Short-term Load Forecasting of Plugged-In Electric Vehicles

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Last but not least, I would like to thank Korina, my brother Marios and my parents for their support and constant encouragement.

Abstract

Prediction of electrical grid load due to electric vehicle charging

New reports predict that the penetration levels of electric vehicles will surge across Europe the following years, as zero emissions vehicles become the mainstream item for consumers and vehicle manufacturers will introduce many new full electric models. In certain parts of Europe, like Norway, more than 50% of new car sales are electric. This will result in a heavy electrical power demand that should be predicted.

Many prediction studies were made, mainly focused on the energy consumed by the vehicle and the time it stayed parked in certain locations. The intention is to examine the effect of the electricity price on these prediction models, hoping that it will ease the grid of huge charging loads during peak hours. This is accomplished by using an artificial intelligence algorithm in order to calculate the probability of charging a vehicle and then an optimization algorithm that allots the charging power in time slots based on the electricity price of each slot.

Results are positive. Less cars are connected to charging stations; the charging of these cars was deemed unnecessary by the algorithm because they had enough energy to return to their home charging stations. The cars that eventually connected required less energy, because again the algorithm charged them with the necessary power only, which led to a load reduction. The optimization algorithm shifted the load towards low-demand time slots, where electricity is cheaper. Furthermore, when grid was on its peak hours, fully charged cars supported it by connecting on it and providing energy (Vehicle-to-Grid (V2G)).

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Introduction

1.1 | Necessity of Electric Vehicles

Global Warming is the most serious threat the humanity faces (Xin-hua, 2008). It is safe to assume that CO_2 emissions play a key role in this new danger, and therefore humanity must reduce its consumption (Chen Ya-lin, 2009).

A part of these emissions is from the exhausts of vehicles and the best way to reduce them is by driving less[1] and by using public transport more. A not so aggressive method is the Hybrid Electric Vehicle (HEV) and more importantly, the Plug-in Electric Vehicle (PEV). It has zero CO_2 emissions, it is more efficient than Internal Combustion Engine (ICE) vehicle and has instant acceleration (Mehrdad Ehsani, 2009). The fuels used for PEV more commonly are electrical energy from batteries and hydrogen from fuel cells (Muhammad Sifatul Alam Chowdhury, 2016) and can be produced using "green" methods, such as wind turbines and solar panels. It can become the technology that can drive humanity to the future.

1.2 | Charging Methods

1.2.1 | Charging Stations

In order to satisfy the charging needs of PEV, charging stations were constructed. They are convenient like gasoline stations and can be integrated easily on existing gasoline stations or highway rest areas (Taoyong Li, 2018). As already mentioned, charging stations can be fueled by renewable energy resources like wind turbines or photo-

[1] For more information see: `http://www.deq.idaho.gov/pollution-prevention/p2-for-local-govts/how-to-implement-p2/`

voltaic panels and store the energy into batteries. There are three levels of charging. Level-1 charging at $6KW$ $(120V, 15-20A)$, also known as AC-Charging, Level-2 charging at $6KW$ $(240V, 32A)$, also known as AC-Charging and Level-3 charging at $30KW$ $(480V, upto 300A)$, known as DC-Charging or supercharging.

For this thesis the level-2 AC charging is mostly used and when the algorithm thinks it is necessary, the Level-3 DC-Charging is used.

1.2.2 | Wireless Charging

A new trend in technology is the Wireless power transfer and and application of this technology is in vehicle charging. This method enables cars to charge while stationary (like in traffic lights) or while in motion (inside tunnels). The two most widely used methods of wireless charging for vehicles are inductive power transfer (Kesler, 2018) and capacitive power transfer (Chunhua Liu, 2017). A nice advantage of this technology is that it can lower the battery capacity of vehicles (Lalit Patnaik, 2018; Seungmin Jeong, 2019). Still, this is a quite new technology and not the preferred one for vehicle charging yet.

1.3 | Motivation

The forecasting of the vehicular charging load on a system can help the energy providers plan the energy production so it meets the needs for charging, and predict as well the future growth on this specific demand. Failure to predict this load can cause severe problems on the grid and the energy production facilities, as the power generation engines will struggle to answer to this huge load (C.H. Dharmakeerthi and Saha, 2011; Daijiafan Mao, 2017; Xuesong Zhou and Gao, 2017). Therefore, it is vital to analyze the effect of Plug-in Electric Vehicle (PEV) charging when planning the distribution network and the energy generation facilities that support it.

1.4 | Aims and Objectives

- Validate the hypothesis that the electricity price will greatly affect the driver's decision to charge the car
- Decrease the grid load even more by not providing unnecessary charging to the vehicles
- Support the grid with vehicle battery energy in case the grid experiences heavy loads
- Help the driver reduce the charging costs of the vehicle

1.5 | Document Structure

In Chapters 2 and 3, the various tools that were important for writing the thesis are described and there is a short analysis of the algorithm that this work is based one. In Chapter 3 a detailed description of all the steps the proposed algorithm contains and the data that used as input is presented. In Chapter 5 the results of the thesis' algorithm are presented and in Chapter 6 the conclusions that are derives from the previous Chapter.

2

Background

The coding for the needs of this thesis was done exclusively in **Matlab** and every function or algorithm needed was either constructed by the author or taken from Matlab libraries.

2.1 | Dynamics of Vehicles

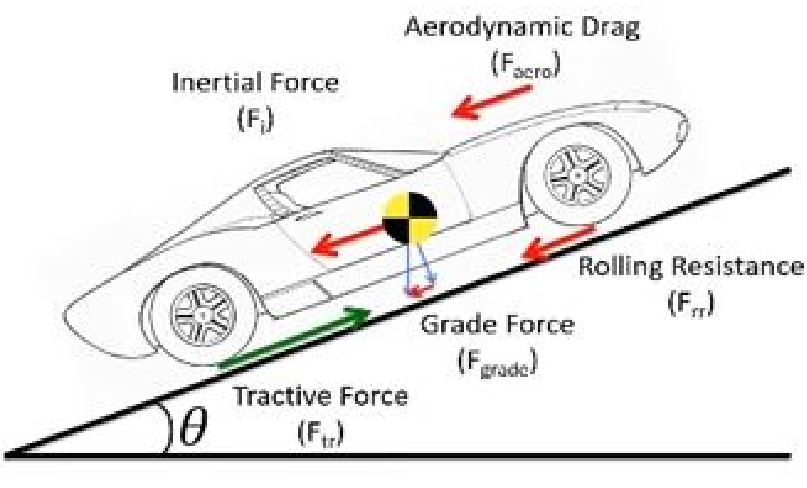


Figure 2.1: Forces that influence vehicle motion.

Vehicle Dynamics is a part of automotive engineering, based on classical mechanics. It analyzes the dynamic behaviour of the vehicle, on a given solid surface. Many aspects of the vehicle can affect its dynamics, like the drivetrain, suspension, tires and aerodynamics.

For this thesis, a simple two-axle vehicle model is used, as shown in figure 2.1. This model analyzes all forces acting on vehicle (*Tractive Force, Aerodynamic Drag, Rolling Resistance and Grading Resistance*).

The deriving equations of motion are further analyzed in Chapter 4.1.2.

2.2 | Fuzzy Engines

A process to mimic the complex decision making and the logic of human thought needed in order to quantify the probability of charging the vehicle. Fuzzy Logic is the perfect tool for this study; it is a flexible and easy to implement machine learning technique and is highly suitable for uncertain or approximate reasoning.

A fuzzy interference machine will look at all the data (inputs), it will fuzzify them (convert crisp numbers into fuzzy sets) and then it will compare them with a set of rules and decide which is the best action to follow. At last, it will de-fuzzify the output into a crisp value, in this study the probability of charging the vehicle. An example of such system is shown in figure 2.2, which the exact same fuzzy machine created for this study.

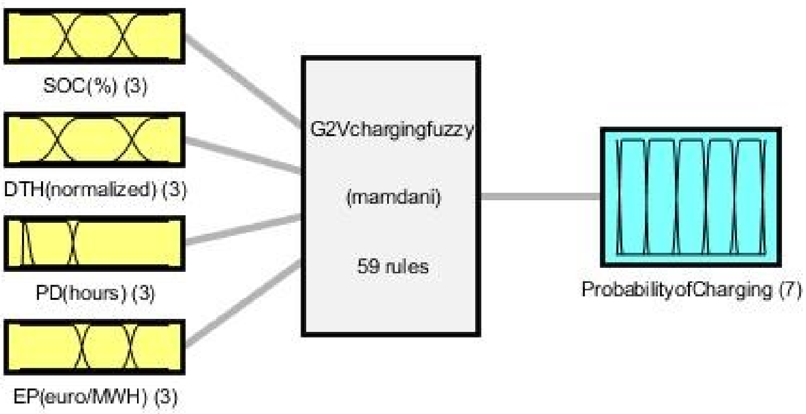


Figure 2.2: Flowchart of a fuzzy engine.

Fuzzy logic is widely used for commercial and practical purposes, because it helps you to deal with the uncertainty in engineering. Even automotive companies use it in their products, like Nissan which implemented it for Anti-lock brakes.

2.3 | Optimization Algorithms

Optimization algorithms are processes that are executed iteratively and compare various solutions until an optimum solution is found. These solutions are subject to various limitations or criteria. There are many types of minimization algorithms, like linear and non-linear or large-scale and medium-scale.

For this study, I need a *minimization*, which has the form:

$$\text{Given } f : A \to \Re \text{ search } x_0 \in A \text{ such that } f(x_0) \leq f(x) \text{ for all } x \in A$$

A detailed analysis of the minimization algorithm used follows in Chapter 4.3.

3

Related Work

There is a lot of work done on short-term load forecasting because it is a very important process during the planning and operation of electrical utilities.

3.1 | Load forecasting with historical data

Most of the methods used for this type of load forecasting are statistical techniques, including *Multiple Linear Regression, Stochastic Time Series, General Exponential Smoothing, State Space Method and Knowledge-Based Approach*, as described in (I. Moghram, 1989).

An example is the method used in (Kejun Qian, 2011), where the authors used *time-series* data of electric vehicle charging loads. They modeled a *stochastic nature* for PEV by assuming that the time the vehicle starts charging is a variable, based on the electricity tariff. They also created a *probability distribution* for the distance travelled by the vehicle till the stop by using *historical data (traffic patterns)*, in order to calculate the initial State of Charge (SOC) of the vehicle. The battery type of the vehicle would determine the load characteristics in the end. They calculate the final load by multiplying the traffic characteristics with the charging characteristics of the battery type for each car, for each hour.

Another example is the study (Sungwoo Bae, 2012). For this paper, the authors are interested in a specific charging location. They use a *fluid dynamic model* to predict the arrival of vehicles at the specific location and then, with the help of *queuing theory*, the charging load is calculated. Again, all the data are statistical (for example, the vehicles arrive at the entrance of the charging station at a rate of 3 vehicles per minute).

