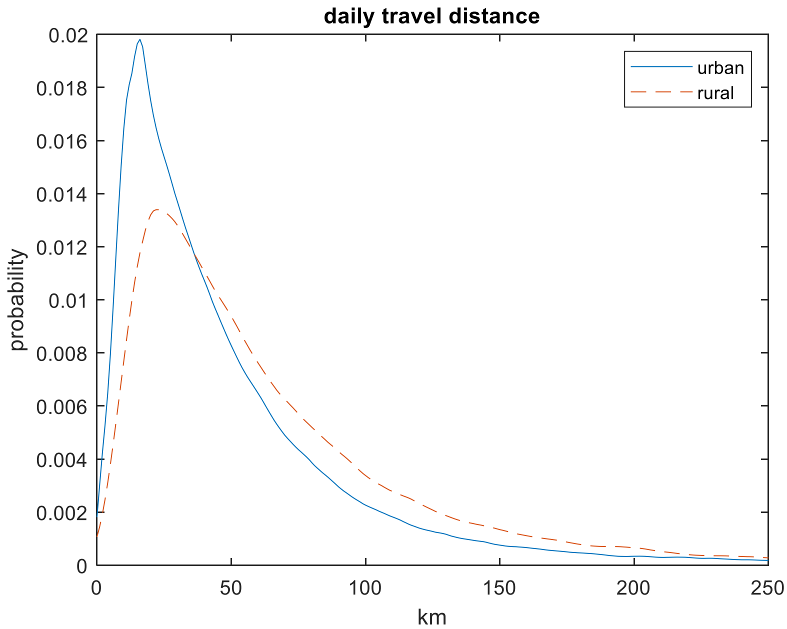


*Figure 3-12: Daily distance distribution*

The daily travel distance had to be limited, as travel distances in north America are typically longer than in Greece and the following pdf was obtained.

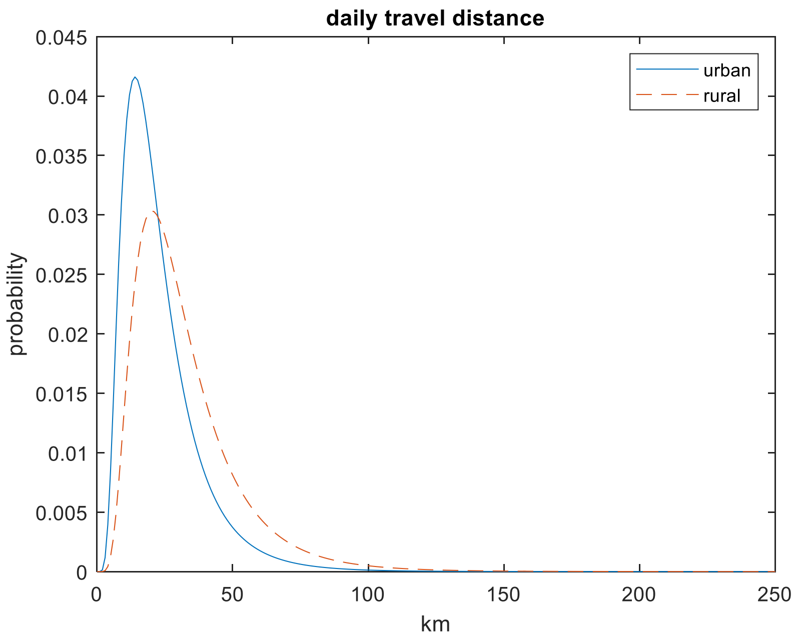


*Figure 3-13: Daily distance after modification (Greece)*

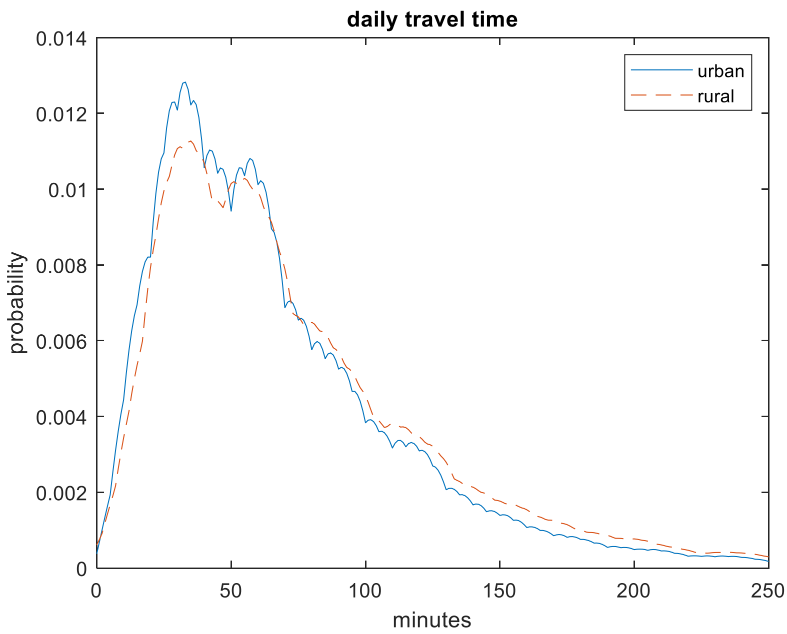


*Figure 3-14: Daily travelling time distribution*

The most noticeable difference is on the daily travel distance as people in rural areas have to travel more kilometers to reach their destinations and they may also need to travel between cities.
In order to assign the distance travelled for each trip during the day, a daily distance value is initially generated from the probability distribution function and then the total distance is allocated among the number of trips that the driver will do during this day.

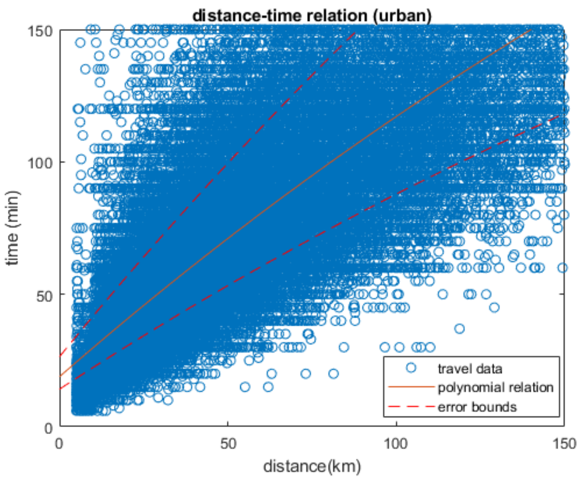


*Figure 3-16: Time-distance relation of urban places*

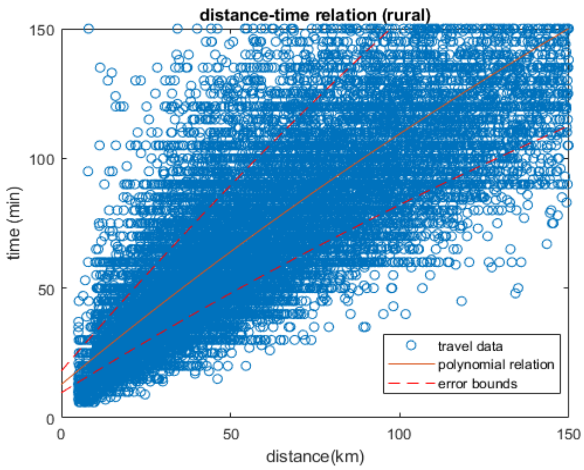


*Figure 3-15: Time-distance relation of rural places*

Using the relation of travelling time and distance we try to estimate the driving time for the distance that was allocated in each trip. In this way all the necessary statistics are available to produce a big number of realistic tours the drivers will do in order to satisfy their needs.

## 3.4 Trip purpose decision making

The purpose of the next trip is very important because it determines how much time will the vehicle be parked in the target destination. During the trip generation process, the cumulative distribution functions (CDF) of the departure times are used, for the different purposes of travelling.
A time interval (a,b) is defined and by using equation (3.3) the area corresponding to the current time is selected (Figure 3-19). The chosen time interval is 15 minutes before and 15 minutes after the time that the driver is going to depart for his next trip. Then, the difference of the CDFs is multiplied with the percentage from the purpose distribution for each respective purpose. As a result, the probabilities are now normalized for all the purposes and the ratio depends on both the current time of departure and the total number of every purpose of travelling. This way the sum of the probabilities is equal to 1 and by generating randomly a positive number below or equal to 1, the most probable next purpose for the driver is picked.

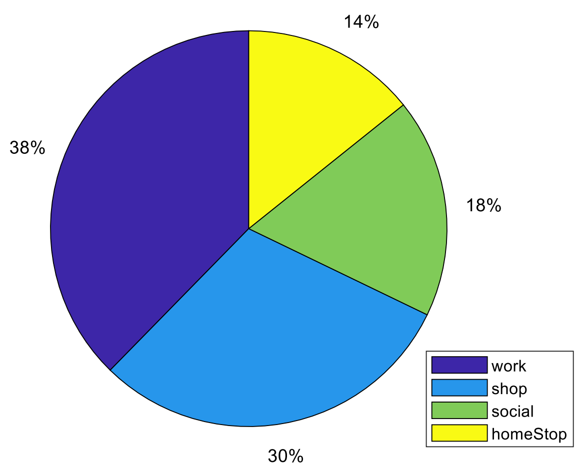


*Figure 3-17: Distribution of trips based on purpose (urban)*

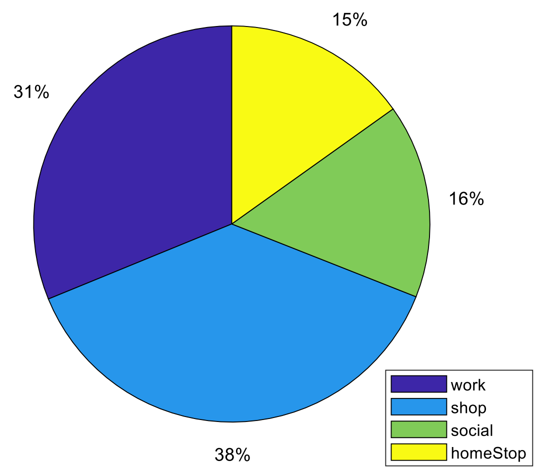


*Figure 3-18: Distribution of trips based on purpose (rural)*

$$F_X(x) = P(X \leq x) \tag{3.2}$$

$$P(a < X \leq b) = F_X(b) - F_X(a) \tag{3.3}$$

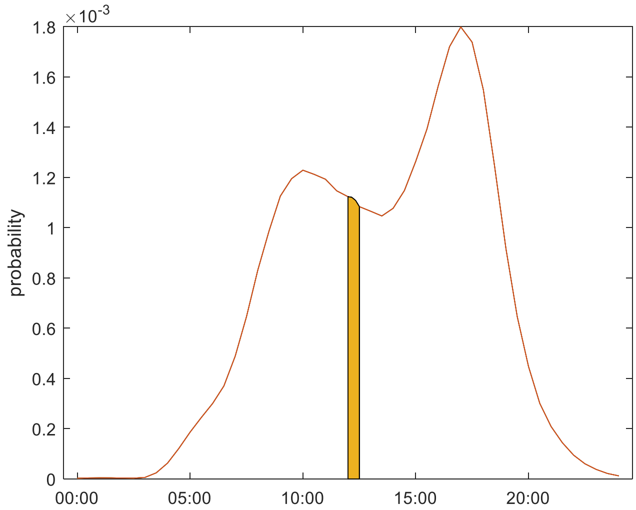


*Figure 3-19:Area formed from the time interval (t-15,t+15)*

## 3.5 Tour Generation algorithm

Using the travel pattern characteristics described in the previous sections, the following logic for generating daily tours is applied:

1. All vehicles start from home and a number of trips N is generated from Figures 3-1 or 3-2.
2. A departure time is assigned for the first trip from the distribution in Figure 3-3.
3. The total day distance is generated from Figure 3-12
4. Using the method described in paragraph 3.4, the purpose of the next trip that depends on the known departure time is assigned.
5. Allocate a part of day's total distance to the current trip and assign the travelling time of the trip using the time-distance relation in Figures 3-14,3-15.
6. The parking time is generated from the dwelling time distributions of each purpose of parking.
7. If the current trip is not the second before the last, then go to step 4 and decide the next trip purpose

8. If it is then the last trip is for returning home and the remaining distance is allocated to it.

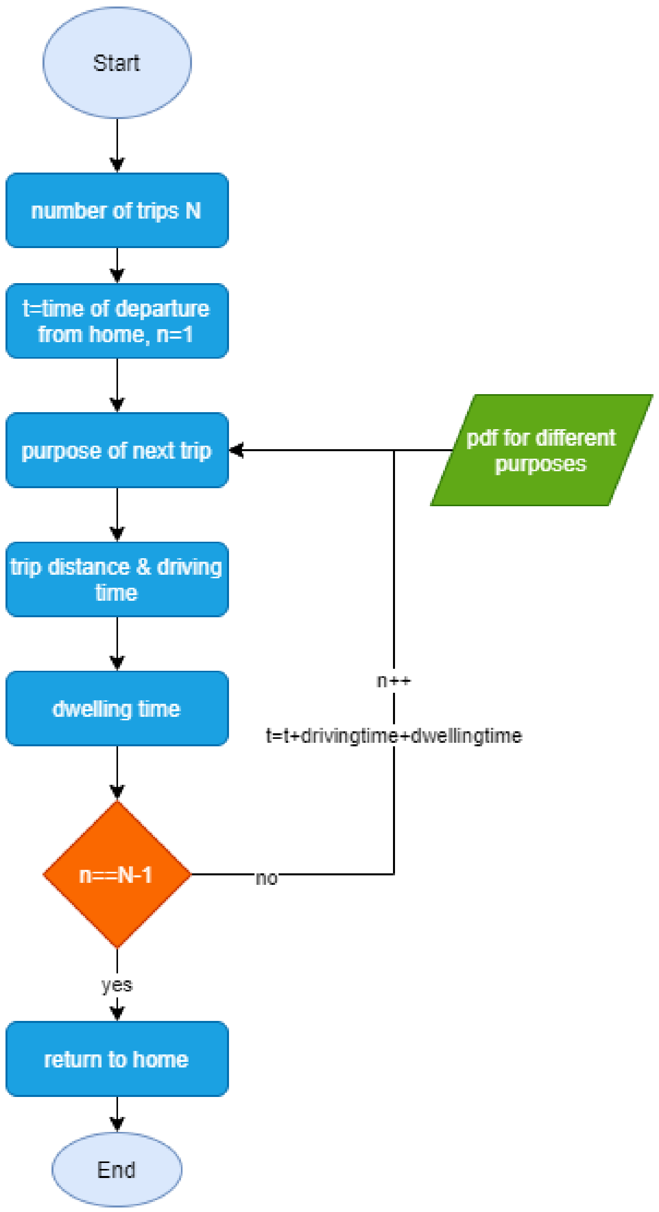


*Figure 3-20: Flowchart for tour generation algorithm*

## 3.6 Tour generation results

By executing the tour generation algorithm enough times, the distribution of the vehicle fleet location can be shown throughout the day.
As it can be seen, urban and rural results do not have much divergence due to the highly similar statistics and while the driving distance is longer for rural areas, driving time is similar due to higher speeds. The difference will be apparent only in the energy consumed as a result of longer mileage.

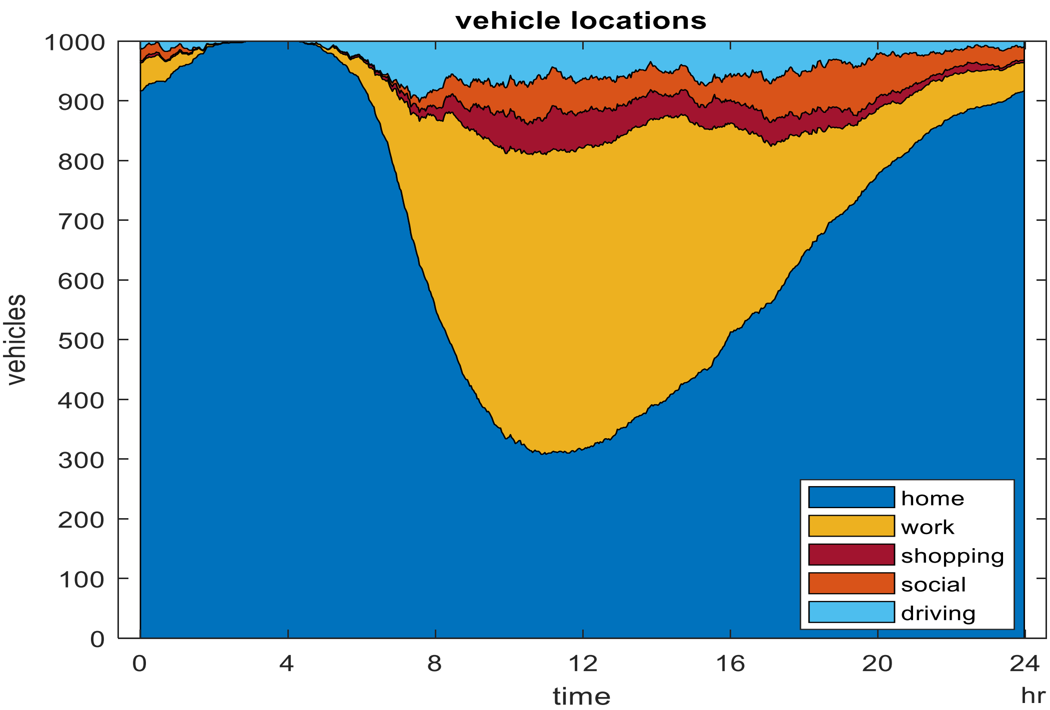


*Figure 3-21: Vehicle location distribution during the day*

# CHAPTER 4

## Load Estimation Algorithm

In this part of the study, the method that was applied for the load calculation of a PEV fleet will be described. Tours generated from the travel characteristics of the previous chapter are used and two charging strategies, namely; Dumb charging and Smart charging, are implemented. A fuzzy logic based method was developed to emulate each driver's decision regarding the target state of charge when the vehicle will depart for the next trip.