3.2 | Load forecasting with real-world driving data

The authors of these studies preferred to use *real-world driving data* for their algorithms, because it provides a more realistic scenario of driving habits; the driver will not change the routes he prefers to follow just because he changed a vehicle.

A first method is described at (Soheil Shahidinejad, 2012). The authors study the profile of the charging load that a power system will receive due to charging the batteries of electric and plug-in hybrid electric vehicles. For their study, they used *real world data recorded for the duration of a year* and include information about the location, speed and other parameters of a big fleet of conventional vehicles. They proposed the use of a *fuzzy Inference System* that uses the State of Charge (SOC) of the battery and the estimated parking duration of the vehicle, which are the two main influential factors for the charging decision making process according to them. A backward vehicular simulation is used to calculate the SOC of the vehicles. After the probability of charging is calculated through the fuzzy inference system for each hour, they multiply the number of electric cars with the probability of charging for this specific hour and multiply again with 1.6KW, which is the rate of Level-1 (AC) charging. By doing this for every hour of the day, they acquire the final result.

This inspired the authors of (Nima Ghiasnezhad Omran, 2014) to progress the algorithm one step more and add the input Distance to Home (DTH) in the fuzzy inference system. They base that on the fact that drivers will prefer to charge their vehicles at home due to cheaper electricity and longer down-times for the vehicles at home for example. This makes their algorithm *location based*. Again, a mathematical model is used to process *real world driving cycles* and a fuzzy engine calculates the probability of charging. They focus their study on two shopping malls, and use the same technique as in Chapter 3.1 to calculate the charging load of these locations during the period that the malls are open (08:00 to 23:00 and 09:00 to 24:00).

4

My Approach

Based on the studies of the Chapter 3, I created and propose my own algorithm for forecasting the Charging Load of Plug-In Electric Vehicle.

Drivers will prefer to charge their Plug-in Electric Vehicle (PEV) at home, due to various reasons like cheaper electricity price and long parking duration during night, for example. Despite that, some charging will happen to off-home locations, like the drivers' workplace or at a shopping center. Drivers will decide to charge their vehicles at a location based on information provided by car (like the battery's State of Charge) and their previous experiences and instinct. The intention of this thesis is to try to predict the Grid Load due to PEV charging at various parking locations.

To imitate the drivers' reasoning behind charging their vehicles at an off-home location, a **fuzzy interference engine** is used. For the location-based vehicular load prediction system of (Nima Ghiasnezhad Omran, 2014), the vehicle's **State of Charge (SOC)**, **Parking Duration (PD)** and **Distance to Home (DTH)** were used as inputs to the fuzzy engine. Unlike this, the **Electricity Price (EP)** is implemented as well as an input in the fuzzy engine of the method used in this thesis. The price that the drivers will pay after they charge their vehicles will have a huge contribution on whether or not they will plug in their vehicles to the chargers. Two fuzzy interference systems are created, one simple *Grid-to-Vehicle (G2V)* system and one *Vehicle-to-Grid (V2G)* system in order to take into account the ability of the vehicles to provide energy back to the grid if needed, or when the electricity price is high for example, so drivers can earn some money. An **optimization** is also used to minimize the cost of the energy received or given to the grid during the parking event.

The flowcharts in Figures 4.1 and 4.2 showcase the algorithm I created for the *Short-Term Load Forecasting of Plug-in Electric Vehicles.* Real-world drive-cycles and vehicle specifications were used to compute the inputs of the fuzzy decision making unit and other statistical information for each parking event. The result is the average **Probability of Charging (POC)** for 24 hours at a specific location for a vehicle with given characteristics. This, combined with local parking characteristics and the optimization in price, results in the wanted local charging demand. The algorithm is further analyzed in the following sections.

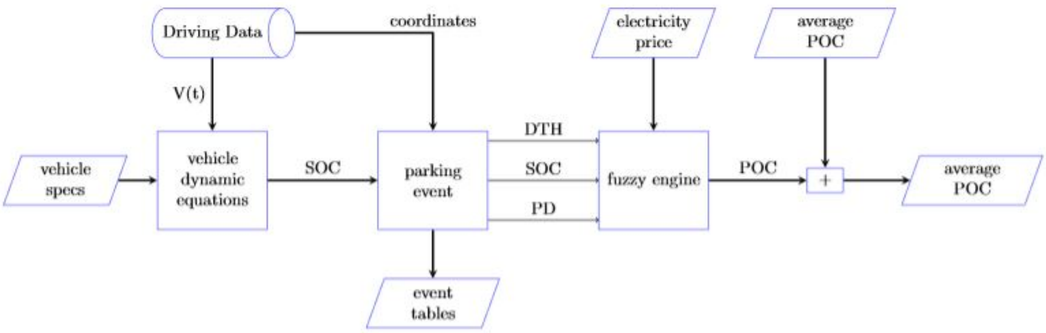


Figure 4.1: First part of the algorithm.

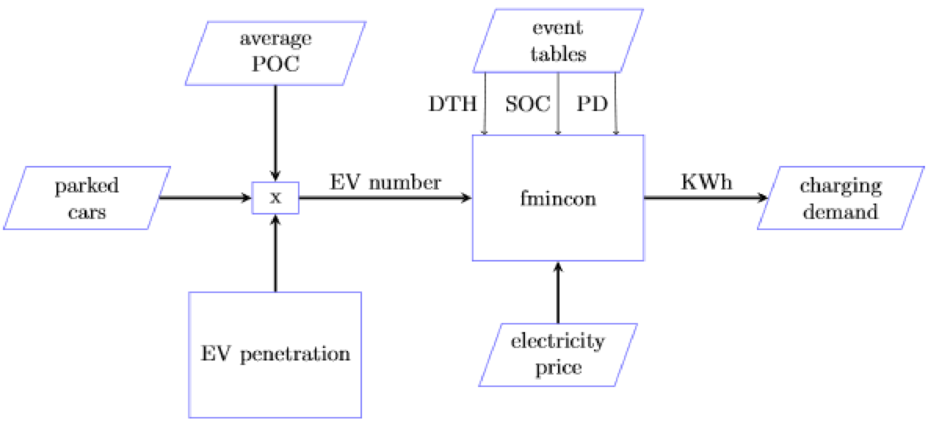


Figure 4.2: Second part of the algorithm.

4.1 | Data & Data Processing

4.1.1 | Input Data

For the needs of this study, real-world driving data from the city of Winnipeg[1] (Ashtari A., 2010; Shahidinejad, 2010) were used. This set includes data from 76 different drivers with diverse demographic characteristics (age, gender, driving habits etc.). The **time and date of each event, coordinates of the car, car speed as well as notifications for events (home/work/shop parking) were recorded** for different days around the year for each driver. An example with some rows of one of the tables is shown in table 4.1

Table 4.1: Driver data example

Trip	Date	Time	12h	Latitude	Longitude	Speed Limit	Speed	Place	Duration
1	14/9/2019	8:45:07	AM	0.0001	0.0013	80	49.28	Travel	-
.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.
1	14/9/2019	10:45:07	AM	0.0071	0.0068	60	0	Shop	79
1	14/9/2019	12:04:08	AM	0.0071	0.0068	60	0.37	Travel	-
.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.
5	18/9/2019	8:45:07	PM	0.0	0.0	50	0	Home	592

In order to validate the study more, two more variations of the data were created. For the first variation, it was considered that some of the drivers may forget to plug-in their vehicles on the chargers the moment they arrive home, and as such, leave their homes without full batteries (SOC<85%). All other data variables remained the same.

For the second instance, random alterations to the speed of the vehicle (± 20%) were made, to take into consideration some more quick or more slow drivers. Again all other data from the sets remained the same. As a result, the algorithm was simulated for **228 different driver data sets.**

The data were accessed row by row by the algorithm. The *Speed* of the vehicle was the input to a set of equations described in Section 4.1.2, and the *Place* was checked in each iteration in order to see if there is a parking event. Each event contributes to the final 24-hour POC regardless of the driver or the date; only the time of the event is important.

[1]More information: `https://mspace.lib.umanitoba.ca/handle/1993/3997`

4.1.2 | Vehicle Dynamic Equations

For the purpose of calculating the SOC of the battery in each trip and based on Newton's second law of motion, the following model of equations was developed (Mehrdad Ehsani, 2009).

$$F_{TR} = m_v * a + F_{ad} + F_{roll} + F_g \tag{4.1}$$

$$F_{ad} = \frac{1}{2} * ad * A_f * C_d(v - v_w) \tag{4.2}$$

$$F_{roll} = 0.001(1 + \frac{v}{100}) * m_v * \cos\theta \tag{4.3}$$

$$F_g = m_v * g * \sin\theta \tag{4.4}$$

where F_{TR}, F_{ad}, F_{roll} and F_g are the Tractive Force, Aerodynamic Drag, Rolling Resistance and Grading Resistance respectively (all in N). A_f is the vehicle frontal area (m^2), ad is the air density ($ad = 1,225\frac{kg}{m^3}$), C_d is the vehicle drag coefficient and v_w is the wind velocity ($\frac{m}{s}$). m_v is the vehicle mass (kg), a is the vehicle acceleration ($\frac{m}{s^2}$) and v is the vehicle speed (m/s). θ is the road grade. θ and v_w are set to 0 for this study.

The instantaneous mechanical power ($Watt$) is given by

$$P = F_{TR} * v \tag{4.5}$$

which is converted to mechanical energy ($Joules$)

$$E_m = \int_{t_0}^{t_{end}} P * dt, P > 0 \tag{4.6}$$

and Regenerative Braking Energy ($Joules$)

$$E_{reg} = \int_{t_0}^{t_{end}} P * dt, P < 0 \tag{4.7}$$

In order to calculate the total required electrical energy from the battery, E_m and E_{reg} are used, as shown below

$$E_e = \frac{Em}{n_T * n_M} - E_{reg} * n_G * n_{reg} + E_{HC} \tag{4.8}$$

where E_e is the total electrical energy from the battery (J) and n_T, n_M, n_G, n_{reg} are the efficiencies of transmission, motor, generator, regenerative braking system respectively. E_{HC} is the amount of energy consumed by the vehicle's air-condition for heating and cooling purposes.

Finally, the State of Charge (SOC) (%) is calculated with the help of a simplified expression (Fazal U. Syed, 2006).

$$SOC = SOC_0 - \frac{100}{3600 * C_b * V_b} * E_e \tag{4.9}$$

where C_b is the battery capacity (Ah), V_b is the nominal terminal voltage of the battery (V) and SOC_0 is the SOC at the beginning of the trip.

4.2 | Fuzzy Engine

In order to create a fuzzy logic system, a linguistic approach must be used as described in (L.A.Zadeh, 1975; Mamdani, 1977). The 4 inputs SOC, DTH, PD and EP are treated as linguistic variables and are fuzzified into fuzzy membership functions. Then all applicable rules from the rule table are executed and the respective output functions are computed. To get the output value of the fuzzy engine, the output functions are defuzzified.