### 4.1 Desired State of Charge at departure – Fuzzy logic

An important part of this study is the target energy that each driver will decide upon, to ensure that the available energy will be sufficient for the next trip. The selected target must also be feasible considering the infrastructure and equipment available. Even if the driver wishes so, he may not exceed the maximum capacity of his PEV battery or if the parking duration is not long enough, the desirable charging state may not be achieved (though it is ensured that it will be enough for the next trip). In these cases, the target energy has to be set to the highest possible value.
Due to the high number of vehicles that are considered in this study a fast but reliable method must be applied to minimize the calculation time requirements of the problem but also represent the way of thinking that real drivers would have. The tool that was chosen to fulfill these criteria is fuzzy logic.

#### 4.1.1 Fuzzy logic

The term fuzzy is used when a problem has variables that are not true or false like in the Boolean system but can be partially true or false. Fuzzy logic provides flexibility for decision making because it considers these uncertainties of the variables. It consists of four core parts:

- Rule Base: It contains the representation knowledge of the system that is being studied in the form of a set of rules and IF THEN conditions. Those rules are usually provided by experts of the study field to make the decision making more realistic

- Fuzzification: It converts real numbers (e.g. from the system's sensors) into fuzzy sets that are used in the rules defined in the Rule Base
- Inference Engine: It decides the matching degree of the fuzzy inputs according to each rule and determines which rules are to be applied depending on the input
- Defuzzification: It converts the fuzzy output of the inference engine to a crisp value so it can be used by real systems.

The Membership function that is mentioned above is a graph that correlates the input value to a membership value between 0 and 1.

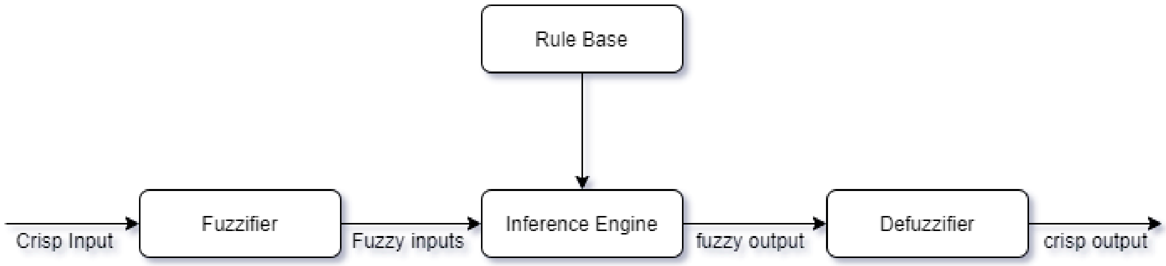


*Figure 4-1: Architecture of a fuzzy logic system*

For this study analysis, two fuzzy models were created. The first emulates the decision making of a driver when energy can only be transferred from the grid to the vehicle and only when it is necessary. The second enables the driver to inject excess energy to the grid from his vehicle (G2V). The inputs of those two fuzzy systems are identical (SOC and price) while there are some changes regarding the rules and the target output.
A representation of the fuzzy system can be shown in the following figure:

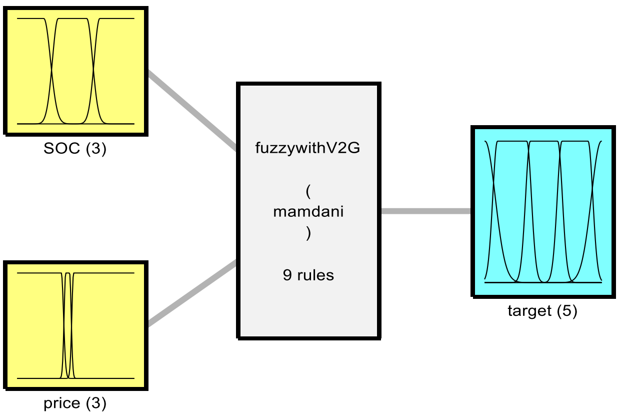


*Figure 4-2: Representation of the proposed Fuzzy System*

### 4.1.2 Inputs

Two identical inputs were created in the two systems. The assigned linguistic values are based on logical assumptions and the membership functions were designed with symmetry in mind to provide more uniform values.

The membership function of  electricity price is shown in Figure 4-3. It has to be noted that the average price, for the time periods that the vehicle is parked, is used as input and not the price at the time of arrival to the parking spot. Three linguistic terms describe the price as cheap, average and expensive. The bounds were set after examining the electricity price of Greece for the day that is used in this study. In the majority of time, it is between 67 and 72 €/MWh and that is why this area is defined as average.

State of charge is known to the driver of the vehicle at any time and it is the most important factor for him when is making the decision to charge and how much. The linguistic terms used are low, medium and high. The membership function is shown in Figure 4-4. SOC represents the percentage of the available energy according to the maximum usable capacity and not the nominal value.

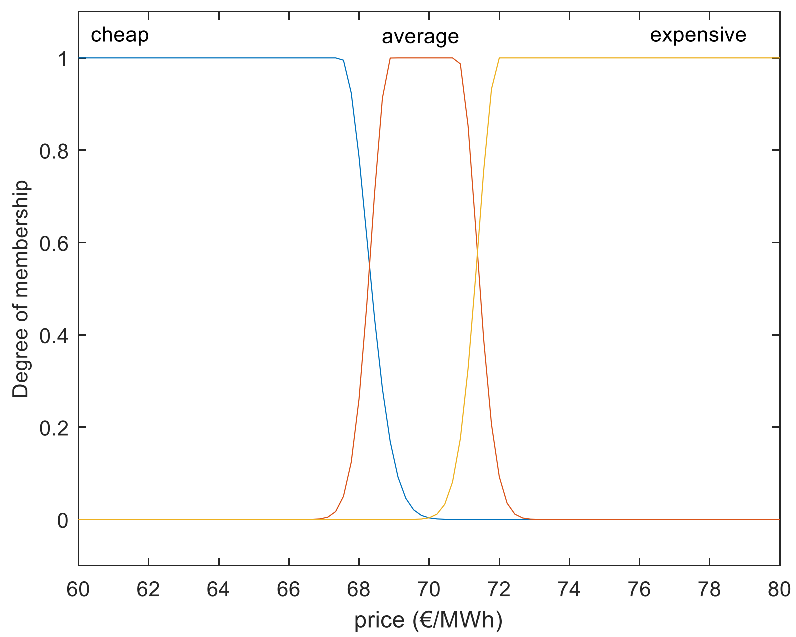


*Figure 4-3: Membership function of price*

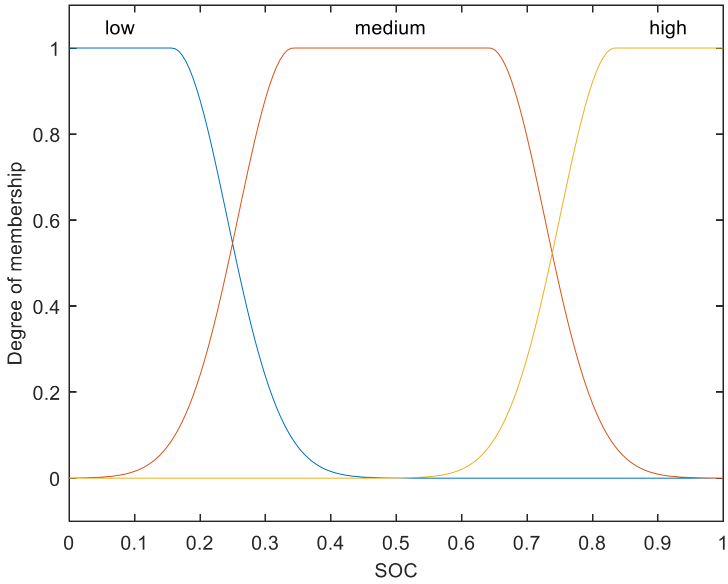


*Figure 4-4: Membership function of SOC*

### 4.1.3 Rules

Two sets of rules were created for the different fuzzy systems. Each of them has 9 rules yielded by every different combination of fuzzy inputs. The most of the differences between those two are observed when the SOC or price are high and expensive respectively. When there is no energy injection option, then the driver is less likely to charge his vehicle while if he had that option then he would probably decide to make some profit by transferring energy to the grid.
For the defuzzification, the centroid method was selected, which is based on the center of gravity of the fuzzy set. For the maximum and minimum, OR and AND operators were used respectively.

**Table 4-1. Fuzzy Rules for the simple charging inference system**

| If SOC is | AND price is | Then target is |
|---|---|---|
| low | cheap | high |
| low | average | medium-high |
| low | expensive | medium-low |
| medium | cheap | medium-high |
| medium | average | medium |
| medium | expensive | nocharge |
| high | cheap | medium-low |
| high | average | nocharge |
| high | expensive | nocharge |

**Table 4-2. Fuzzy Rules for the V2G charging inference system**

| If SOC is | AND price is | Then target is |
|---|---|---|
| low | cheap | high |
| low | average | Medium |
| low | expensive | medium-low |
| medium | cheap | medium-high |
| medium | average | medium |
| medium | expensive | medium-low |
| high | cheap | high |
| high | average | Medium-high |
| high | expensive | medium |

### 4.1.4 Output

There is only one output for both fuzzy systems. It represents the target energy that the vehicle will have at departure time and it is expressed as a percentage quantity. For the V2G fuzzy system, the percentage refers to the whole usable capacity because drivers have the option to have less energy at departure in comparison to the energy when they arrived at the parking spot. It must be noted, that this fuzzy system emulates the driver's desired target and that may not be feasible, due to technical constraints like short parking duration. In these cases, the closest value possible to the desired target is assigned.
For the simple charging fuzzy system, the percentage refers to only the available charging capacity and not the whole capacity. The difference from the previous fuzzy system is that is has one additional possible output value named "nocharge" which is assigned when the SOC is sufficient for the next trip or the price is high during the parking period. It can be seen in Figure 4-5 on the edge bottom left corner to ensure null charging energy. Additional checks are done on the target value in both systems to ensure that there is enough energy for the next trip.

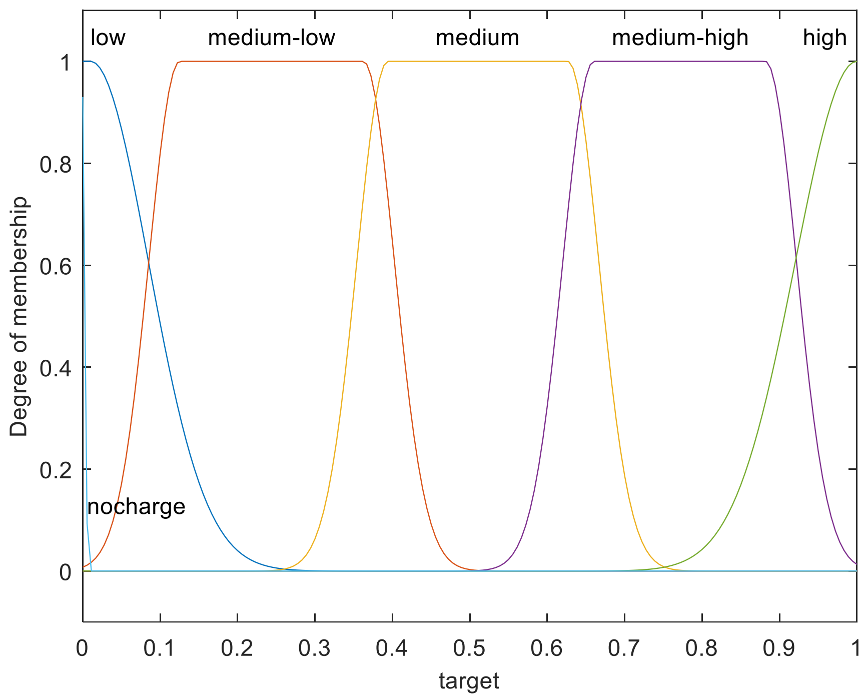


*Figure 4-5: Output of fuzzy system (G2V only)*

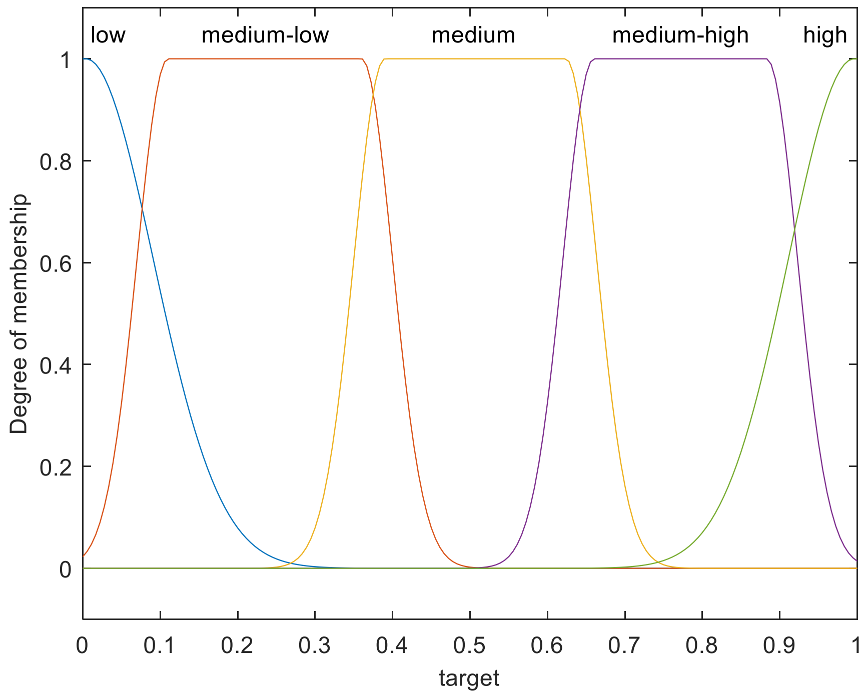


*Figure 4-6: Output of fuzzy system (V2G)*

## 4.2 Dumb charging

With the dumb charging strategy, the vehicle is charged with constant electrical power, from the beginning of the parking event until SOC reaches the assigned target. Aside from the fact that the fuzzy charging system ensures that the SOC target is lower during high price periods, no other measures are taken to distribute the charging load away peak load times which burdens both the power network operators and the cost of charging.
To model this charging strategy, the total time frame of the simulation was divided in 144 time slots of 10 minutes each (Δt). The state of the vehicle is recorded at each time slot. Using the departure and arrival times obtained from the travel patterns, the state is updated if necessary from driving to parked/charging and vice versa at each time slot. An overview of the transitions is shown in Figure 4-7.

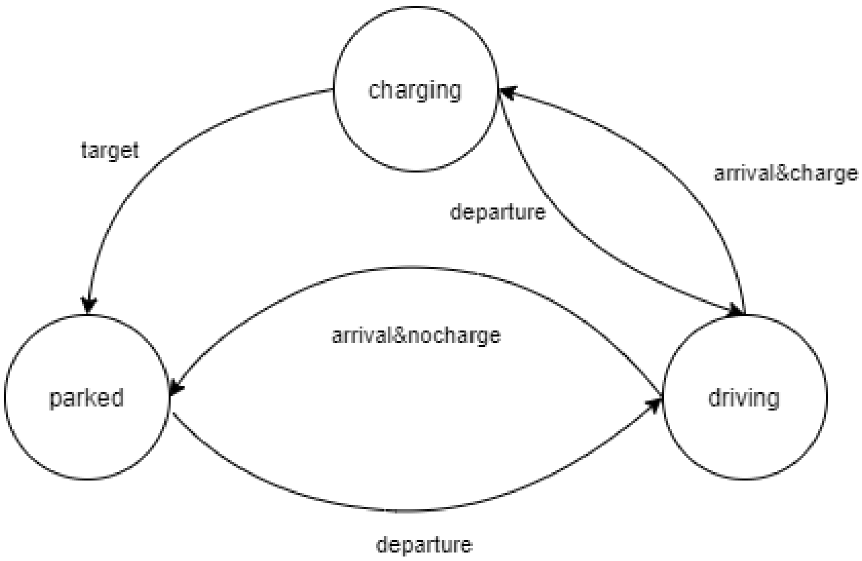


*Figure 4-7:Possible states and transitions*

In charging state, the SoC of the battery is updated with equation ( 4.1) which uses the available charging power that depends on the location that the vehicle is parked and the efficiency of charging.
An overview of the algorithm for this charging strategy can be seen in Figure 4-8. The starting time of the algorithm (t=0 in the flowchart) is considered to be 4 in the morning and the total simulation time frame is 24 hours, that is, until 4 am of the next day. The reason for that is to examine the charging behavior during early hours of the morning without cutting them off at 00:00 and compare the results with the respective ones from the smart charging that will shift the load to the off-peak hours.

$$SoC(i,t) = SoC(i,t-1) + 100 * \frac{P_{ch}(i,t) * n}{E_{bat,max}} * \Delta t \qquad (4.1)$$

where SoC (in %) is the state of charge of PEV's battery, $i$ denotes the $i$th PEV, $t$ denotes $t$th time period from a set of T periods (144 periods for a whole day), $P_{ch}$ (in kWh) is the electrical power used for charging, n (in %) is the efficiency of charging and $E_{bat,max}$ (in kWh) is the maximum energy that can be stored in the battery.
During the driving state, the energy consumed in each time slot is calculated by equation ( 4.2) in order to estimate the SoC of the battery at the arrival time.

$$EnergyConsumed = distance * cosmumption \tag{4.2}$$

Where distance (in km) is distance travelled in the previous trip and consumption (in kWh/km) is the energy consumption per km for the specific vehicle type.
The time needed to reach the target energy by charging with maximum power can be found with:

$$t_{ch} = \frac{SoC_{target} - SoC_{arr}}{P_{ch}} * E_{bat,max} \tag{4.3}$$

Where, $SoC_{target}$ (in %) is the desired SoC at the end of the charging period and $SoC_{arr}$ (in %) is the SoC at arrival.
For the worst case scenario, $P_{ch}(t)$= $P_{max}$, but with some minimum communication with the charger a smoother load can be obtained for the same target ( 4.4)

$$P_{ch}(t) = \frac{SoC_{target} - SoC_{arr}}{t_{dt} - t_{arr}} * E_{bat,max} \tag{4.4}$$

Where $t_{dt}$ and $t_{arr}$ (in hours) is the departure and arrival time, respectively.

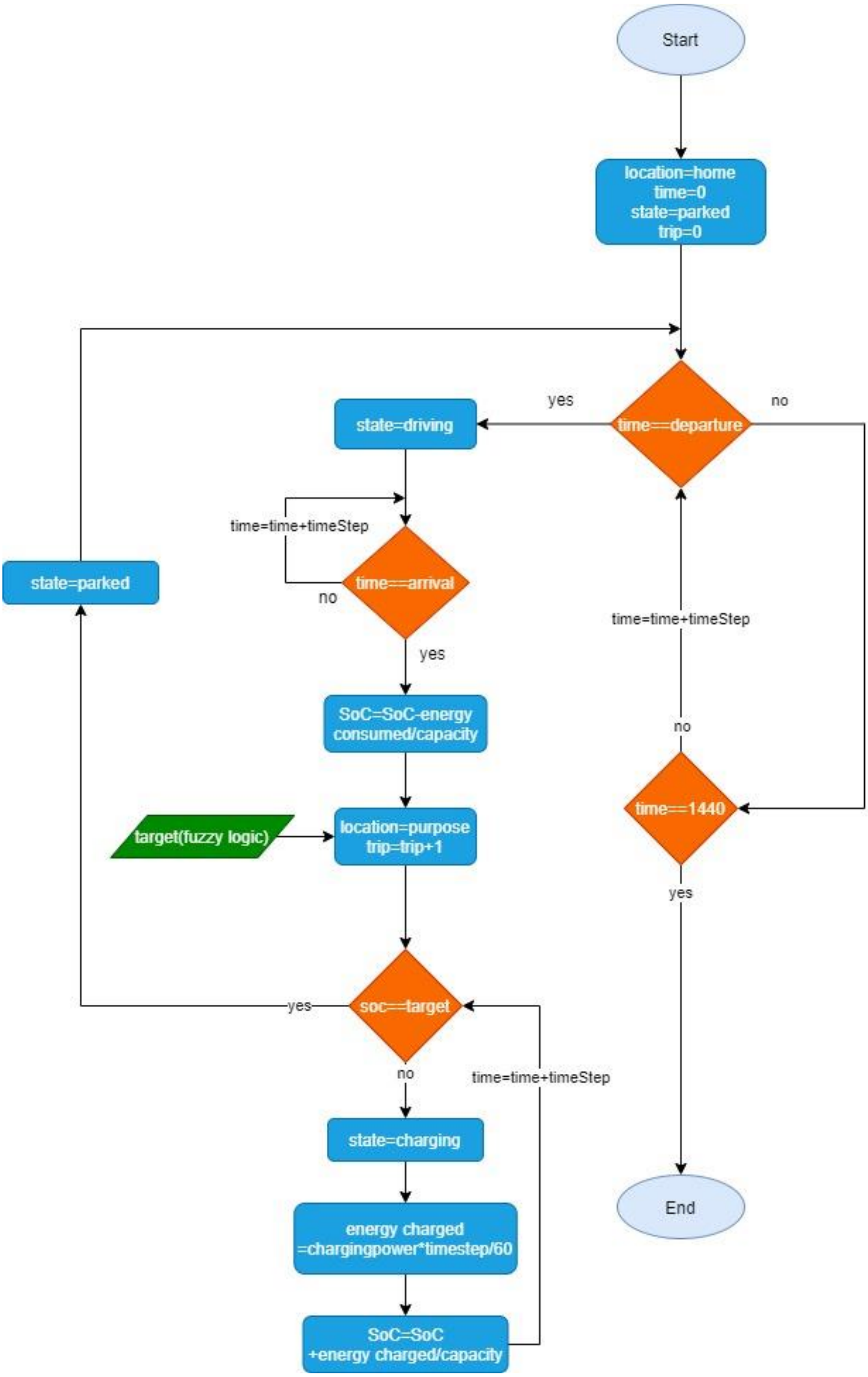


*Figure 4-8: Flowchart of dump charging tour simulation*

## 4.3 Smart charging

The Smart charging strategy can be applied by using linear programming optimization and more specifically the fmincon matlab function. In order to use fmincon, the problem must be formulated in the appropriate matrices that the function accepts as inputs. Also the right constraints that describe the problem must be defined.
The optimization problem that must be solved is the following:

$$min \sum_{t0}^{td} P_{ch}(t) * EP(t) * \Delta t \tag{4.5}$$

Where, $P_{ch}$ (in kW) is the electric power the PEV exchanges with the electricity grid and it can be positive while it is charging and negative when it injects power to the grid (V2G enabled), EP(t) (in €/MWh) is the electricity price during time period t, Δt is the time interval used (set to 10 minutes in this study).
*t0* is the time that the vehicle reaches its destination and connects to the grid and *td* is the time that it is unplugged from the network and departs from the parking location. Since the same vehicle may have to stop multiple times during the day, the objective function has to be applied for every stop and for every vehicle.

The optimization function is subject to some linear constraints in order to describe the limitations of both the PEV charging process and the driver's needs.

$$P_{min} \leq P_{ch} \leq P_{max} \tag{4.6}$$

$$SoC_{min} \leq SoC \leq SoC_{max} \tag{4.7}$$

$$SoC_{td} = SoC_{target} \tag{4.8}$$

Where, $P_{min(max)}$ (in kW) is the minimum (maximum) electric power the PEV can exchange with the electric grid, $SoC_{min(max)}$ (in %) is the minimum (maximum) electric energy that can be stored by the PEV and $SoC_{td}$ (in %) is the stored energy at the time of departure.

### 4.3.1 Extensive approach

These constraints need to be in the form $A * x \leq b$. Where, A is a matrix which in this case represent the time slots that the vehicle is parked, x is a vector representing the electrical power that will be used to charge the battery and b is a vector used to define the current energy stored to the battery.

Each element of x defines the electrical power that will be used in that particular time slot and is constrained by ( 4.6)

For the matrix A, 2 sub-matrices are needed in lower triangular form, in order to ensure that energy in the battery is within the bounds of capacity in every time slot of the day. The first sub-matrix (SoC<0) has the following form:

$$A_1 = \begin{pmatrix} 1 & 0 & 0 & \dots & 0 \\ 1 & 1 & 0 & \dots & 0 \\ 1 & 1 & 1 & \dots & 0 \\ 1 & 1 & 1 & \ddots & 0 \\ 1 & 1 & 1 & \dots & 1 \end{pmatrix} \tag{4.9}$$

In every timeslot,( 4.10) must be satisfied:

$$E_{init} + chargedEnergy - consumedEnergy \leq E_{bat,max} \tag{4.10}$$

So, by reformulating the equation above, the first part of b vector will be

$$b_1(t) = E_{bat,max} - E_{init} + E_{cons}(t) \tag{4.11}$$

Where $E_{init}$ (in kWh) is the initial stored energy at t=0 and $E_{cons}(t)$ is the energy in kWh, that the vehicle has consumed for its previous trips until timeslot t.

The second sub-matrix (SoC>0) is the same with the first but must be multiplied with -1 to change the direction of the inequality, as fmincon accepts only constraints in the form of $A * x \leq b$.

$$A_2 = -A_1 \tag{4.12}$$

Again, the charged Energy for every timeslot is bounded by ( 4.13)

$$E_{init} + chargedEnergy - consumedEnergy \geq E_{bat,min} \tag{4.13}$$

And the respective b vector will be:

$$b_2(t) = E_{bat,min} - E_{init} + E_{cons}(t) \tag{4.14}$$

For the stored energy target constraint, a vector is necessary for each stop that the vehicle does during the day. The number and the places of non-zero elements depend on the time of parking during the day.

$$A_3 = [0 \dots 0\ 0\ 1\ 1 \dots 1\ 1\ \ 0\ \ 0 \dots 0\ ] \tag{4.15}$$

Regarding the charging energy, it must correspond to the target energy as in the following:

$$E_{arr} + chargedEnergy = E_{td} \tag{4.16}$$

Where $E_{arr}$ (kWh) and $E_{td}$ (kWh) is the energy at time of arrival and departure respectively.
Hence, the final subvector $b_3$ vector will be:

$$b_3 = E_{td} - E_{arr} \tag{4.17}$$

By concatenating the Sub-matrices, the final form of A is obtained:

$$A = \frac{\Delta t}{60} * \begin{pmatrix} A_1 \\ A_2 \\ A_3 \end{pmatrix} = \frac{\Delta t}{60} \begin{pmatrix} 1 & 0 & 0 & \dots & 0 \\ 1 & 1 & 0 & \dots & 0 \\ 1 & 1 & 1 & \dots & 0 \\ 1 & 1 & 1 & \ddots & 0 \\ 1 & 1 & 1 & \dots & 1 \\ -1 & 0 & 0 & \dots & 0 \\ -1 & -1 & 0 & \dots & 0 \\ -1 & -1 & -1 & \dots & 0 \\ -1 & -1 & -1 & \ddots & 0 \\ -1 & -1 & -1 & \dots & -1 \\ 0 & 1 \dots & 1 & 0 \dots & 0 \end{pmatrix} \tag{4.18}$$

Finally, the full mathematical expression for this problem will have the following form:

$$A * x \leq b \Rightarrow$$

$$\frac{\Delta t}{60} \begin{pmatrix} 1 & 0 & 0 & \dots & 0 \\ 1 & 1 & 0 & \dots & 0 \\ 1 & 1 & 1 & \dots & 0 \\ 1 & 1 & 1 & \ddots & 0 \\ 1 & 1 & 1 & \dots & 1 \\ -1 & 0 & 0 & \dots & 0 \\ -1 & -1 & 0 & \dots & 0 \\ -1 & -1 & -1 & \dots & 0 \\ -1 & -1 & -1 & \ddots & 0 \\ -1 & -1 & -1 & \dots & -1 \\ 0 & 1 \dots & 1 & 0 \dots & 0 \end{pmatrix} * \begin{pmatrix} x_1 \\ x_2 \\ x_3 \\ \vdots \\ x_n \end{pmatrix} \leq \begin{pmatrix} b_1(1) \\ b_1(2) \\ \vdots \\ b_1(N) \\ -b_2(1) \\ -b_2(2) \\ \vdots \\ -b_2(N) \\ b_3 \end{pmatrix} \tag{4.19}$$

### 4.3.2 Dynamic aggregated battery model

Normally the optimization process would be implemented for every vehicle in the simulation and then then load would be aggregated. In our case though, due to the amount of vehicles, it would take a lot of time to be processed and we wouldn't be able to assess the impact of introduced load to the electricity price.

In order to solve these problems, we use a different method, a dynamical battery that represents the aggregated energy of all the parked vehicles throughout the whole day. When a vehicle departs from a parking location the dynamic battery will lose the target energy that was assigned to this particular vehicle. The results obtained by the aggregate model must be very similar to the detailed simulation, so the linear constraints have to be aggregated too.

The aggregated available charging power at each time slot is the sum of the individual charging powers of all vehicles charging at this particular time slot ( 4.24).

Next, the bounds of the dynamical battery must be determined as in ( 4.22)( 4.23). The bounds of each individual vehicle are calculated in ( 4.20)( 4.21) and then the superposition of the entire fleet produces the lower and upper bounds of the dynamical battery. For the upper and lower bounds, again two lower triangle matrices are needed to implement the battery constraints

When a vehicle departs from a charging parking spot, the charging power and the available energy is removed from the dynamical battery and when it arrives to the next location, they are added again minus the energy consumed on the road. Those changes can be seen in Figure 4-13 for 2 vehicles.

The upper and lower bounds of the dynamic battery (in kWh) are calculated by:

$$SoE_{low}(t) = \begin{cases} \max\left(E_{arr} - (t - t_{arr}) \cdot \frac{\Delta t}{60} \cdot P_{max}, E_{bat,min}\right), & SoE_{low}(t-1) + E_{av,ch}(t) > E_{td} \\ E_{td} - E_{av,ch}(t), & else \end{cases} \quad (4.20)$$

$$SoE_{up}(t) = \begin{cases} \min\left(E_{arr} + (t - t_{arr}) \cdot \frac{\Delta t}{60} \cdot P_{max}, E_{bat,max}\right), & SoE_{up}(t-1) - E_{av,ch}(t) < E_{td} \\ E_{td} + E_{av,ch}(t), & else \end{cases} \quad (4.21)$$

Where $E_{av,ch}(t)$ (in kWh) is the maximum possible energy left to charge during the time before departure.

Specifically for the lower bound, it is defined according to the following logic. When the vehicle arrives it begins to inject energy to the grid until it reaches minimum permitted SoC or when $E_{av,ch}(t)$ is barely enough to reach the target SoC by charging at maximum power before leaving. For the upper bound the same logic applies but the vehicle first charges at maximum power and then injects the energy until the target SoC.

For the time slots that the vehicle will be in the road, both bounds are set to zero.