For this study analysis, two fuzzy models were created; one that only the grid can transfer energy to the vehicle (G2V) and another that takes into account the ability to transfer energy from the vehicle's battery to the grid (V2G). Both are Mamdani-type fuzzy models (Mamdani, 1977). A detailed analysis of the fuzzy engines inputs, rule table and output follows.

4.2.1 | Inputs

4 inputs were created, which are the same for both fuzzy engines. The values assigned to each input (for example Medium, High) were based on my instinct and logical assumptions. For example, SOC is medium around 35% and 65%. For the EP, by looking at electricity prices of different days, I assumed that after $75 - 80$ $euro\,/\,MWh$ the price is high and downwards till 40 $euro\,/\,MWh$, the price looks like average.

4.2.1.1 | State of Charge

State of Charge (SOC) is the equivalent of a fuel gauge for the battery pack of a PEV, and the driver is always aware of its value. To protect the health of the battery and prolong the battery's life, the effective range is between 15% and 85%. The linguistic terms used to describe the battery's range are Low, Medium and High and because of the restriction above, a value of 1 is assigned to the areas outside the working range (above 85% or below 85%). The membership functions of SOC are shown in figure 4.3

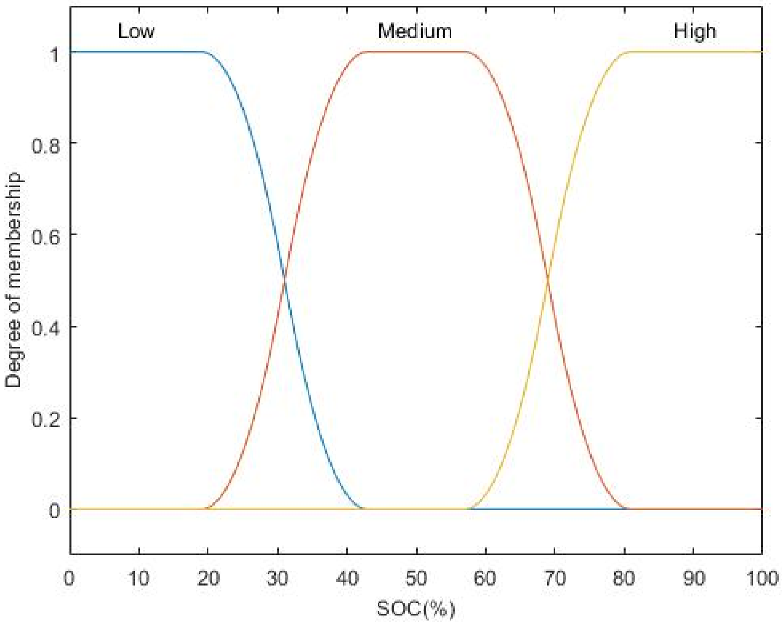


Figure 4.3: Membership function of SOC.

4.2.1.2 | Distance to Home

As already mentioned above, the preferable charging location for the PEV will be each driver's home. And part of the driver's decision to charge or not the PEV is if the remaining SOC is enough to drive the vehicle back at home. This is quantified in the **Distance to Home (DTH)** input of the fuzzy engine, as it isn't difficult for any driver to have an estimation of the distance to home. The DTH variable includes an uncertainty too, because the drivers cannot know the future trips, the traffic and other factors that can affect the actual distance that will be covered till they arrive back at their homes. DTH is subjected to the battery capacity too, since a car with bigger battery capacity can cover bigger distance before the battery is depleted. Thus, DTH will have a normalized form, based on each car's electric range.

DTH is also used as a guide to the minimum energy required from charging; after the car disconnects from the charger, it should have gained at least the power that corresponds to the DTH. The Electricity Price and the option to give power to the grid affect how much more energy will be stored in the PEV battery.

Again, DTH will be described by 3 membership functions labeled Short, Average and Long as in figure 4.4.

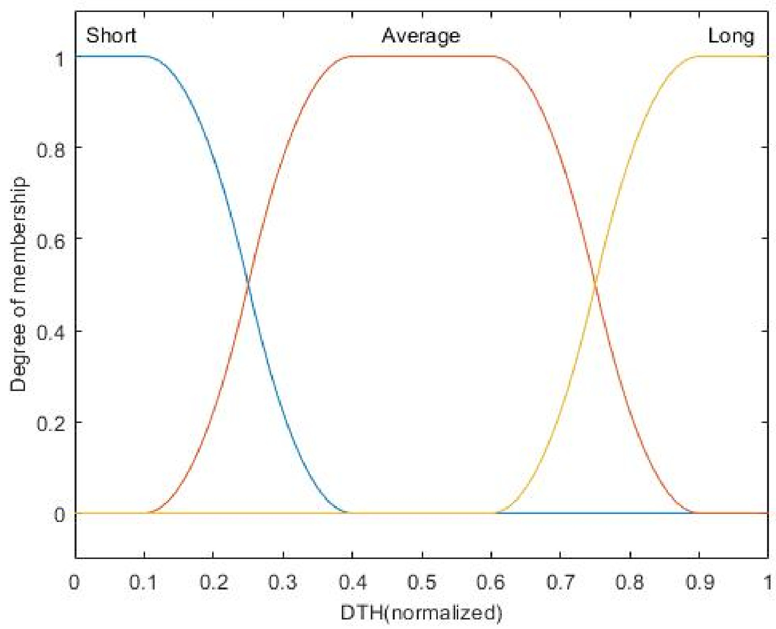


Figure 4.4: Membership function of DTH(normalized).

4.2.1.3 | Parking Duration

Drivers are unable to know exactly the amount of time they will spent at a parking location. Therefore, **Parking Duration (PD)** is an estimation of the time spent there. To describe PD, three linguistic terms will be used, named Short, Average and Long, as shown in figure 4.5. All 3 represent a period of time; for example, Long is any PD above 3,5 hours (again based on my intuition and personal habits). And this is an easier way to represent the PD because drivers know if it will be a short stop or a longer one.

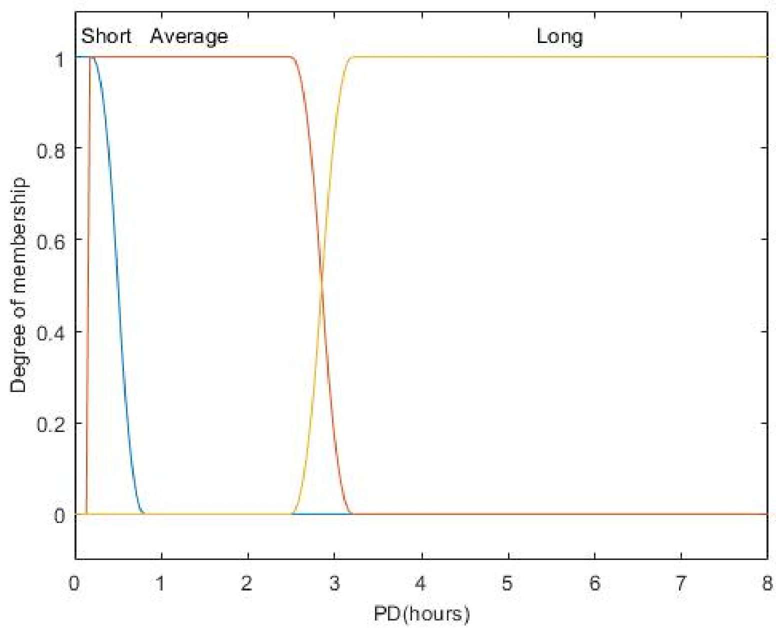


Figure 4.5: Membership function of PD.

4.2.1.4 | Electricity Price

Electricity Price (EP) is a variable drivers will be aware of at the parking location as soon as they arrive at the charging stations. The view of a high or low price can affect the decision quite a lot. For example, a high price will make a driver very reluctant to connect his car to the charging station unless SOC is not enough to reach home and the car must be charged. On the other hand, if SOC is more than enough to reach home and there is an option to give power to the grid, a high electricity price makes it very appealing to the driver to connect the car.

EP depends on the the season, demand, type of fuel used to produce electricity (diesel, coal, gas, renewable resource) and can be fixed or vary with time. This is determined by the electricity provider and can have different time steps. Shopping centres can affect the price too, in order to make it more tempting for drivers to park, charge their cars and eventually, spent more time (and money?) in the shops. For this study, a variable EP with a step of 30 minutes is used.

Three linguistic terms describe EP as Low, Average and High, as shown in figure 4.6. These terms can be easily affected by season or time of the day. For example, a price considered “High” during spring may be considered as “Average” or even “Low” during summer season because of the higher energy demand due to cooling (air condition demand).

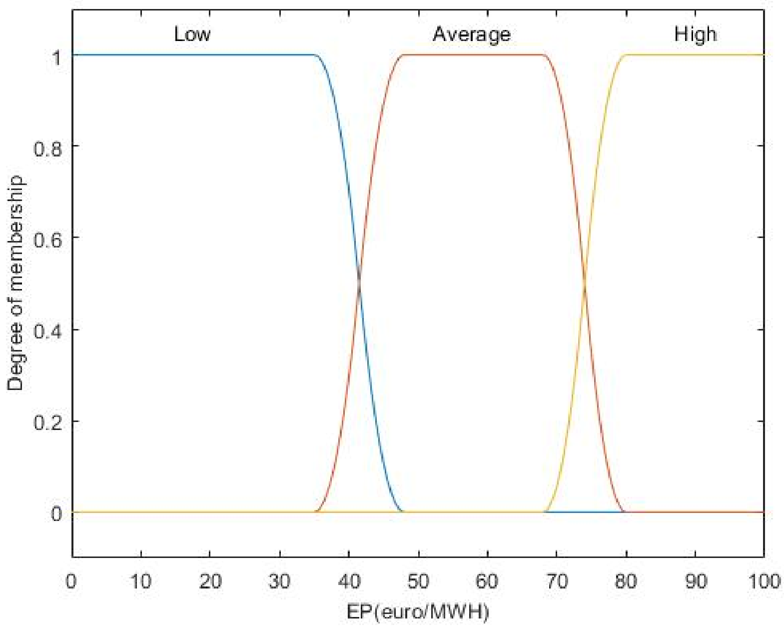


Figure 4.6: Membership function of EP.

4.2.2 | Rule Tables & Defuzzification

For the two different fuzzy engines two different sets of rules were constructed; the first one is about a simple charging algorithm, without the ability to give power to the grid (Grid-to-Vehicle (G2V)). The second fuzzy engine will make it possible for a car to return power to the grid (Vehicle-to-Grid (V2G)). They both have the same inputs and output and only the rules table changes. Changes occur on occasions where electricity price is “Average” or “High” and there is enough energy on the battery to return to home for charging. While when there is no V2G option the drivers wouldn't plug in their vehicles, it is highly possible to connect them and have some profit when they can sell energy to the grid.