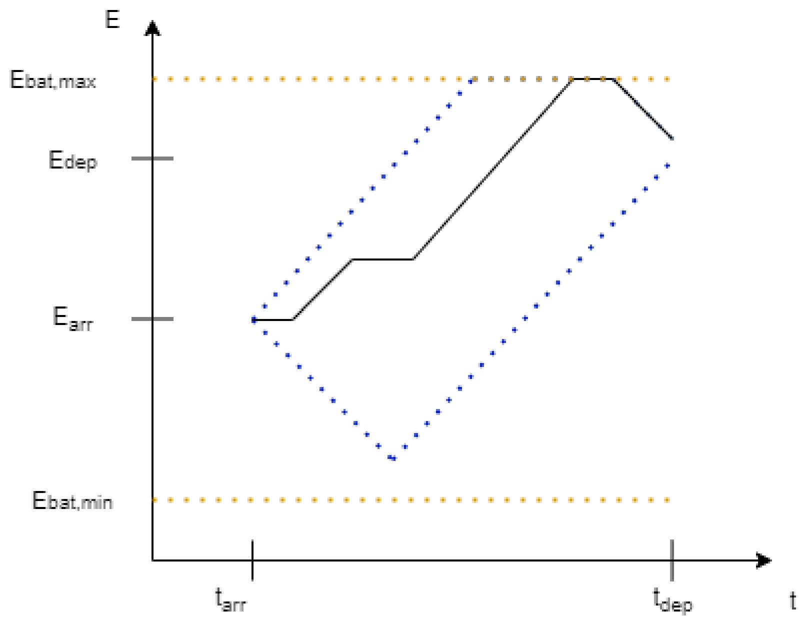


*Figure 4-9: SoC bounds (optimization window)*

Then both bounds are aggregated to represent the capacity of the total battery of the fleet

$$SoE_{up}^{aggr}(t) = \sum_{i=1}^{n} SoE_{up}(t,i) \tag{4.22}$$

$$SoE_{low}^{aggr}(t) = \sum_{i=1}^{n} SoE_{low}(t,i) \tag{4.23}$$

The available maximum electrical power must also be aggregated to match the power of the whole battery.

$$P_{max}^{aggr}(t) = \sum_{i=1}^{n} P_{max}(t,i) \tag{4.24}$$

Like the detailed method, two lower triangle matrices are needed but no extra vectors are used because the target energy at departure is taken account of during the calculation of the bounds.
So the final form of the optimization will be:

$$\frac{\Delta t}{60}\begin{pmatrix} 1 & 0 & 0 & \dots & 0 \\ 1 & 1 & 0 & \dots & 0 \\ 1 & 1 & 1 & \dots & 0 \\ 1 & 1 & 1 & \ddots & 0 \\ 1 & 1 & 1 & \dots & 1 \\ -1 & 0 & 0 & \dots & 0 \\ -1 & -1 & 0 & \dots & 0 \\ -1 & -1 & -1 & \dots & 0 \\ -1 & -1 & -1 & \ddots & 0 \\ -1 & -1 & -1 & \dots & -1 \end{pmatrix} * \begin{pmatrix} x_1 \\ x_2 \\ x_3 \\ \vdots \\ x_n \end{pmatrix} \leq \begin{pmatrix} SoE_{up}^{aggr}(1) \\ SoE_{up}^{aggr}(2) \\ \vdots \\ SoE_{up}^{aggr}(N) \\ -SoE_{low}^{aggr}(1) \\ -SoE_{low}^{aggr}(2) \\ \vdots \\ -SoE_{low}^{aggr}(N) \end{pmatrix} \qquad (4.25)$$

The aggregated stored energy at every time slot is estimated by:

$$SoE_{aggr}(t+1) = SoE_{aggr}(t) + dSoC(t) + x(t) * n * \Delta t \qquad (4.26)$$

An example of the aggregation of two vehicles s shown in the following figures. Note that in Figure 4-12 the current SoC continues to remain inside the bounds by using dSOC to dynamically add or subtract energy when an arrival or departure has occurred.
Furthermore, a representation of a bigger fleet is provided in Figure 4-14.

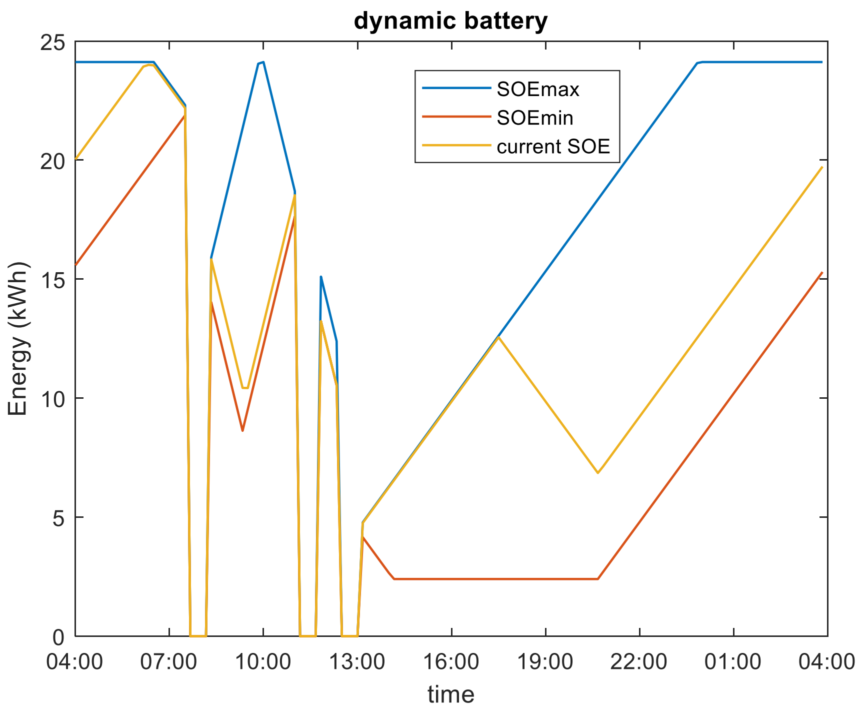


*Figure 4-10: 1st vehicle*

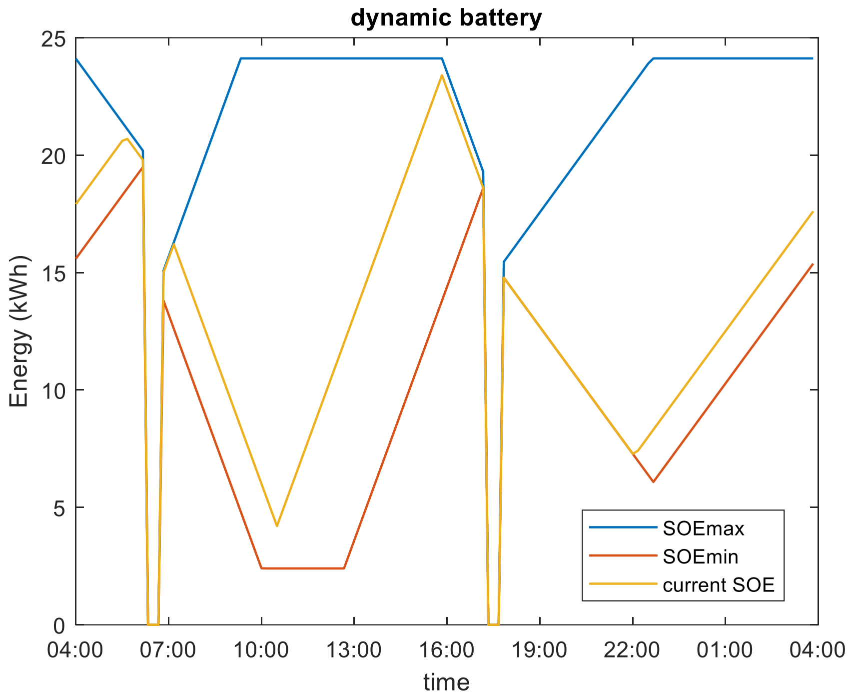


*Figure 4-11: 2nd vehicle*

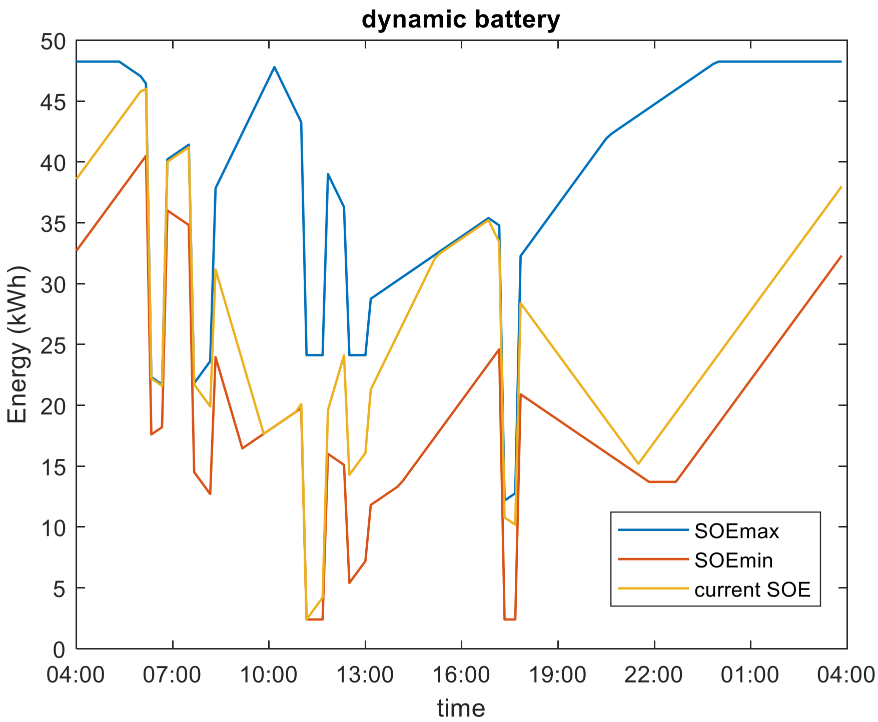


*Figure 4-12: aggregation of the two vehicles*

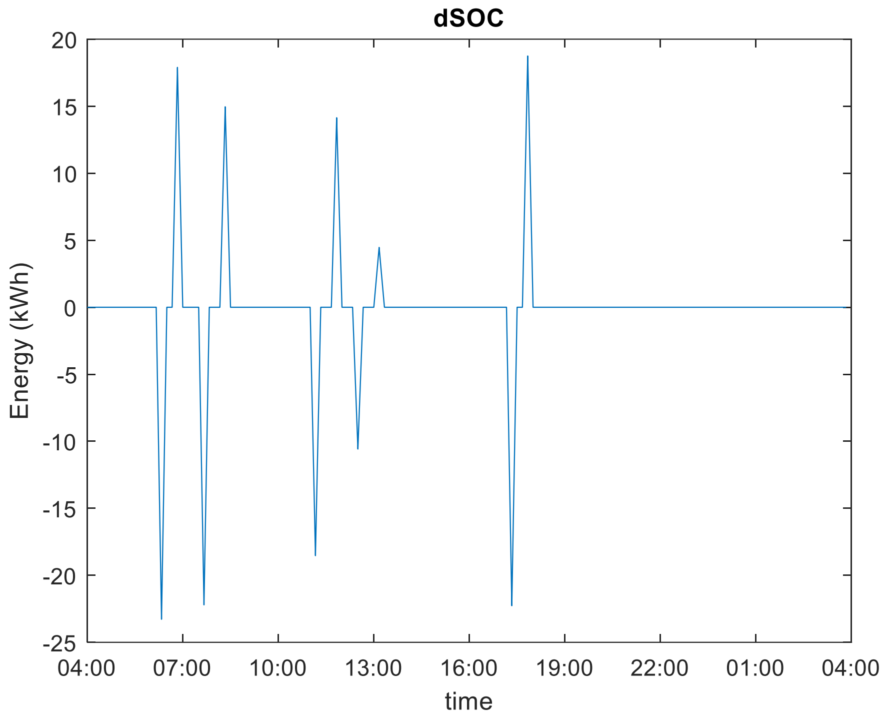


*Figure 4-13: Energy additions and deductions during arrivals and departures*

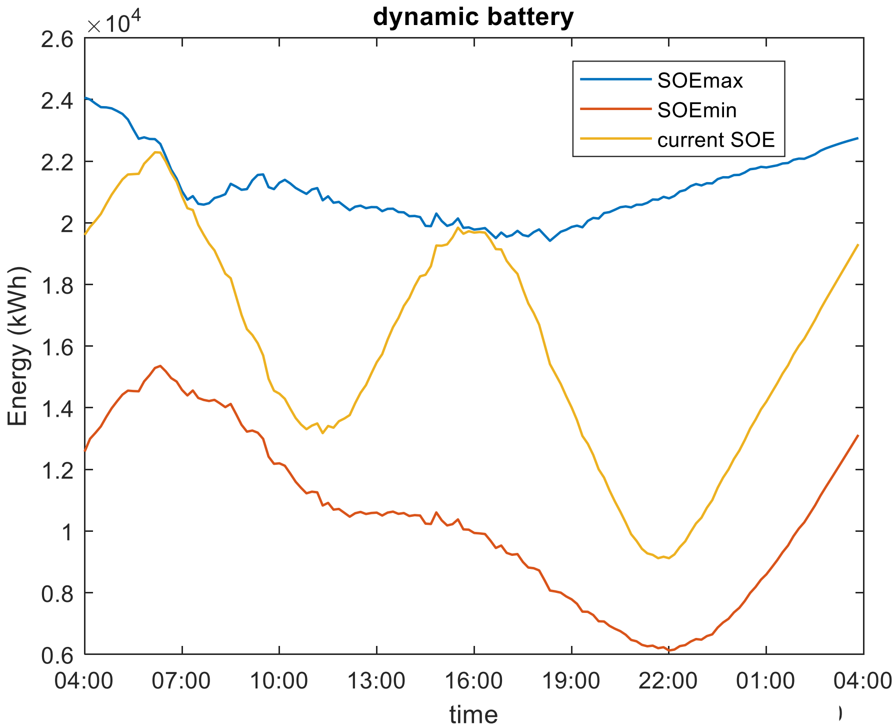


*Figure 4-14: aggregation for 1000 vehicles*

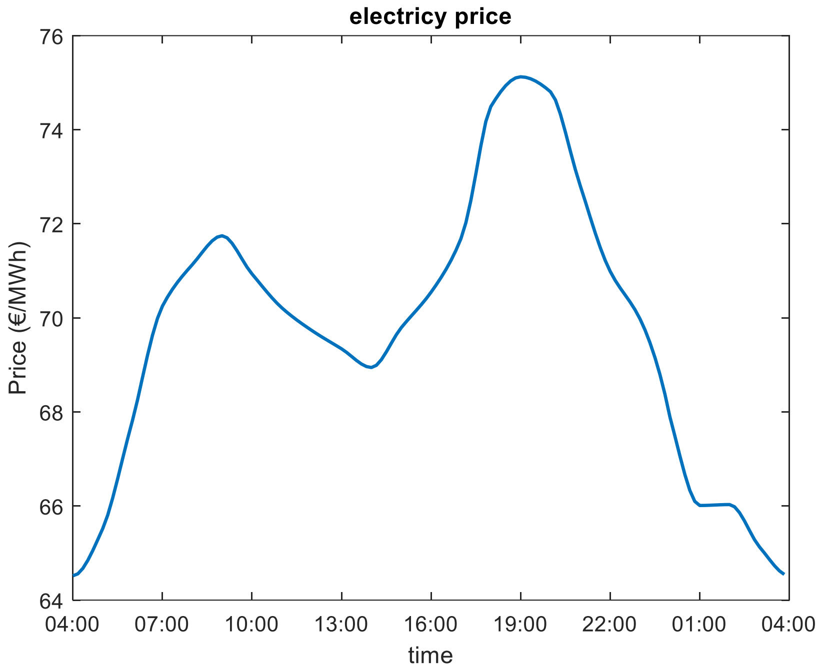


*Figure 4-15: electricity price used for the simulations*

## 4.3.3 Detailed vs Aggregate Battery model

The comparison of the two different methods using the same input parameters can lead to some interesting conclusions. While the shape of the load during the day is similar, there are some minor differences that reflect the advantages of a centralized approach e.g. an aggregator to the application of smart charging. During the extensive optimization a single vehicle may opt to provide energy to the grid even on low price time periods just because its current SoC is more that its target SoC. With the Dynamic Battery however, the “greater picture” is known to the system and the optimization will decide to charge more energy in low price periods and inject the energy only when the price is high. While in real systems such perfect knowledge for the whole fleet may not be obtainable, it can provide the margin of improvement of the single vehicle optimization by using an aggregator and is nonetheless a good indication of the best case scenario. The main advantage of the aggregated method still remains the vastly reduced processing time for a large PEV fleet. Comparison between the simulation times can be seen in Table 4-3.

In the following table the simulation times are recorded. The CPU used is the i7-4790 (4 cores) and parallel execution (parfor) is applied.