For the first fuzzy engine, there were created 59 rules and for the second 73, as shown in tables 4.2 and 4.3. Both of the rule sets use the fuzzy "AND", which is implemented with the "min" method and before the defuzzification, the output is described by using seven linguistic terms, as in figure 4.7. For the defuzzification the algorithm which finds the center-of-weight of the area under the curve is used.

All rules are designed based on what an average driver would decide to do, given the 4 inputs of SOC, DTH, PD, EP. The further from home the driver is and the lower the SOC, the bigger the chance to charge the vehicle. PD and EP will increase or decrease the chance too; the higher the electricity price, the lower the chance. But in extreme cases (if DTH is"Long" and SOC is "Low" for example), the driver wouldn't care about the duration of the parking or the electricity price at that moment. This is taken into consideration too and in such cases, PD and EP have little to no impact on the final result. Of course, for the second scenario with the V2G option, the driver would be more tempted to connect the car when the price is high in many occasions, so he could earn some money. Again, all the rules are based on my personal experiences.

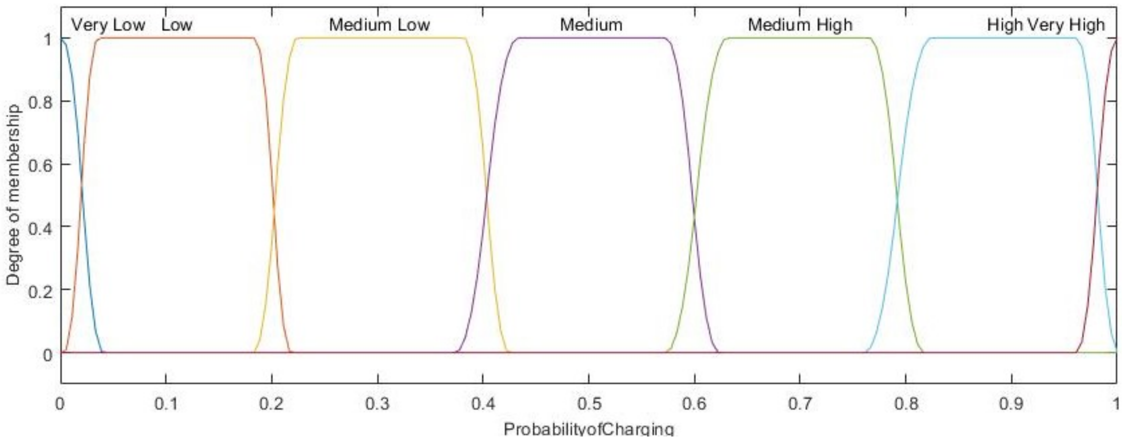


Figure 4.7: Output of fuzzy engine.

Table 4.2: Rules of the Grid-to-Vehicle Fuzzy Engine.

if *SOC* **is**	**AND** *DTH* **is**	**AND** *PD* **is**	**AND** *EP* **is**	**then** *Probability of Charging* **is**
Low	Short	-	High	Very Low
Low	Short	Short	Average	Very Low
Low	Short	Short	Low	Low
Low	Short	Average	Average	Low
Low	Short	Average	Low	Medium Low
Low	Short	Long	Average	Low
Low	Short	Long	Low	Medium Low
Low	Average	Short	High	Very Low
Low	Average	Short	Average	Medium Low
Low	Average	Short	Low	Medium
Low	Average	Average	High	Low
Low	Average	Average	Average	Medium High
Low	Average	Average	Low	High
Low	Average	Long	High	Medium Low
Low	Average	Long	Average	High
Low	Average	Long	Low	Very High
Low	Long	-	High	Medium Low
Low	Long	Short	Average	Medium Low
Low	Long	Short	Low	Medium
Low	Long	Average	Average	Medium High
Low	Long	Average	Low	High
Low	Long	Long	Average	High
Low	Long	Long	Low	Very High
Medium	Short	Short	Average	Very Low
Medium	Short	Short	Low	Very Low
Medium	Short	Average	Average	Low
Medium	Short	Average	Low	Low
Medium	Short	Long	Average	Low
Medium	Short	Long	Low	Medium Low
Medium	Short	-	High	Very Low
Medium	Average	Short	-	Low
Medium	Average	Average	High	Low
Medium	Average	Average	Average	Medium Low
Medium	Average	Average	Low	Medium Low
Medium	Average	Long	High	Low
Medium	Average	Long	Average	Medium
Medium	Average	Long	Low	Medium
Medium	Long	Short	Average	Medium
Medium	Long	Short	Low	Medium
Medium	Long	Average	Average	Medium High
Medium	Long	Average	Low	High
Medium	Long	Long	Average	Very High
Medium	Long	Long	Low	Very High
Medium	Long	-	High	Medium Low
High	Short	-	-	Very Low
High	Average	Short	Average	Very Low
High	Average	Short	Low	Low
High	Average	Average	Average	Low
High	Average	Average	Low	Medium Low
High	Average	Long	Average	Medium Low
High	Average	Long	Low	Medium
High	Average	-	High	Very Low
High	Long	Short	Average	Medium
High	Long	Short	Low	Medium
High	Long	Average	Average	Medium
High	Long	Average	Low	High
High	Long	Long	Average	High
High	Long	Long	Low	Very High
High	Long	-	High	Medium Low

Table 4.3: Rules of the Vehicle-to-Grid Fuzzy Engine.

if *SOC* **is**	**AND** *DTH* **is**	**AND** *PD* **is**	**AND** *EP* **is**	**then** *Probability of Charging* **is**
Low	Short	Short	Low	Very Low
Low	Short	Short	Average	Very Low
Low	Short	Short	High	Low
Low	Short	Average	Low	Low
Low	Short	Average	Average	Low
Low	Short	Average	High	Medium Low
Low	Short	Long	Low	Very Low
Low	Short	Long	Average	Medium Low
Low	Short	Long	High	Medium Low
Low	Average	Short	Low	High
Low	Average	Short	Average	Medium High
Low	Average	Short	High	Medium Low
Low	Average	Average	Low	High
Low	Average	Average	Average	Medium
Low	Average	Average	High	Medium Low
Low	Average	Long	Low	Very High
Low	Average	Long	Average	High
Low	Average	Long	High	Medium High
Low	Long	Short	Low	High
Low	Long	Short	Average	Medium High
Low	Long	Short	High	Medium
Low	Long	Average	Low	Very High
Low	Long	Average	Average	High
Low	Long	Average	High	Medium High
Low	Long	Long	-	Very High
Medium	Short	Short	Average	Low
Medium	Short	Short	High	Medium Low
Medium	Short	Average	Average	Medium Low
Medium	Short	Average	High	Medium
Medium	Short	Long	Average	Medium
Medium	Short	Long	High	High
Medium	Short	-	Low	Very Low
Medium	Average	Short	-	Medium Low
Medium	Average	Average	Low	Medium High
Medium	Average	Average	Average	Medium
Medium	Average	Average	High	Medium High
Medium	Average	Long	Low	High
Medium	Average	Long	Average	Medium High
Medium	Average	Long	High	Very High
Medium	Long	Short	Low	Medium High
Medium	Long	Short	Average	Medium
Medium	Long	Short	High	Medium High
Medium	Long	Average	Low	High
Medium	Long	Average	Average	Medium High
Medium	Long	Average	High	High
Medium	Long	Long	Low	Very High
Medium	Long	Long	Average	High
Medium	Long	Long	High	Very High
High	Short	Short	Average	Medium
High	Short	Short	High	Medium High
High	Short	Average	Average	Medium
High	Short	Average	High	High
High	Short	Long	Average	Medium High
High	Short	Long	High	Very High
High	Short	-	Low	Very Low
High	Average	Short	Low	Medium Low

(continued. . .)

if *SOC* **is**	**AND** *DTH* **is**	**AND** *PD* **is**	**AND** *EP* **is**	**then** *Probability of Charging* **is**
High	Average	Short	Average	Low
High	Average	Short	High	Low
High	Average	Average	Low	Medium Low
High	Average	Average	Average	Low
High	Average	Average	High	Medium Low
High	Average	Long	Low	Medium High
High	Average	Long	Average	High
High	Average	Long	High	Medium High
High	Long	Short	Low	Medium High
High	Long	Short	Average	Medium
High	Long	Short	High	Medium Low
High	Long	Average	Low	Very High
High	Long	Average	Average	High
High	Long	Average	High	Medium
High	Long	Long	Low	Very High
High	Long	Long	Average	High
High	Long	Long	High	Medium High

4.3 | Optimization Algorithm

A very important feature of this study is the **optimization on the price of the energy.** The algorithm responsible for the charging of the batteries will not just supply them with the maximum available energy. Instead, the algorithm will first check the target SOC of the vehicle (which is enough energy to take the vehicle back to home) and, given the amount of time the car will stay parked as well as the electricity price for this period, it will schedule the amount of energy given to the vehicle so that at time slots with cheap electrical energy, the vehicle will be charged the most. If there is an option to give energy back to the grid, the algorithm will check the time slots where the electrical energy is expensive and schedule the vehicle to give energy then and charge up earlier or later, when the price is again low.

The optimization algorithm will also check if the amount of time the vehicle will stay parked is enough for it to charge the batteries till the target SOC with AC charging (6KW AC charging). If it isn't, fast charging will be used (30KW charger DC charging).

The function used for the development of the optimization algorithm is *"fmincon"* from MATLAB libraries. SOC, PD, DTH, EP as well as vehicle battery capacity, parking hour, charging mode (AC or DC charging) and the functions that will be minimized are given as inputs and the output is the charging load of the grid per hour, due to a specific PEV charging event.

The function to be minimized is:

$$fun = \sum_{t=1}^{T} EP(T) * CH(T) * D(T)$$

where T is the *number of different time slots* during which the car will stay parked, $CH(T)$ is the *Electrical Power* that the car will receive from the charging station during the T time slot (if it has a negative value, it means that the vehicle returned energy to the grid), EP is the *Price of the Electricity* for the time slot T and $D(T)$ is the *amount of time the car stays parked* during the time slot T ($1 \leq D(T) \leq 30\ minutes = 0.5\ hours$)

Furthermore, the minimization is subject to some **linear inequality constraints**, of the form:

$$A * x \leq b$$

where A is the amount of time the car stays parked during the time slot T (*hours*), x is the Electrical Power that the car will receive from the charger (*Watt*) and b is Battery Capacity (*Wh*). Three constraints are needed in order to meet the battery specifications and energy targets:

i. First of all, the energy received by the charger should not charge the battery more than the nominal capacity (85%).

$$\Delta t(T) * CH(T) \leq 85\% - SOC\%$$

For this instance, b is:

$$b_1 = BatteryCapacity * \frac{85 - SOC}{100}$$

ii. Secondly, the battery must not fall lower than 15% of its nominal capacity, in order to secure the longetivity of the battery.

$$\Delta t(T) * CH(T) \geq 15\% - SOC\% \Rightarrow -\Delta t(T) * CH(T) \leq -(15\% - SOC\%)$$

and

$$A * x \leq b \Rightarrow -A * x \geq -b$$
$$-b_2 = BatteryCapacity * \frac{SOC - 15}{100}$$

iii. Last, the car should leave the charging station with energy greater or equal to the target energy (which is the energy needed to return at home location). Again, the constraint looks like:

$$\Delta t(T) * CH(T) \geq target\% - SOC\% \Rightarrow$$
$$-\Delta t(T) * CH(T) \leq -(target\% - SOC\%)$$

and

$$A * x \leq b \Rightarrow -A * x \geq -b$$
$$-b_3 = -TargetBatteryEnergy + CurrentBatteryEnergy$$

A is an $M \times N$ matrix, where M is the number of inequalities, and N is the number of variables. For the first two inequalities, 2 lower triangular $N \times N$ matrices will be needed (A1 and A2), because both of the constraints **must be true for every different time slot T**. Then one more line is needed (A3) for the third constraint. N depends on the PD of the vehicle. It is the number of 30 minute intervals (last interval can be $1 \leq t \leq 30$). The value of A are the minutes of each interval divided by an hour, so it can have the values $0 < A \leq 0.5$.

A1 will look like:

$$A1 = \begin{bmatrix} A_1 & 0 & 0 & \cdots & 0 \\ A_1 & A_2 & 0 & \cdots & 0 \\ A_1 & A_2 & A_3 & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ A_1 & A_2 & A_3 & \cdots & A_N \end{bmatrix}$$

A2 will be the same as A1, but with a minus in front of each value:

$$A2 = \begin{bmatrix} -A_1 & 0 & 0 & \cdots & 0 \\ -A_1 & -A_2 & 0 & \cdots & 0 \\ -A_1 & -A_2 & -A_3 & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ -A_1 & -A_2 & -A_3 & \cdots & -A_N \end{bmatrix}$$

Finally, A3 will look like:

$$A3 = \begin{bmatrix} -A_1 & -A_2 & -A_3 & \cdots & -A_N \end{bmatrix}$$

As a result, the final form of matrix A will be:

$$A = \begin{bmatrix} A_1 & 0 & 0 & \cdots & 0 \\ A_1 & A_2 & 0 & \cdots & 0 \\ A_1 & A_2 & A_3 & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ A_1 & A_2 & A_3 & \cdots & A_N \\ -A_1 & 0 & 0 & \cdots & 0 \\ -A_1 & -A_2 & 0 & \cdots & 0 \\ -A_1 & -A_2 & -A_3 & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ -A_1 & -A_2 & -A_3 & \cdots & -A_N \\ -A_1 & -A_2 & -A_3 & \cdots & -A_N \end{bmatrix}$$

From the form of A, we can count the M dimension, which will be:

$$M = N + N + 1$$

b is an M-element vector related to the A matrix. As a result, the $M = N + N + 1$. Below is the full mathematical expression of both A and b.

$$\begin{bmatrix} A_1 & 0 & 0 & \cdots & 0 \\ A_1 & A_2 & 0 & \cdots & 0 \\ A_1 & A_2 & A_3 & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ A_1 & A_2 & A_3 & \cdots & A_N \\ -A_1 & 0 & 0 & \cdots & 0 \\ -A_1 & -A_2 & 0 & \cdots & 0 \\ -A_1 & -A_2 & -A_3 & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ -A_1 & -A_2 & -A_3 & \cdots & -A_N \\ -A_1 & -A_2 & -A_3 & \cdots & -A_N \end{bmatrix} \times \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ \cdots \\ x_N \end{bmatrix} \leq \begin{bmatrix} b_1 \\ b_1 \\ b_1 \\ \cdots \\ b_1 \\ -b_2 \\ -b_2 \\ -b_2 \\ \cdots \\ -b_2 \\ -b_3 \end{bmatrix}$$

For this study I didn't use any **linear equality constraints**, as I considered the use of them unnecessary.

Finally, the minimization algorithm uses **bounds**. The upper bound is set to 6000 and represents the maximum available energy from the charger (*Watt*), and the lower bound is set to 0. If the charger decides to use Fast-Charging, the upper bound is set to 30000 *Watt*, and if there is an option to return power to the grid, the lower bound is set to -6000 *Watt*.

An example of how fmincon will work is presented in the figure below.

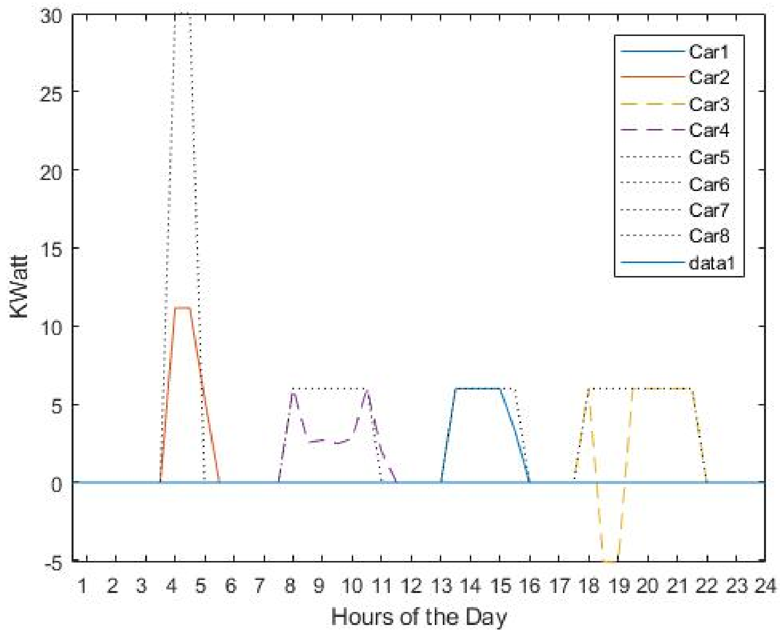


Figure 4.8: Results for 8 cars

Table 4.4: Cars for fmincon example

Car (*kg*)	SOC (m^2)	Target Distance	Parking Duration	Hour	Fast Charg-ing	V2G
car1	30	0.4	129	27	0	0
car2	30	0.4	75	8	1	0
car3	30	0.4	236	36	0	1
car4	50	0.58	187	16	0	1
car5	30	-	129	27	0	-
car6	50	-	187	16	0	-
car7	30	-	75	8	1	-
car8	30	-	236	36	0	-

```
CH =

   1.0e+03 *

    6.0000    6.0000    6.0000    6.0000    3.3335
```

Figure 4.9: car 1

```
CH =

   1.0e+04 *

    1.1155    1.1155    0.5380
```

Figure 4.10: car 2

```
CH =

   1.0e+03 *

    5.9998   -5.0768   -5.1225    5.9999    5.9998    5.9999    5.9999    5.9999
```

Figure 4.11: car 3

```
CH =

   1.0e+03 *

    5.9999    2.5586    2.7031    2.4754    2.8148    6.0000    1.9212
```

Figure 4.12: car 4

The cars 1 and 2 work with G2V algorithm, 3 and 4 with V2G algorithm and 5 to 8 with the base algorithm (they receive max power from the charger till battery is full or till end of parking duration. The charging load of cars 1 to 4 is calculated from Figures 4.9, 4.10, 4.11, 4.12. Each value is about the power given to the car each half-hour the car is parked. For example, for car 3, the car after charge will have

$5.9998 - 5.0768 - 5.1225 + 5.9999 + 5.9998 + 5.9999 + 5.9999 + 5.9999 = 25,79992\ KW$. Because this value is for 30 minute intervals, the energy received will be $12,89995\ KWh$ which divided by the battery capacity will add 25,7% SOC to the battery. The car went in with 30% SOC and the target was 40%. Because the battery must not fall below 15%, the usable SOC was 15%. So, the new SOC for the car will be 40,7% which meets the target constraint.

Car 1 will stop charging when it meets the target SOC while car 5 will continue to give 6kW till the end of the parking. Car 2 will use fast charging with G2V algorithm and car 7 the same with the base algorithm. Cars 3 and 4 both use the V2G algorithm, but fmincon decides not to sell power to the grid for car 4. Cars 8 and 6 have the same inputs as 3 and 4, but use the base algorithm.

This example, not only shows how fmincon will work for different events, but it shows also that a car that connects to the charger at 13:00 will charge the next hours. So, the load for each hour isn't just the summary of the loads of cars charging that hour, but it is the summary of the loads of cars that still charge till that hour.

5

Simulation & Results

In this section all the parameters used for completing the simulations and the results of both new algorithms as well as the results of the algorithm discussed in Section 3 are analyzed.

5.1 | Simulation Parameters

5.1.1 | Vehicle Specifications

The vehicle chosen for this thesis is Tesla Model 3 Standard Range. It is a very common electric vehicle with reasonable price and other manufacturers plan to construct vehicles with quite similar specifications, which makes it a good choice. Table 5.1 contains the PEV specifications and 5.2 the component efficiencies of the car

Table 5.1: Tesla Model 3 Standard Range Specifications.

Curb Mass (kg)	Frontal Area (m^2)	Drag Coefficient	Battery Capacity (KWh)	Electric Range (Km)
1645	2.22	0.23	50	354

Table 5.2: Efficiencies of Drivetrain Components.

Generator	Motor	Transmission	Regenerative Braking
0.8	0.8	0.85	0.7

The charging stations will use level-2 AC charging as default, with $6kW$ maximum power output. The charging algorithm can change it to DC charging and $30kW$ if necessary.

5.1.2 | Other Parameters

The power required for the heating or cooling of the vehicle is considered to be constant and equal to $P_{HC} = 500W$. Heating and cooling are a very small portion of energy during a trip, and it will impact the results only a little, so it is safe to assume it constant.

Finally, for the 24 hour electricity price, the system marginal price in *Figure 5.1* was selected, from ADMIE[1], of a typical day that has peaks and lows at different parts of the day in order to showcase the abilities of the algorithm created.