**Table 4-3. Simulation times for different number of vehicles.**

| | 100 | 1000 | 10000 | 100000 | 1000000 |
|---|---|---|---|---|---|
| **Detailed** | 12.4 s | 125 s | 682 s | 5840 s | ~50000 s |
| **Aggregated** | 11 s | 17 s | 20 s | 90 s | 625 s |

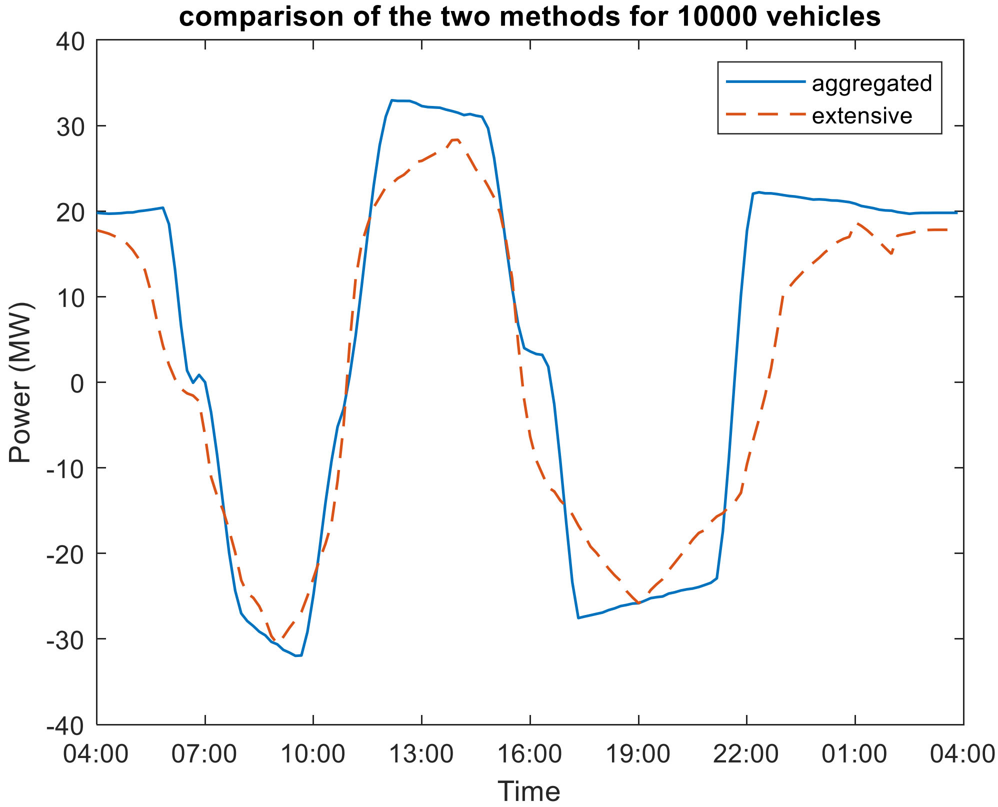


*Figure 4-16: similarity between extensive and aggregated methods*

## 4.4 PEV load impact to the price

While in small PEV penetration scenarios the introduced load of PEVs would not affect the electricity price, a large fleet can modify the electricity price to a great extent. This will in turn alter the behavior of the fleet to accommodate for the changes to the expensive-cheap time periods until the price reach a steady state which will define the equilibrium of the system.
A simple price model is developed to calculate the final price evolution throughout the day. From ADMIE site, the hourly price for a whole year is extracted (24*365 values) and, after removing some outliers, a relation between load and price is formulated that will be used to produce a new daily electricity price by providing the total load of the system with the introduced EV load.
This relation is approximated by a polynomial function ( 4.27) as shown in Figure 4-17.


*Figure 4-17: Polynomial function of price-load*

An iterative process is the applied starting from the reference price, calculating the new load with the dynamic battery smart charging strategy and then using the function ( 4.27), as well as ( 4.28) to get the new system price

$$f = 5.2 \cdot 10^{-10} L^3 - 9.6 \cdot 10^{-6} L^2 + 0.06L - 64.08 \qquad (4.27)$$

Where, L is the current total load of the system in MW

The new price is found by calculating the difference between the current and old price and adjusting by a small factor *l*, in order to enhance the convergence stability of the price (otherwise, with big enough load, it would cause oscillations between the iterations).

$$EP_{new}(t) = EP_{old}(t) + l * (f(L_{tot}) - EP_{old}(t)) \qquad (4.28)$$

The iterative process will be repeated until the new price will be almost identical to the price of the previous round by using the ending condition in ( 4.29) or has completed a max amount of iterations and that is when the system has reached an equilibrium or quite close to it.

$$\sum_{t=0}^{tn} \frac{|EP_{new}(t) - EP_{old}(t)|}{\max(EP_{new}(t)) \cdot 144} < convergence \qquad (4.29)$$

The iteration process is illustrated in the following flowchart:

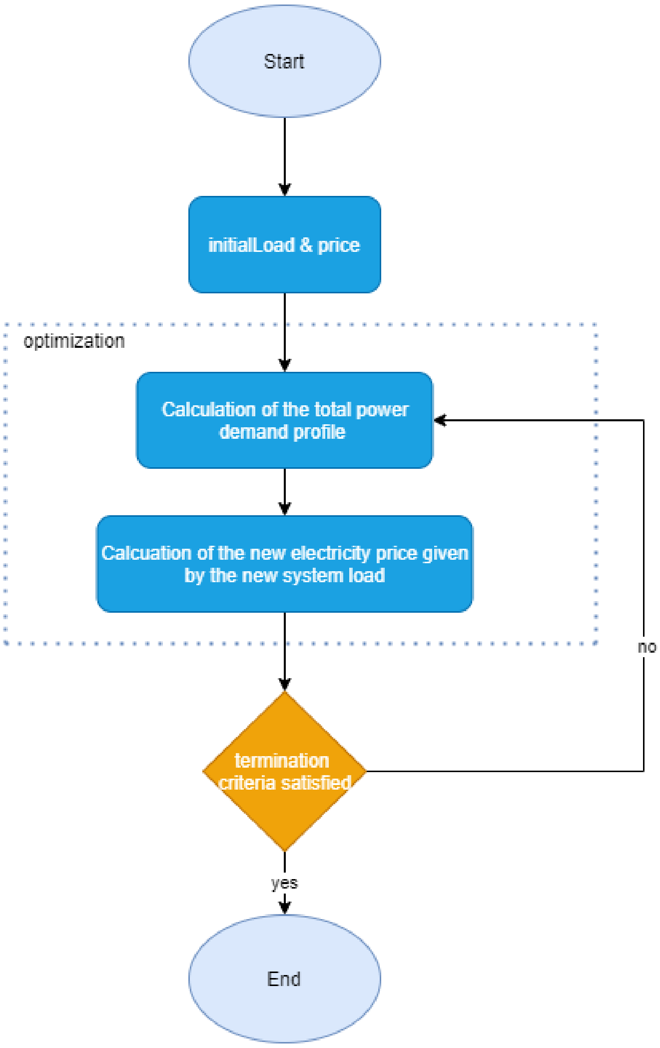


*Figure 4-18: Price alteration flowchart*

# CHAPTER 5

## Simulation Results

In this section, the parameters and the inputs of the proposed model will be presented, as well as the respective results for the different PEV penetration scenarios. The model parameters such as the load or the vehicle fleet population can be changed to represent the national power system of a different country or region.
Three different penetration scenarios are studied, based on how optimistic the integration of EVs will be in Greek market. The results of the developed iteration process are presented for each alternative charging strategy and in every penetration scenario, as well as, important observations about the new load peaks during the day are done.
It must also be noted, that a necessary assumption has been made in this study. According to that assumption the electricity network of Greece is presumed to be entirely interconnected. In reality, both Crete and the smaller islands are not connected to the mainland of Greece, although the interconnection between Attica and Crete is expected to be completed in 2022 (Ariadne interconnection). The number of vehicles in smaller islands is really small so it should not have a large impact in the final results. However, several significant islands are planned to be interconnected with the mainland power system over the next years.

### 5.1 Simulation Parameters

In this study, one vehicle type is assumed to possess a battery large enough to meet the needs of the drivers in their everyday tour. It is logical to assume that a driver will buy a vehicle that is suitable to his daily mileage needs. In Greece, the mileage is not that high and a battery of 30 kWh will suffice according to Table 5-1. The consumption includes the energy required for heating or cooling.

***Table 5-1. Battery Specifications***

| Battery capacity (kWh) | **Usable capacity (kWh)** | **Consumption (kWh/km)** | **Autonomy range (km)** |
|---|---|---|---|
| 30 | 25 | 18/100 | ~200 |

The initial SoC, when the vehicle departs from home at the start of the day is assigned from a normal distribution shown in Figure 5-1, where it is assumed that vehicles depart from home with 80% to 100% of their (usable) battery capacity.

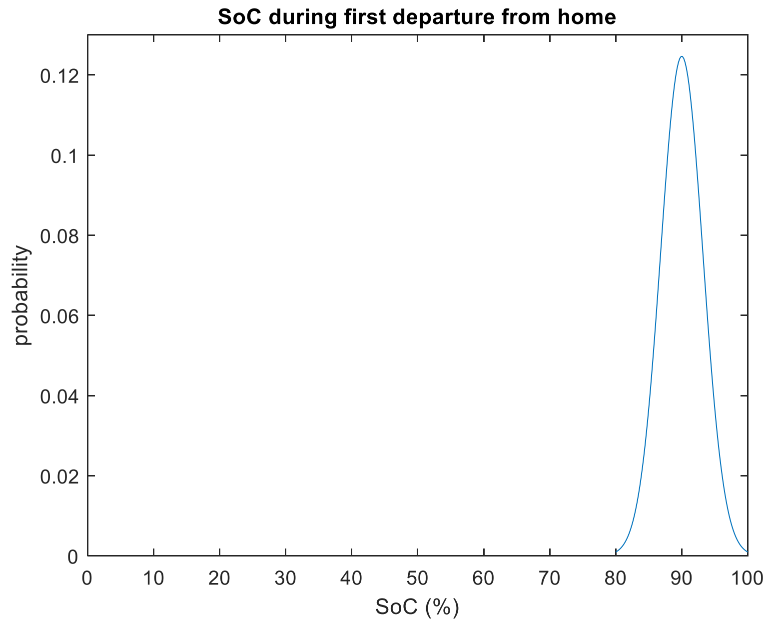


*Figure 5-1: Initial SoC during the 1st departure*

Regarding the initial 24-hour load, the system load in Figure 5-2 was selected, which can be found in ADMIE [30]. The site has a variety of data, including renewable energy source injections and net interconnections. The time series are recorded in hourly values, so linear interpolation was necessary to obtain load values for every time period (10 minutes) of the simulation. This particular load corresponds to the load on 19/1/2019.

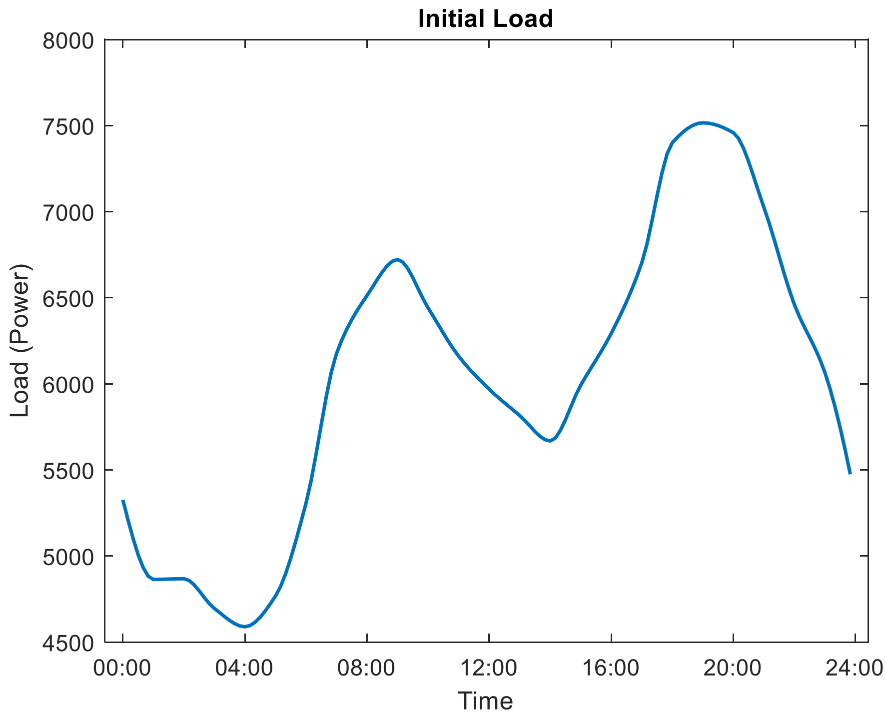


*Figure 5-2: Initial System Load (19/1/2019)*

For the respective electricity price, the relation in Figure 4-17 was used to model the electricity price with regard to the load, as it will be used for the initialization of the electricity price.

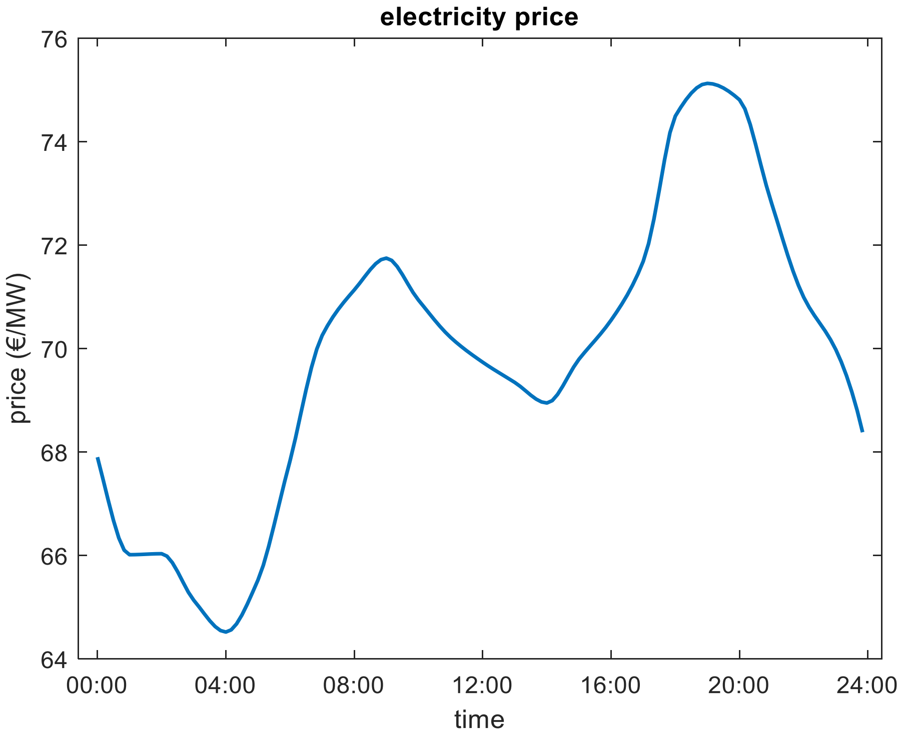


*Figure 5-3: Initial Electricity Price*

The level of charging power holds an important role in estimating the electric load profile. In this study, 3 levels of charging were assumed. Furthermore, charging efficiency is set to 90% to accommodate ac/dc converter and losses from the wall outlet to the battery.

***Table 5-2. Charging levels for the different locations***

| Charging level | location | Power level(kW) |
|---|---|---|
| **Level 1** | Home | 2 |
| **Level 2a** | Work | 4 |
| **Level 2b** | Shopping & Social | 6 |

## 5.2 Penetration scenarios

In order to quantify the number of EVs that will be used throughout Greece, the population of conventional private vehicles has to be considered. The Hellenic Statistical Authority has recorded detailed information of the national vehicle fleet regarding the distribution of vehicles in every region of Greece [31]. For the purpose of this study and by using the driving characteristics from chapter 2, urban behavior will be allocated only in the area of Athens (Attiki) and Thessaloniki. This decision is based on the fact, that the size of cities in North America is greater than those in Greece. Vehicles in other regions will be allocated rural behaviors and mileage.

*Table 5-3. Distribution of conventional vehicles in each region*

| Region | Number of Conventional Vehicles | Percentage |
|---|---|---|
| **Central Greece** | 3,160,664 | 59% |
| **Peloponnese** | 228,570 | 4.2% |
| **Ionian Islands** | 86,030 | 1.6% |
| **Epirus** | 118,827 | 2.2% |
| **Thessaly** | 246,774 | 4.5% |
| **Macedonia** | 949,114 | 17.6% |
| **Thrace** | 125,746 | 2.3% |
| **Aegean Islands** | 178,395 | 3.4% |
| **Crete** | 278,871 | 5.2% |

The final distribution of urban/rural locations can be seen in the following Table.

*Table 5-4. Fleet population of large cities*

| | Number of Conventional Vehicles | Percentage |
|---|---|---|
| **Athens** | 2,974,649 | 55% |
| **Thessaloniki** | 531,675 | 10% |
| **Other** | 1,866,667 | 35% |
| **Total** | 5,372,991 | 100% |

The world (and especially Greece) is still in early stages of EV penetration so only estimations can be made about the exact numbers in the following years. For this reason, different scenarios must be considered.
The project Mobile Energy Resources in Grids of Electricity (MERGE)[32] has completed many evaluations about the impact that EV deployment will have on electricity demand and the market issues that will ensue. In this project, a case study regarding Greece is included. It describes three different penetration scenarios for 2030:

- Low EV penetration rate: It is the most feasible scenario, which states that there will be 5% integration rate.

- Medium EV penetration rate: It is an optimistic scenario. Although it is less likely to occur in reality, this scenario is the recommended as the main focus of the project because valuable information can be obtained about mass integration of EVs to the gird. The rate is around 10%

- High EV penetration rate: It is a very aggressive scenario, very unlikely to occur and it might be used for reference. The integration rate is set to 20%.

*Table 5-5. Final urban/rural distribution*

| | Number of conventional vehicles | Low(5%) | Medium(10%) | High(20%) |
|---|---|---|---|---|
| **Urban** | 3,506,324 | 175,316 | 350,632 | 701,264 |
| **Rural** | 1,866,667 | 93,333 | 186,666 | 373,333 |
| **Total** | 5,372,991 | 268,659 | 537,298 | 1,074,597 |

## 5.3 Dumb charging

As mentioned before, in the dumb charging strategy the charging process is not actively controlled, resulting in new load peaks. In Figure 5-4, the PEV fleet load can be seen for both versions of dumb charging and for every penetration scenario.

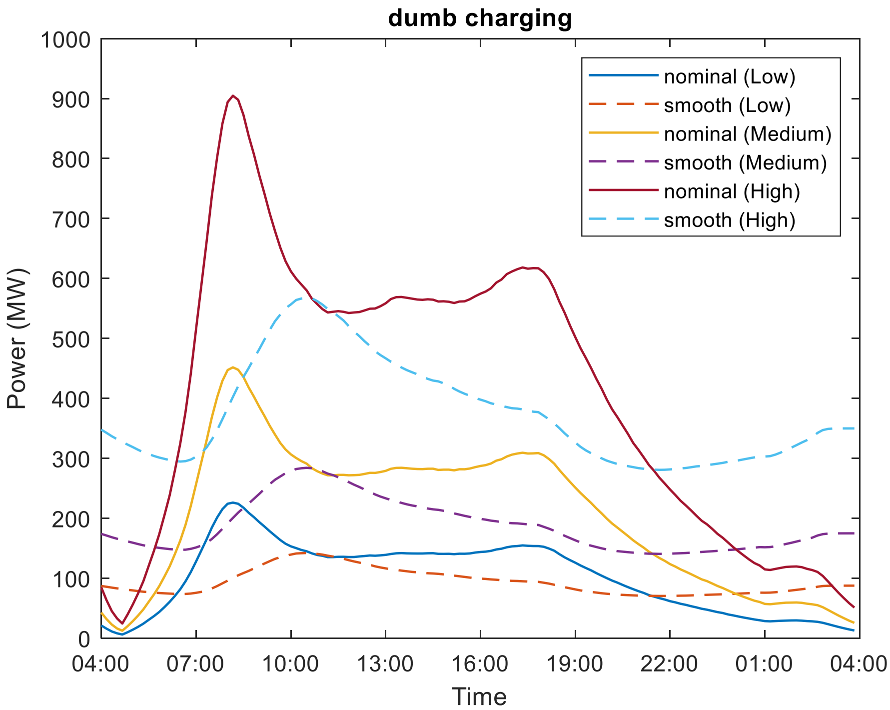


*Figure 5-4: Results for the two different dumb charging versions*

As it can be observed, the PEV load shape correlates with the human driving activity. In the first case of dumb charging (nominal) the PEVs charge with maximum power. In this case the load peak is around 8:00-9:00 in all scenarios. This occurs because most of the vehicles travel around 7:00-8:00 especially for work purposes and then they are being charged with maximum power, thus resulting in a quite steep load peak. A smaller peak can be seen

around 18:00 when many drivers return home from their work or start their evening activities. Moreover, in the early morning hours (3:00-6:00) the introduced load is minimal to nonexistent, as the mobility is reduced in these hours and most of PEVs have finished charging by then.
In the second case of dumb charging (smooth), the new load is more evenly spread out. Now the peak is around 10:00-11:00 due to the fact that this is the time of most concurrent charging. Most vehicles are in a workplace or a public station by that time and they have not departed yet. After that, the load decreases steadily until the morning hours, at which again the number of concurrent charging is higher due to vehicles not having reached the target for the end of the day.
In all scenarios, the results are quite similar for the same mode of dumb charging. Only the PEV load magnitude is amplified, due to the increased number of vehicles. While in the low penetration scenario, the difference is not that tremendous, in the high penetration scenario the difference between the respective peaks can be more than 300 MW, proving the need of at least a primary control of the charging process, even if it is not smart charging.

In the following figures, the new total load of the power system (PEV included) can be seen in each penetration scenario and in comparison with the initial load of the system. The power demand of PEVs burden the system during peak load periods while load valleys during the morning or the midday are not altered significantly. This is extremely evident in the high penetration scenario, where the new peak is 8000 MW, while the initial was 7400 MW.

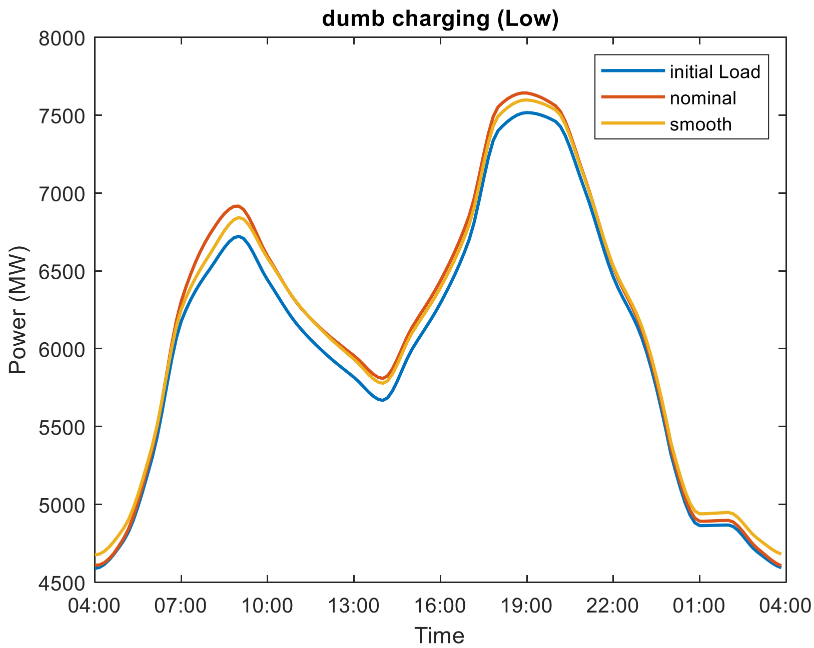


*Figure 5-5: Total load for the low penetration scenario*

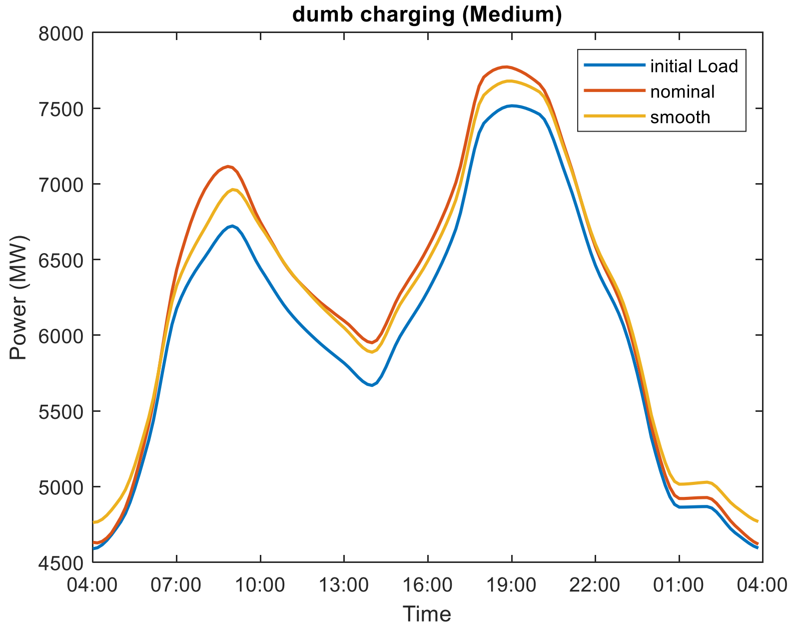


*Figure 5-6: Total load for the medium penetration scenario*

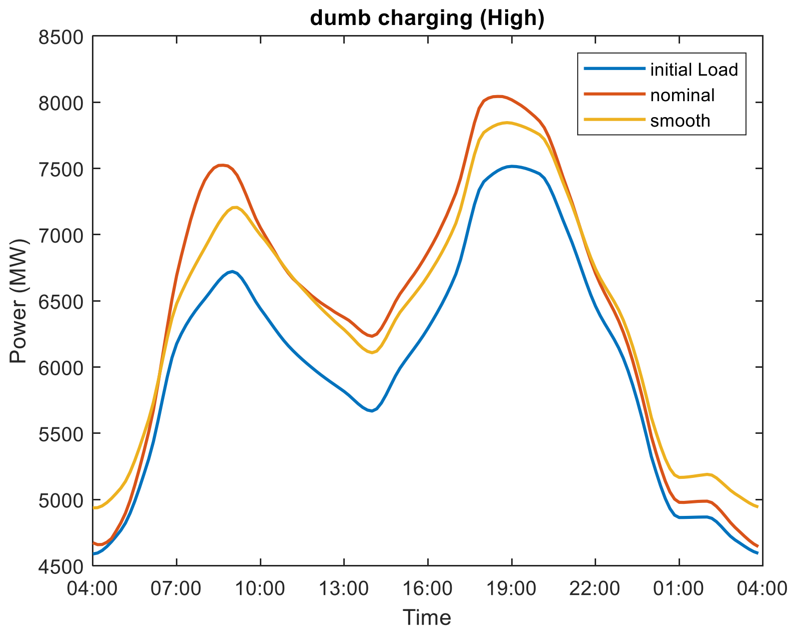


*Figure 5-7: Total load for the high penetration scenario*

## 5.4 Smart Charging – G2V

With smart charging, PEVs tend to be supplied with energy during low system load and avoid peaks of load when it is possible. Note that V2G is not used in this section. In our case, this availability is constrained by the bounds of the dynamic battery, as well as the number of vehicles charging at each time period of the day. In Figure 5-8, the smart charging load results can be seen for every scenario.

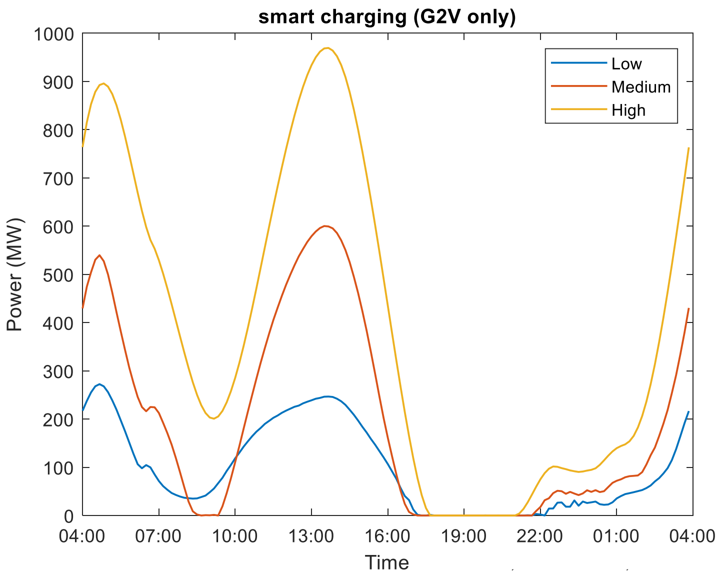


*Figure 5-8: Load results when smart charging is applied*

The results have similar shape in every scenario. The optimization process leads to zero charging power in the time periods from 18:00 to 21:00, where the electricity price is at its highest, in all scenarios. It also tries to minimize the charging energy during 8:00-9:00 due to the local maximum of the price. In contrast, the PEV load maximizes at 5:00 and 14:00 when the electricity price has global and local minimum values, respectively.

### 5.4.1 Low penetration scenario

In this scenario, the introduced load is quite small compared to the initial load of the power system. This is why only small variations appear in both price and load iterations, although it is evident that the increase of price in the peak of 9:00 causes a slight increase to load valleys. The dynamic battery cannot be charged more during the morning hours due to the downward trend of its bounds (caused by the rush hour in the morning).

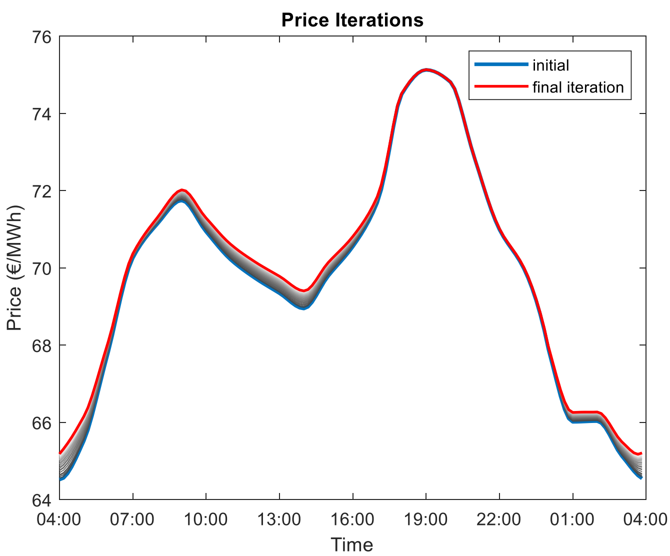


*Figure 5-9: Price alterations during the iterations (G2V only-Low)*

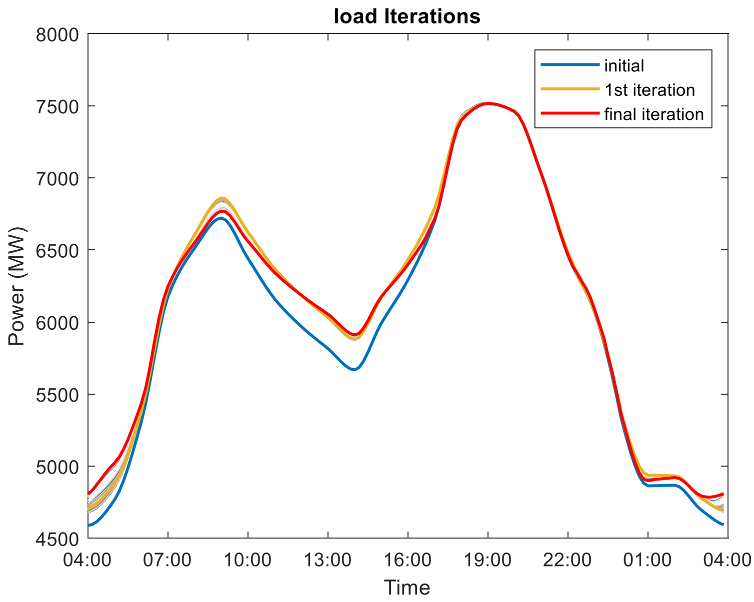


*Figure 5-10: Load alterations during the iterations (G2V only-Low)*

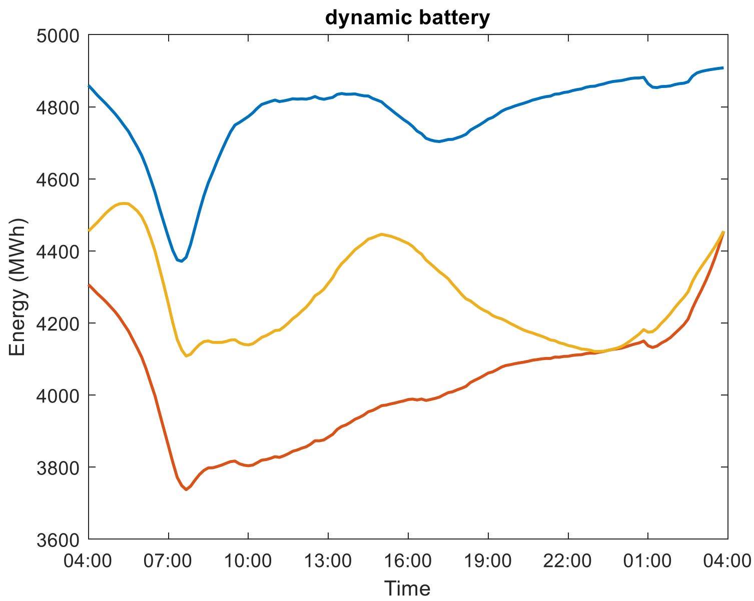


*Figure 5-11: Aggregated battery representation for the final iteration (G2V only-Low)*

### 5.4.2 Medium penetration scenario

In this scenario, the PEV load is substantial compared to the initial load of the power system. PEVs recharge their batteries during the morning hours as much as possible (bounded by the dynamic battery and aggregated electric power) or fulfill their midday charging needs during the valley (10:00-16:00) of the load and they avoid the load peaks.