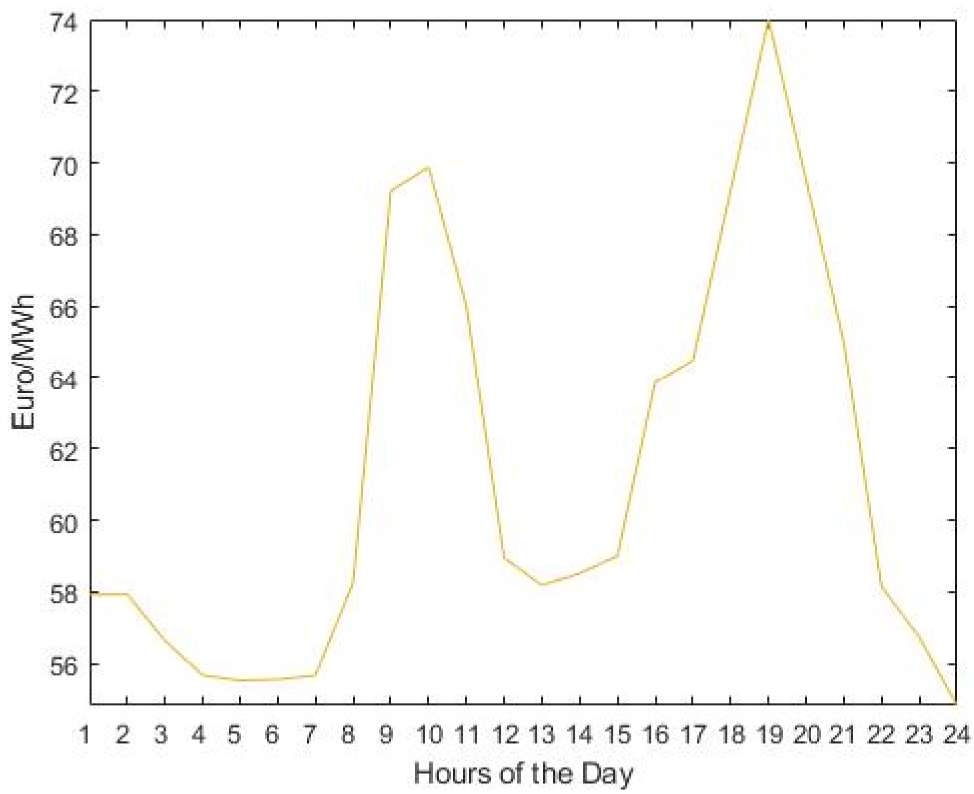


Figure 5.1: The price of the electricity during the day.

[1]More information: http://www.admie.gr/en/operations-data/electricity-power-market-participation/market-data/

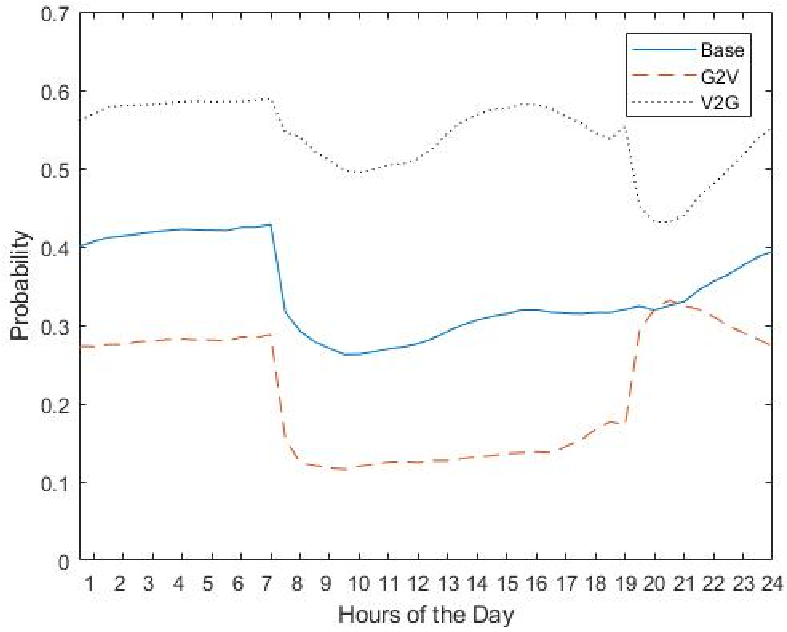
5.2 | Probability of Charging Simulation & Results

The flowchart in Figure 4.1 describes the method followed in order to calculate the Probability of Charging. I used the same method for both the algorithms I created (one with grid-to-vehicle energy transfer and one with bidirectional energy transfer between the vehicle and the grid) as well as for the algorithm I based my thesis on, in order to compare the results later on.

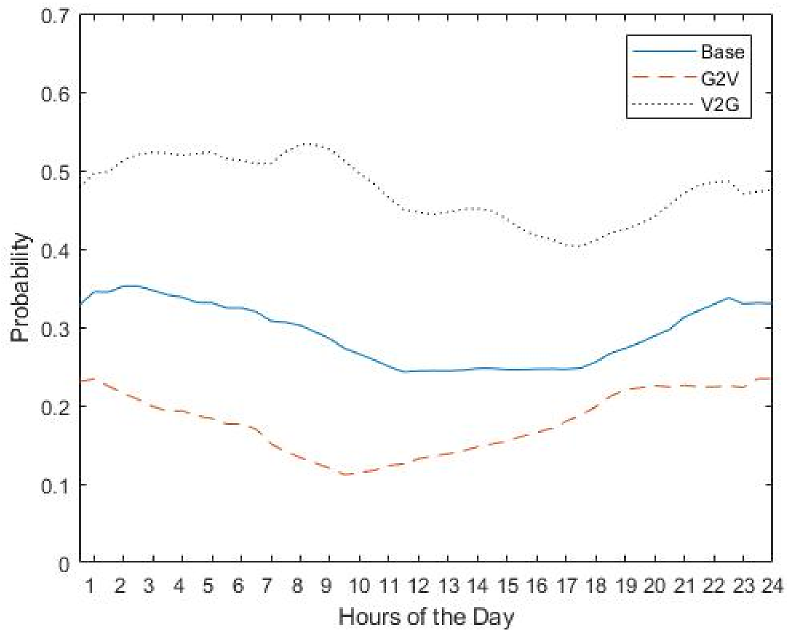
As mentioned in the previous Section, three sets of Data were used. For the first and the third, it was assumed that drivers will *leave their homes with fully charged cars (SOC* $=$ 85%*).* For the second set, they will leave their homes with *vehicles charged between* 65% *and* 85%*.* Homes will be the preferred location for charging the vehicles, and this is made possible with the above assumptions. PEV are *not allowed to fall lower than* 15% *battery* during the trips; the lower the battery is, the bigger the probability of charging becomes. In cases the battery is too low and the DTH (it acts as the target distance of the vehicle) is too long, the car is charged with **probability 1** to avoid the battery being depleted. Charging events can occur at work or at shopping centers, and visits there are recorded during the Data Processing. Of course, charging at home locations is granted, so the probability of charging at home is 1 and not calculated during the next stages.

When there is a *Work or Shop* event, the SOC calculated by the equations (4.1) - (4.9), the DTH calculated by the latitude and longitude variables from the data set, the PD from the Data and the EP by Figure 5.1 are given as inputs to both the fuzzy engines, in order to get two probabilities of charging, one for each algorithm created. The same probability is given to every hour or time slot that the car stays parked. This is repeated for every parking event of the data set. Then, for each different hour of the day, the probabilities of events that happened in each hour contribute to the *average probability* for this specific hour.

In order to validate the thesis more, a scenario of the algorithm the thesis was based on was computed, with the same data used for the two simulations above, but with different fuzzy engine. In Figure 5.2, the results of the base algorithm and of both proposed ones (G2V and V2G) are presented. In both graphs (a) and (b), the probabilities follow similar patterns.



(a) Work Probability of Charging



(b) Shop Probability of Charging

Figure 5.2: Probabilities of Work & Shop Charging

In graph (a), the G2V probability is almost always lower than the base algorithm one, being higher only early in the morning where the electricity price is quite low. The difference becomes smaller as the price drops (around 13:00) and bigger when the price rises (after 7:00 and 18:00). Unlike that, the V2G probability is always higher than the other two. It takes its lower values early in the morning and around 15:00, where electricity price takes its lowest values and is highest around 11:00 and 20:00, where electricity has its higher prices.

In graph (b), again the G2V probability is the lowest with V2G being the highest. Shop probabilities follow more similar patterns than work probabilities.

Early during the day (till 9-10 in the morning), the probability of charging is higher because the cars at work or shop charging stations did not charge their batteries at home overnight. On the contrary, cars that arrive at work or shop charging stations later during the day have their batteries charged, and so the probability of charging drops.

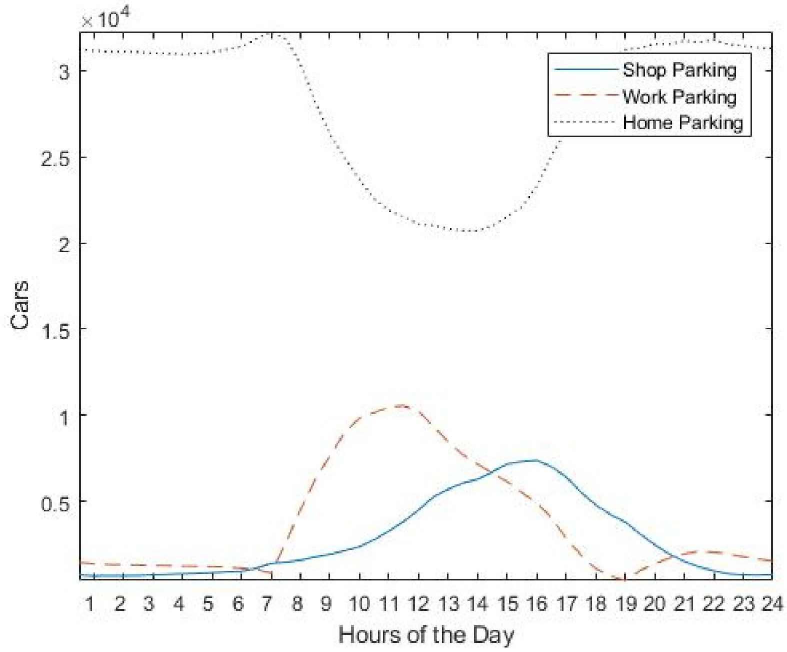


Figure 5.3: Cars participated in parking events

In Figure 5.3, the parked cars for home, work and shop events are presented. They are the same for the 3 different algorithms, because the data used are the same. As already mentioned, the heavy load is expected from cars parked at home, and in the figure they are six times more than the cars parked at work or shop for every hour.

5.3 | Charging Load Simulation & Results

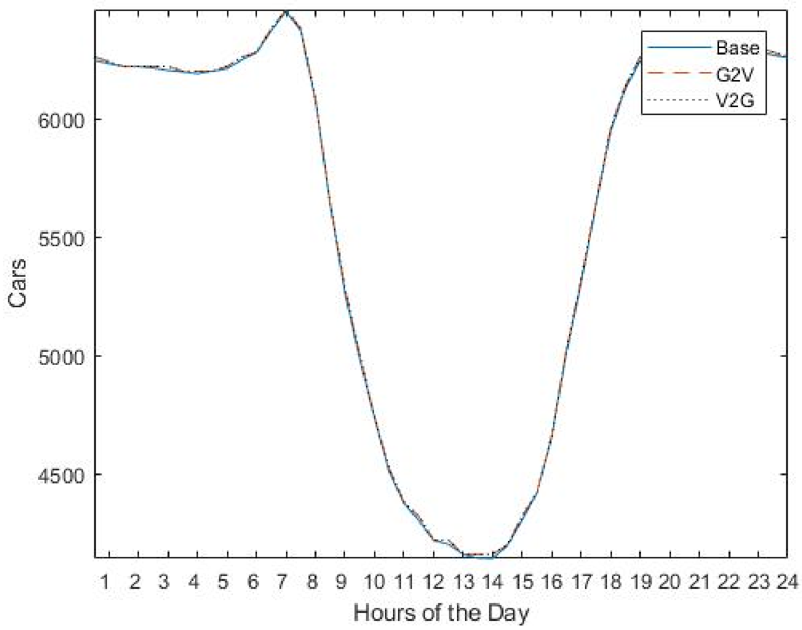
In order to calculate the load on the grid due to electric vehicle charging, the number of parked cars at the locations of interest, the average probability of charging for each location and the local PEV penetration levels where used, as shown before in flowchart 4.2. The result is the number of cars that will charge at the specific location each hour of the day. For each car, DTH, SOC and PD are randomly selected from the event tables that where created during the processing of the real-world driving data and the charging load is computed.