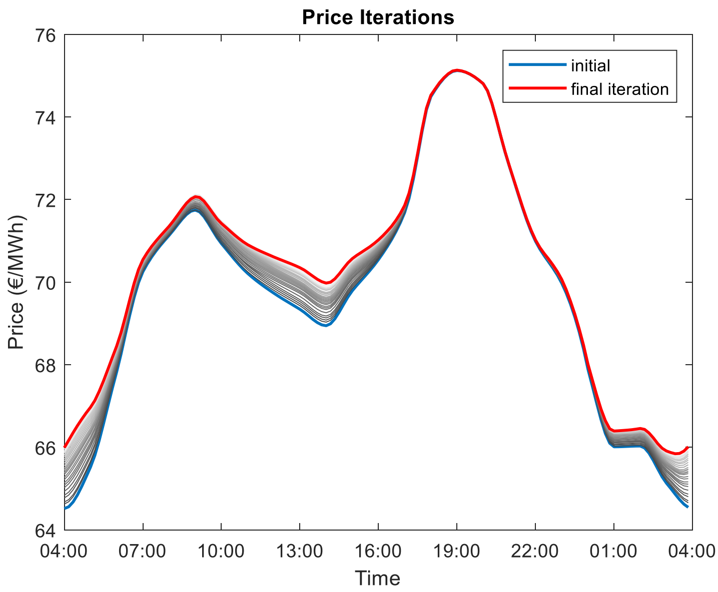


*Figure 5-12:Price alterations during the iterations (G2V only-Medium)*

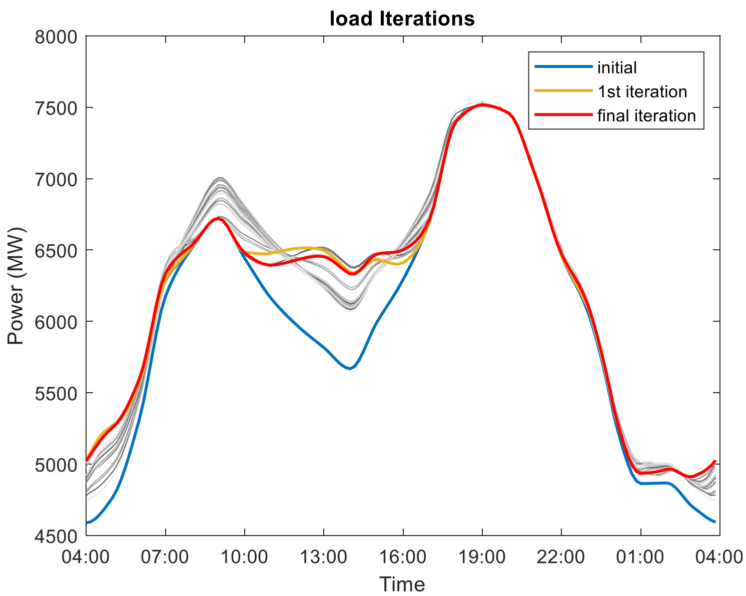


*Figure 5-13: Load alterations during the iterations (G2V only-Medium)*

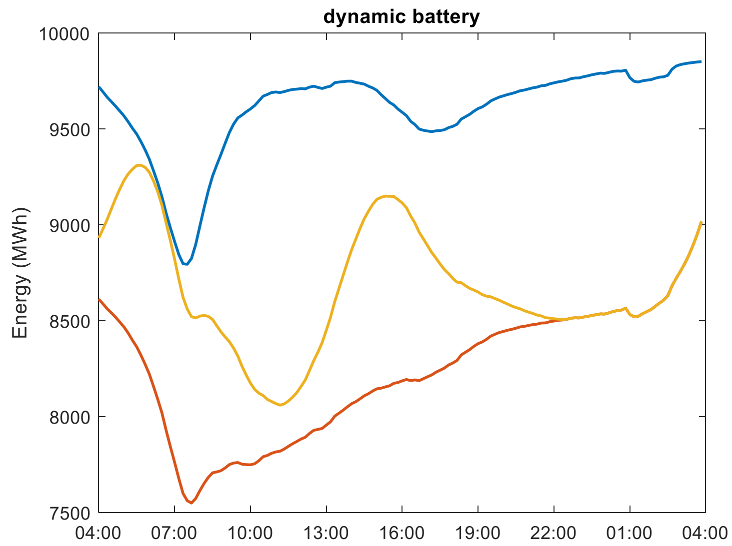


*Figure 5-14: Aggregated battery representation for the final iteration (G2V only-Medium)*

### 5.4.3 High penetration scenario

In this case, the electricity price change is significantly affected by PEV load. Due to the high enough PEV load, the midday valley is not deep enough to satisfy the charging needs, so some charging during the smaller peak (9:00) is necessary. Nevertheless, the highest peak is yet again avoided, so the system does not need further facilities to accommodate the increased load.

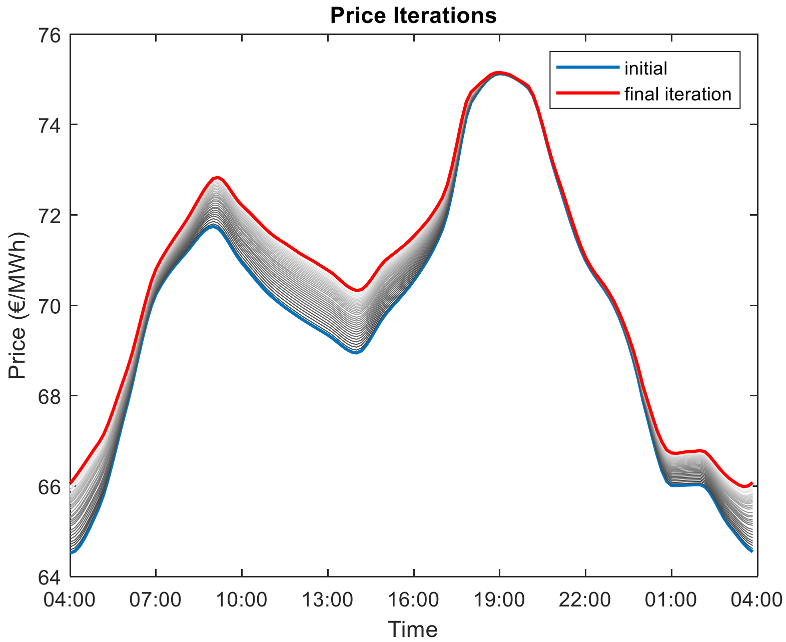


*Figure 5-15: Price alterations during the iterations (G2V only-High)*

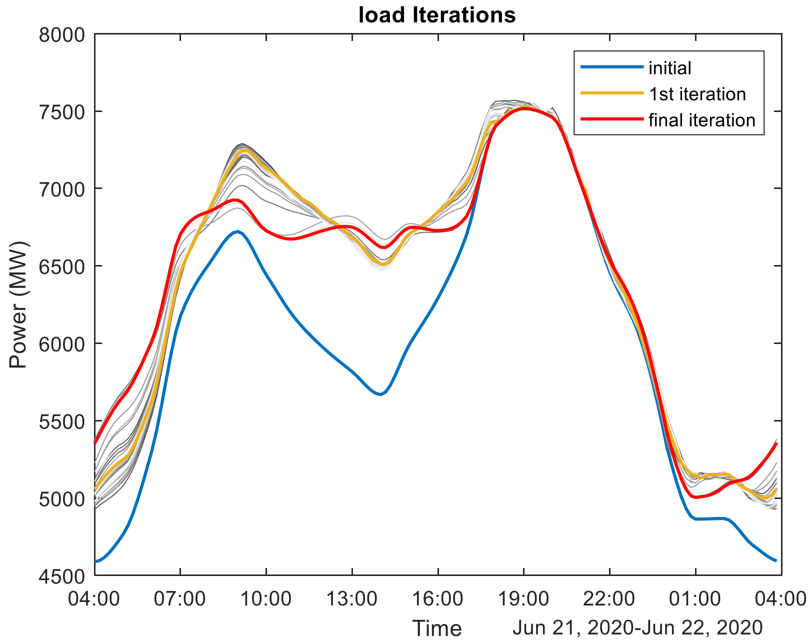


*Figure 5-16: Load alterations during the iterations (G2V only-High)*

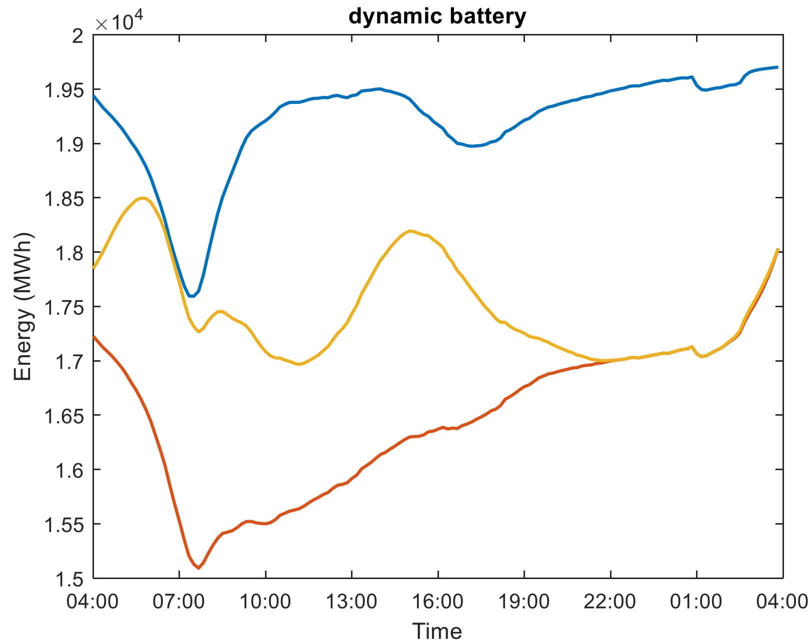


*Figure 5-17: Aggregated battery representation for the final iteration (G2V only-High)*

## 5.5 Smart Charging – G2V & V2G

With V2G enabled, PEVs are able to inject energy to the grid and shift their charging in low price time periods. As it can be seen in the figure below, the introduced load has essentially the reverse shape of the initial load of the power system, supporting the grid in high electricity price periods and charging during low price periods. While in higher penetration scenarios there should be a higher energy injection availability (greater vehicle number), it is observed that the support load is similar in all 3 cases. This happens due to the proportional charging need, as well as the increased value of the electricity price equilibrium. What mostly changes between scenarios, is the charging load during the morning hours, as it still remains the most economic time of recharging.

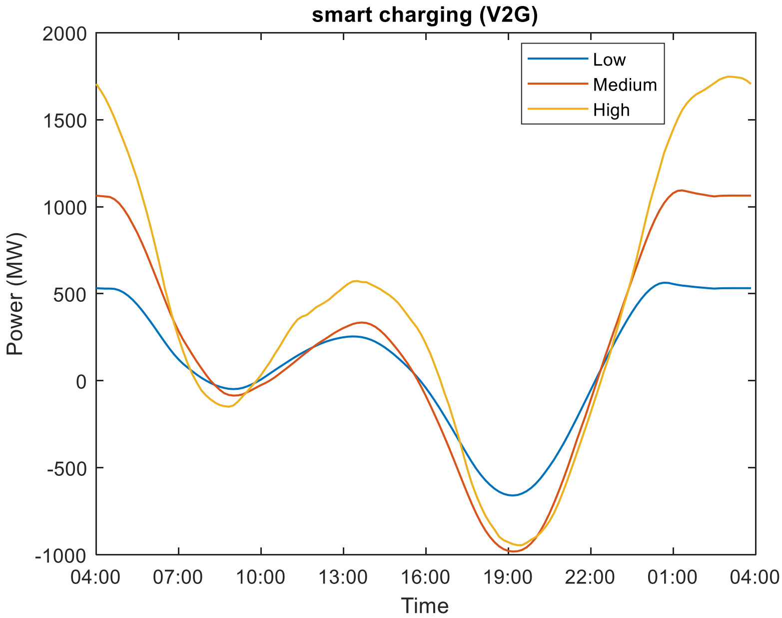


*Figure 5-18: Load results when V2G is applied*

### 5.5.1 Low penetration scenario

In this scenario, the electricity price is affected more than in the simple smart charging due to the benefits of V2G. On the other hand, the load is not altering that much during the iterations, because the optimal load stays almost the same. PEVs are injecting energy at almost full rate during the peak of 19:00, while the same happens to a smaller extent at the smaller peak of 9:00. The total charged energy during the morning valley is a little higher, as a result of the ability to inject energy when possible and not storing the extra energy for the next day.

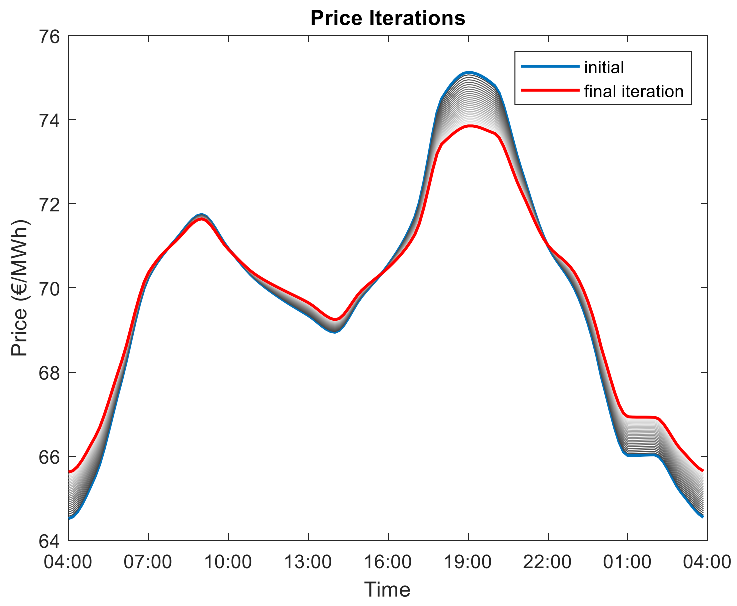


*Figure 5-19: Price alterations during the iterations (G2V&V2G-Low)*

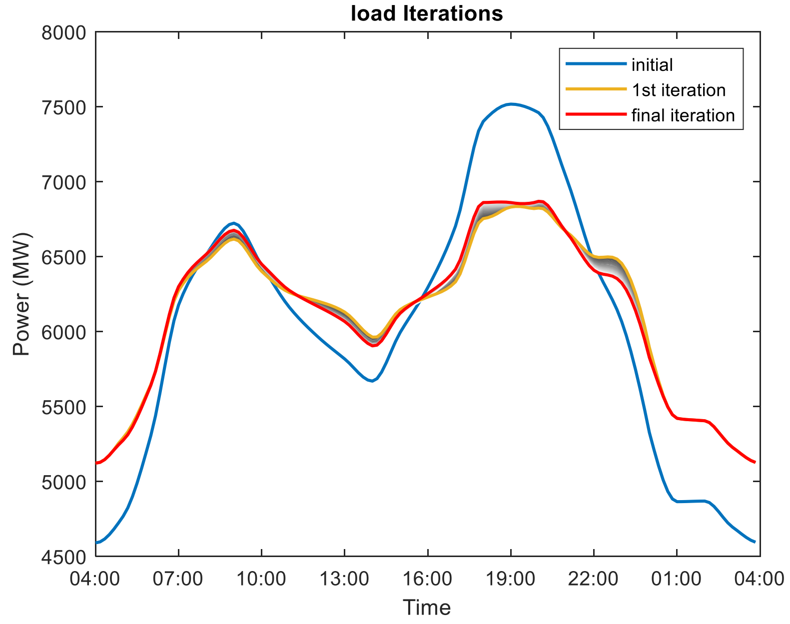


*Figure 5-20: Load alterations during the iterations (G2V&V2G-Low)*

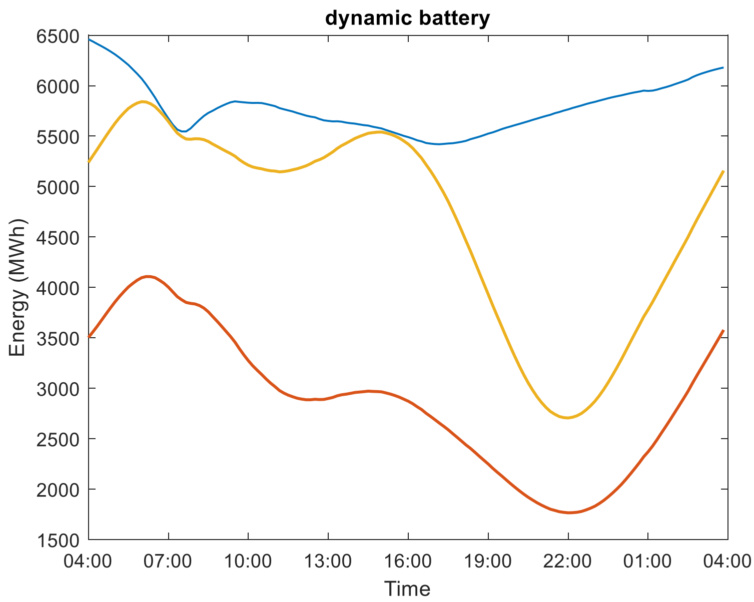


*Figure 5-21: Aggregated battery representation for the final iteration (G2V&V2G-Low)*

### 5.5.2 Medium penetration scenario

In this case, the electricity price is greatly affected by the PEV load, which in turn results in an increased effect on the PEV load. As the price gradually falls during the peak of 19:00, the total load is rising because it is no longer so profitable to inject more energy. It can be seen that the highest peak (19:00) has in fact become equal to the smaller one (9:00) due to the auxiliary service of V2G, while the midday valley has been risen a little.