The figures below present a comparison between **Base Algorithm** (the algorithm this thesis is based on), **G2V algorithm** which is the first algorithm proposed in the Sections above and **V2G algorithm**, the second algorithm proposed. Again, the results for the "simple" algorithm were constructed according to the method that was proposed in (Nima Ghiasnezhad Omran, 2014).

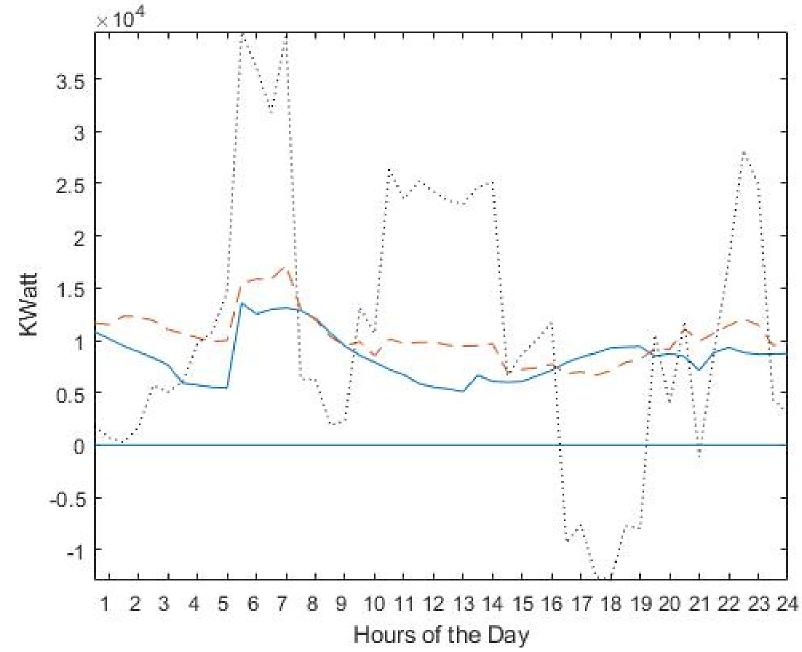
Figure 5.4 represent the results from charging at home locations. The cars that will eventually charge for the three algorithms are the same. This happens because all vehicles will connect at home chargers (probability of charging is 1). The two proposed algorithms follow the fluctuations of price and seem to have a little bigger overall load value than the base algorithm. The optimization function **lowers the load during high electricity price periods** (08:00-12:00 and 17:00-21:00) and peaks around 06:00, 12:00, 23:00 where the electricity price has local minimum values.

Furthermore, the second algorithm proposed supports the grid during peak hours with very good amounts of energy. During 17:00-21:00 the power is peaking at 15MW/h. At 18:00 there are around 6000 cars parked, and they all give to the grid a maximum of 6000$Watt$, so the grid can receive up to a maximum of 36MW.

The charging load at home locations for the two proposed algorithms is higher than the base algorithm. This is justified because the new algorithms charge the vehicles at off-home locations with a little more than enough power to get back home (unlike the base algorithm which gives maximum available energy for the duration of the charging), and they fill up the batteries at home after.



(a) Total cars charging at home

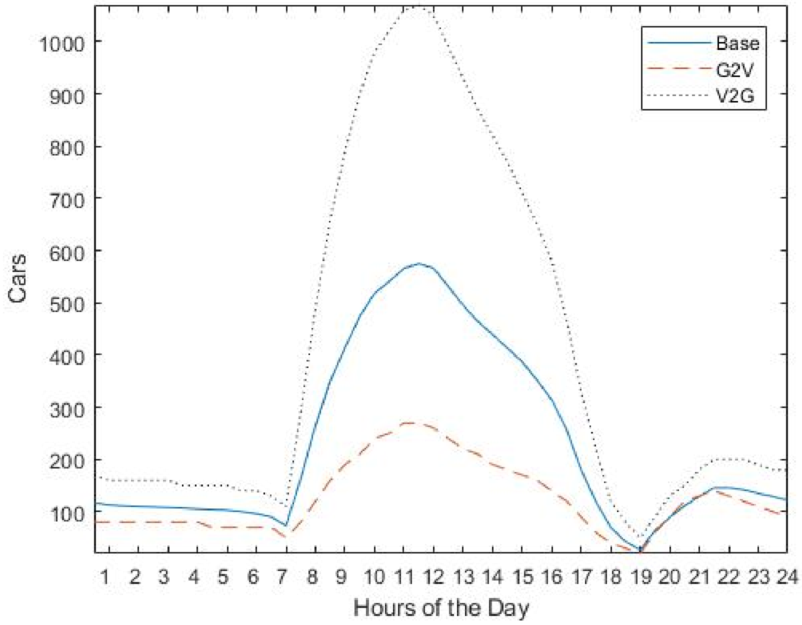


(b) Charging load at home

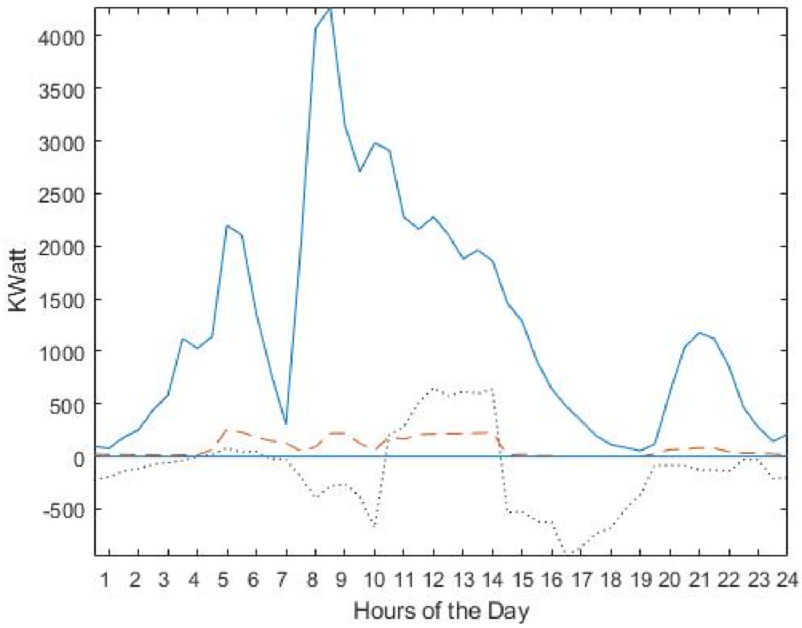
Figure 5.4: Results for charging at home

Similar results appear in Figures 5.5, 5.6. This time, the vehicles that will eventually connect to the charging stations for both work and shop events of the G2V algorithm are between the half and three quarters of the vehicles that would park with the base algorithm. This is justified from the Probability of Charging results. Considering that the optimization algorithm chooses how much energy it will support the vehicles with, the load is the one tenth of the base. On the contrary, the second proposed algorithm decides to connect double the vehicles. But it will not charge the vehicles till the price is low enough. The V2G algorithm will give energy from the parked vehicles to the grid when the PEV have high SOC or the electricity price is high.

For example, at 18:00 at shop, there are around 400 cars connected and the grid receives $2MW$. So, each car would give about $5KW$, or around 10% SOC. Between 13:00 and 15:00, the V2G algorithm will need about 4 times the load of the G2V algorithm, in order to recharge vehicles that already gave energy back to the grid or they are planned to give when the electricity price value rises again. The base algorithm will give the maximum power available to every car, unless they are full. At 13:00 with 500 vehicles that charge, the maximum load would be $3MW$, so the value of $1MW$ is correct.

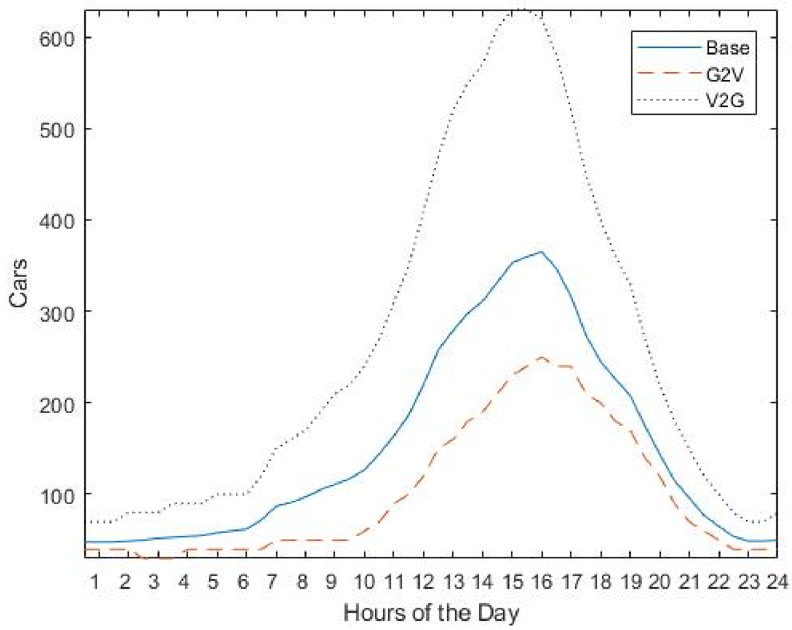


(a) Total cars charging at work

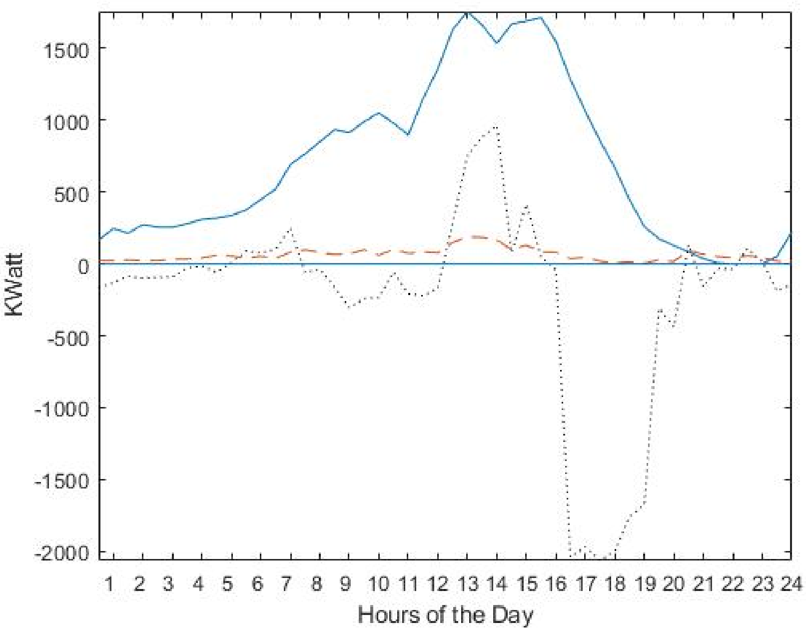


(b) Charging load at work

Figure 5.5: Results for charging at work



(a) Total cars charging at shop



(b) Charging load at shop

Figure 5.6: Results for charging at shop

The last of the result figures represents the total load due to PEV charging. The load from charging the vehicles at home is the dominant, as expected. But the proposed algorithms of this thesis **postpone heavy charging loads** for periods where the grid load is low, and as a result the electricity price too.