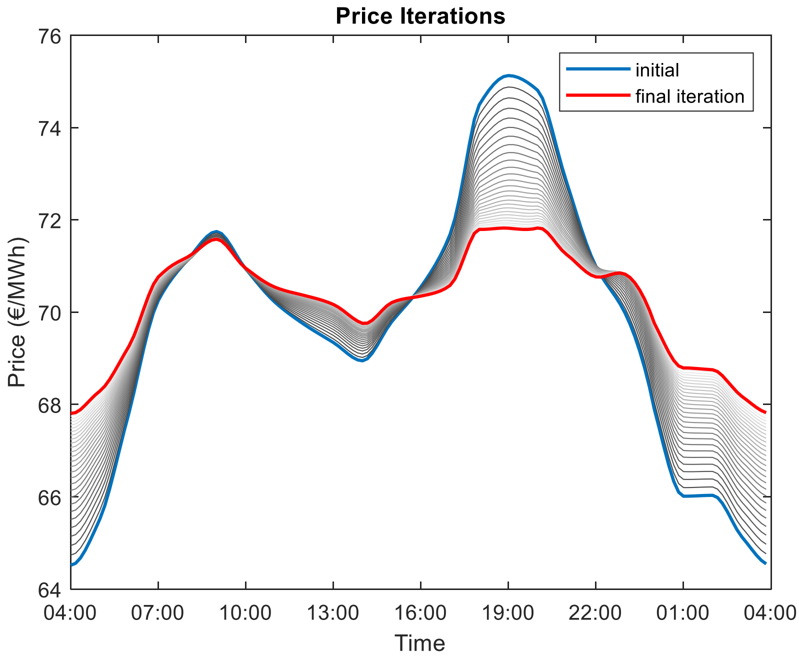


*Figure 5-22:Price alterations during the iterations (G2V&V2G-Medium)*

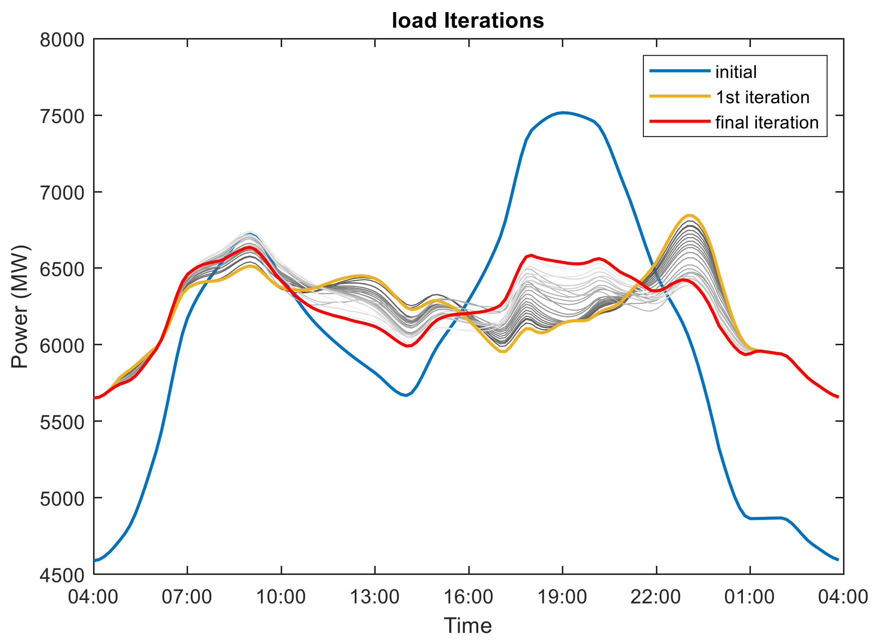


*Figure 5-23: Load alterations during the iterations (G2V&V2G-Medium)*

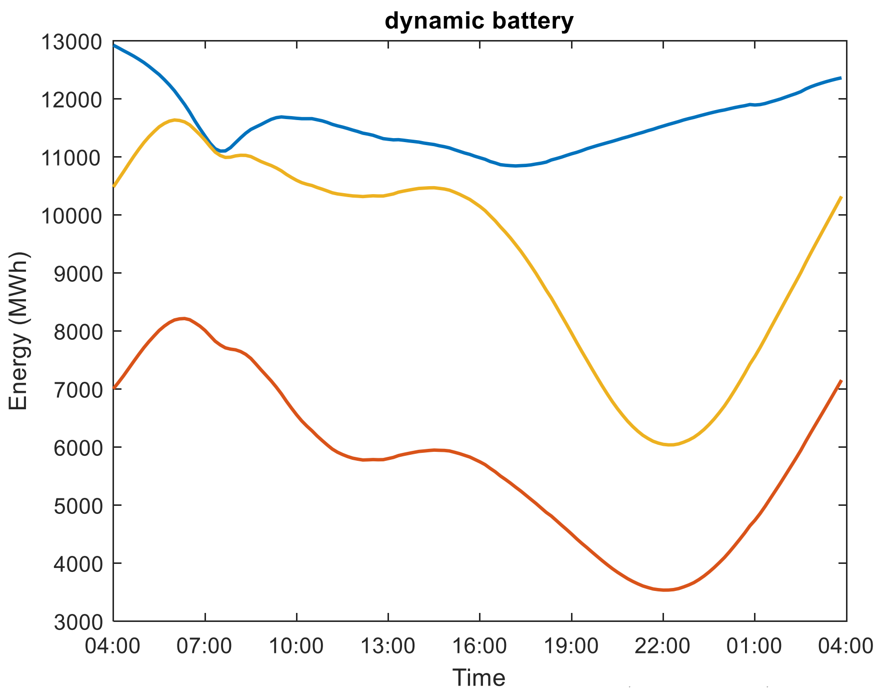


*Figure 5-24: Aggregated battery representation for the final iteration (G2V&V2G-Medium)*

### 5.5.3 High penetration scenario

In this aggressive scenario for PEV penetration rate, the PEV load is of the comparable magnitude as the initial load, which causes major changes to electricity price and an unsteady convergence of the load. This results in a quite flat price and load where the difference between valleys and peaks is around 350 MW. This proves that the electricity distribution grid can support the penetration of a large fleet provided that the entire fleet can offer auxiliary services to the system, which is an ideal condition.

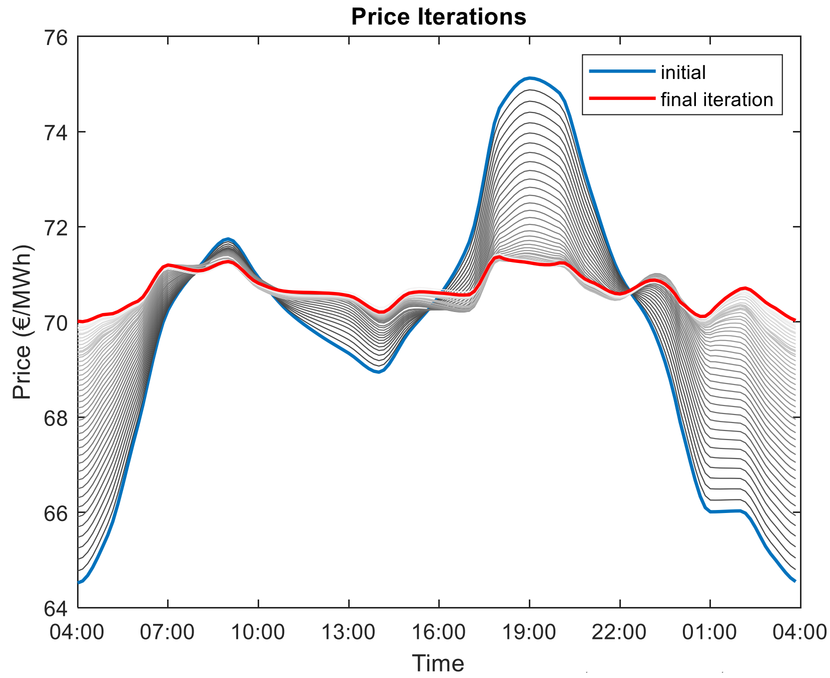


*Figure 5-25: Price alterations during the iterations (G2V&V2G-High)*

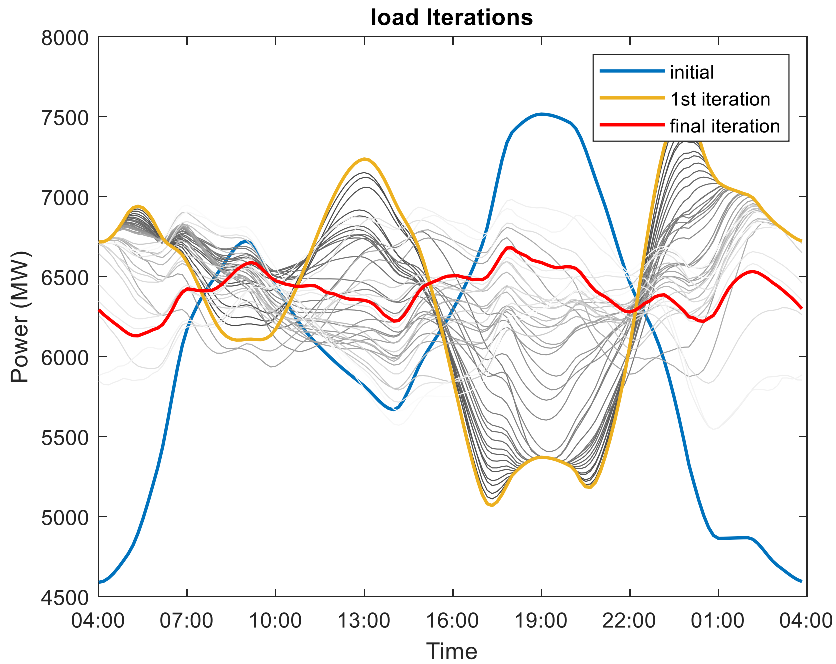


*Figure 5-26: Load alterations during the iterations (G2V&V2G-High)*

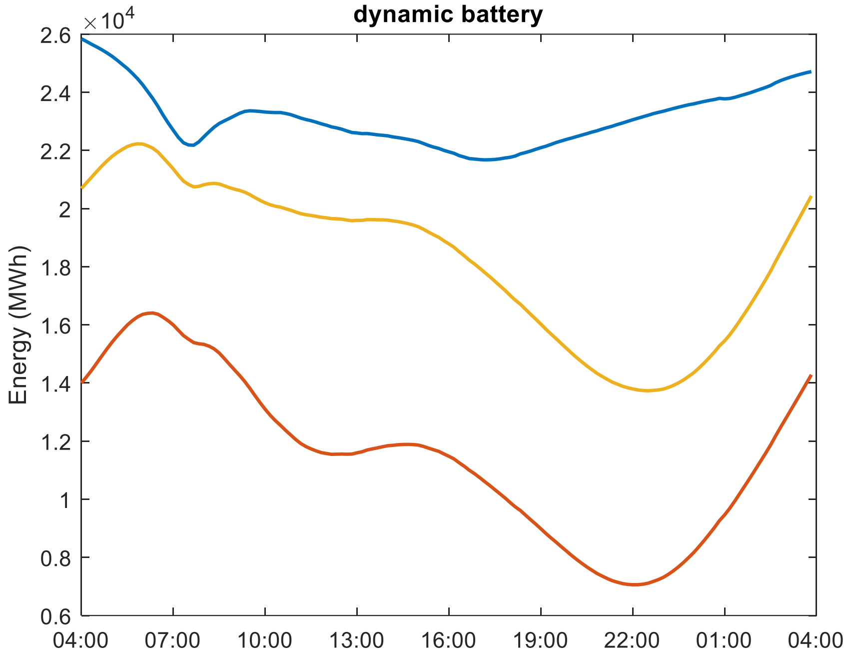


*Figure 5-27: Aggregated battery representation for the final iteration (G2V&V2G-High)*

## 5.6 Mixed charging strategy

The scenarios in the previous sections showcase the algorithms that were developed in this study but assume that all the drivers will follow the same charging strategy. In this paragraph, the PEV load results of a more realistic mixed charging strategy are presented for every penetration scenario. It is assumed that the shares of the charging strategies are the following:

- 40% simple smart charging
- 40% dumb charging (20% nominal and 20% smooth)
- 20% smart charging with V2G

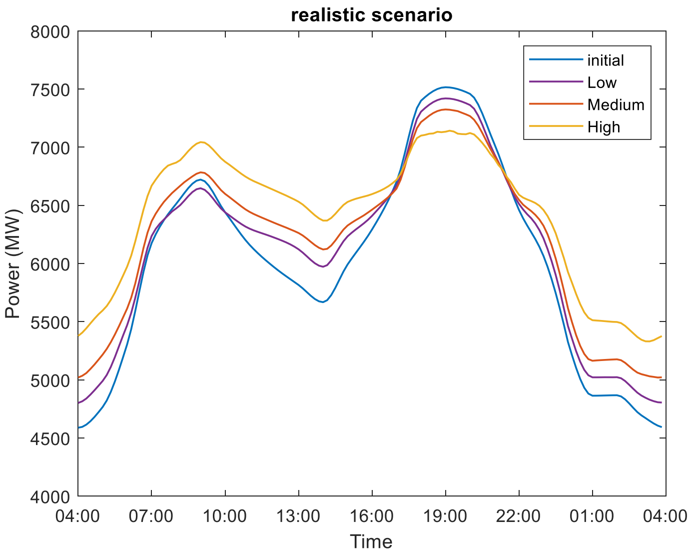


*Figure 5-28: Total system load by applying the mixed strategy*

It can be observed from Figure 5-29 and Figure 5-28 that, even with only 20% of PEVs actually applying V2G, the new system load does not have higher peaks during the 19:00 peak and in the aggressive penetration scenario the two peaks are equal at 7000 MW. The load valleys are adequately filled, despite the quite large percentage of dumb charging, although the difference from the ideal pure smart charging is evident

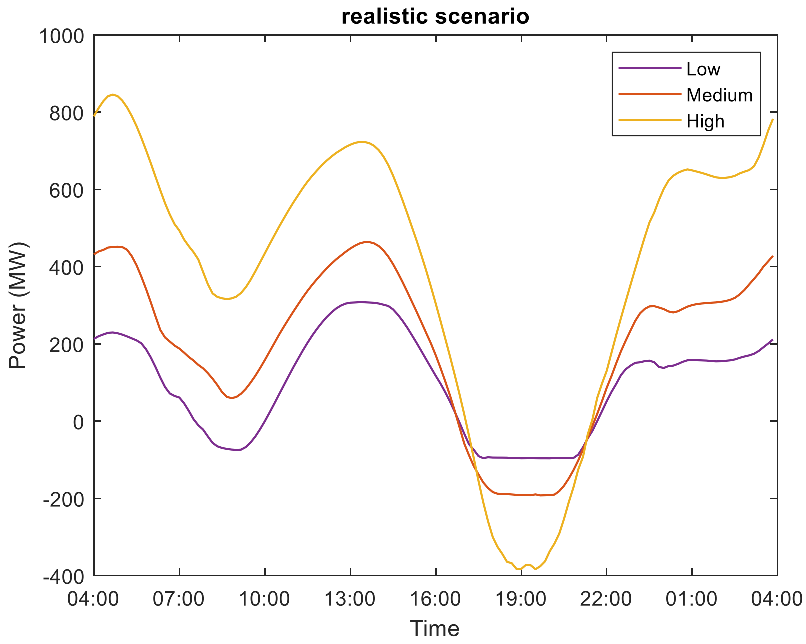


*Figure 5-29: Load results from the mixed strategy*

# CHAPTER 6

## Conclusion

### 6.1 Achieved aims and objectives

This study aimed at estimating the possible future impact of plug-in electric vehicle charging load, that will be introduced to a large electric power system by 2030. Three different penetration scenarios were assumed according to the study "Merge" to assess the effects of varied number of PEVs.
Traffic patterns from an extensive survey were analyzed and some distributions like travel distances were truncated to fit Greek standards.
By applying different charging strategies, some interesting inference has been drawn. The timing of the charging is a vital factor in the smooth operation of the electric grid. If vehicles are left uncontrolled, the introduced load can occur during peak load periods, which can have various consequences both to the quality of service and to the cost of electricity. So regulations must be encouraged in order to prevent increased load peaks. By enabling the vehicles to inject energy to the grid, PEVs can actually become a significant auxiliary service instead of a stability threat.
Finally, the iteration based method that has been used to model the impact of the new load from PEVs to the electricity price, provides more realistic results, as not only the PEVs respond to the system price, but also the price is widely affected by new load.
With the observations of the results, it is concluded that the infrastructure of Greece can support the penetration of 1,000,000 EVs but only if G2V and smart charging is widely practiced.

### 6.2 Future work

The proposed method for PEV load forecasting can already be applied to a large fleet but can become more accurate by using real life mobility of EVs. This can happen when their use is more widespread and the relevant data become publicly accessible.
Furthermore, the model can be enhanced by adding the ability of frequency support to the grid by the PEVs, so they can suppress its fluctuations.
Lastly, the price model and fuzzy target system used in this study can be enhanced by taking into account more parameters to ensure higher accuracy.

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