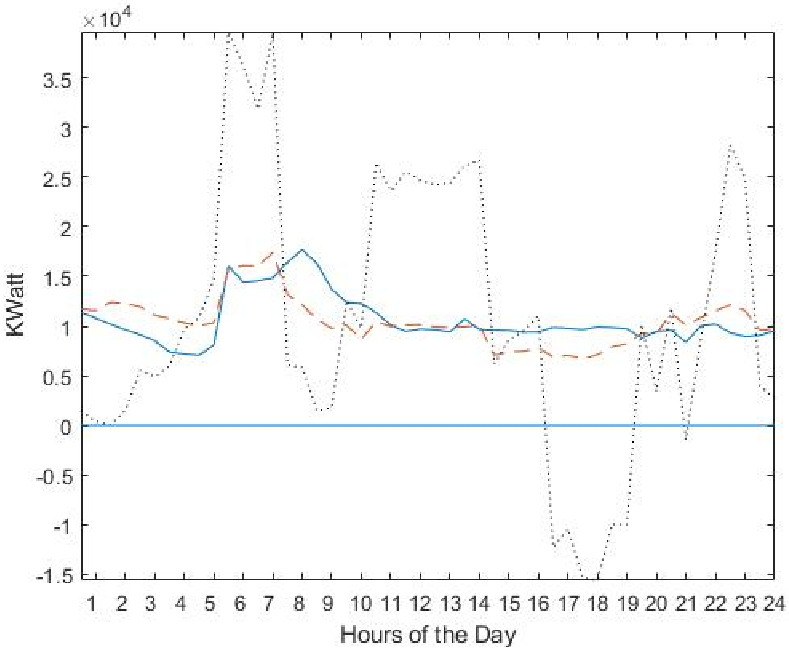


Figure 5.7: Total load

The figures 5.8, 5.9, 5.10 below describe the behavior of the vehicles at home, work and shop. The solid line represents the base algorithm, the dashed line represents the G2V algorithm and the dotted line represents the V2G algorithm. The blue line represents the summary of the cars that charge each hour. The red line is the number of cars disconnected this hour and the green is the number of the cars connected. The black line represents the cars that keep charging from the previous hour, which are the total cars of the previous hour minus the cars that disconnected this hour.

At home, the cars have the same behavior for all three algorithms, which is expected because all cars charge at home regardless the algorithm. The slight differences exist because cars are selected randomly for each hour, for all three algorithms. And so, there is a high possibility that the selected cars don't have the same Parking Duration and disconnect at different hours for each algorithm. As expected, when the total number of cars decreases, the number of disconnected cars is greater than the connected cars.

At work and shop, cars behave with the same principles. The only difference with the home behavior is that the V2G algorithm's cars are the most, so the dotted lines are always on top. Then the solid line follows, of the base algorithm. And the one with the smaller value is the line of the G2V algorithm.

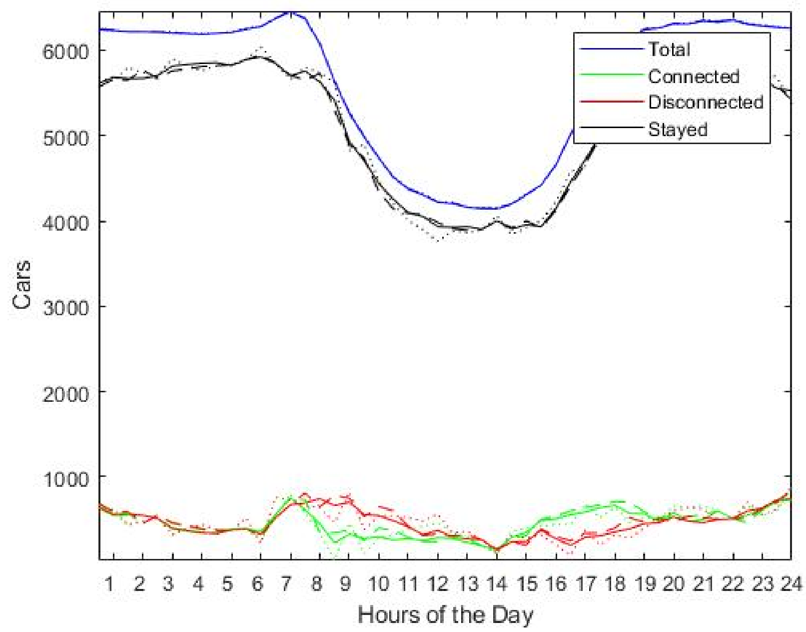


Figure 5.8: Car behavior at home

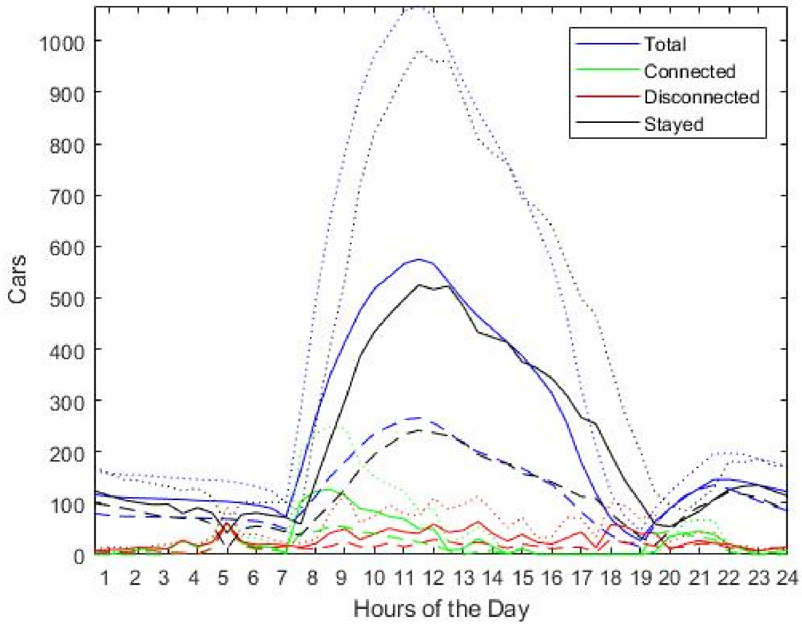


Figure 5.9: Car behavior at work

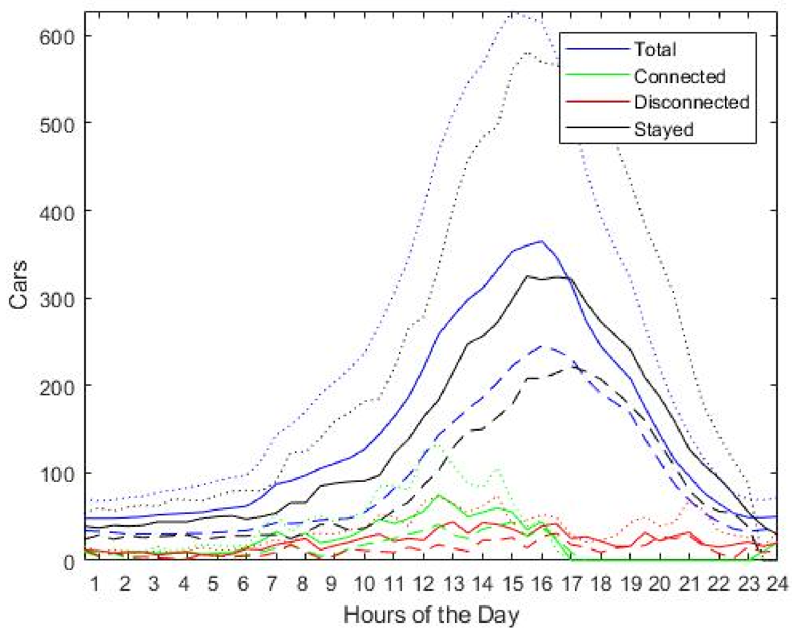


Figure 5.10: Car behavior at shop

In order to see the effect of a smaller battery on the charging load, the same results were tested with 20% of the vehicles having 50KW batteries and the other 80% having 25KW batteries.

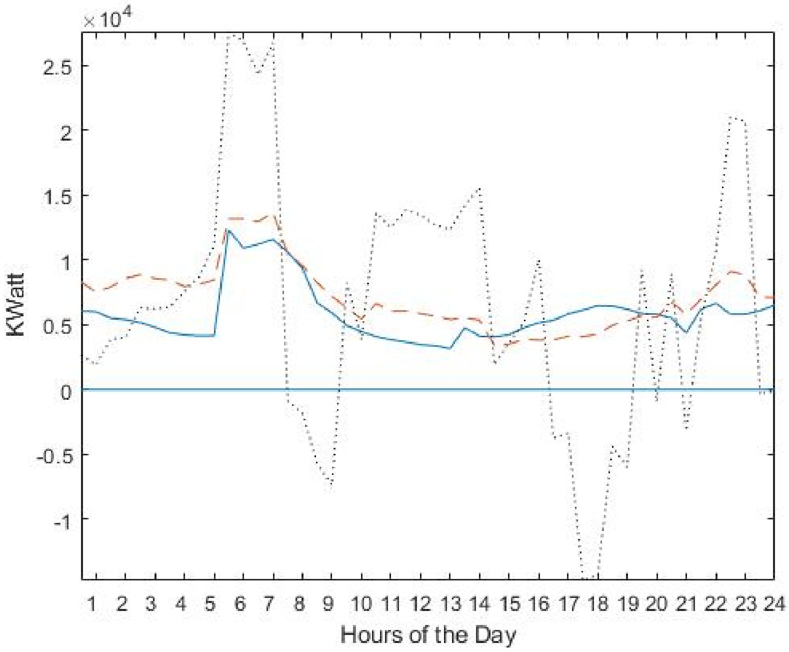
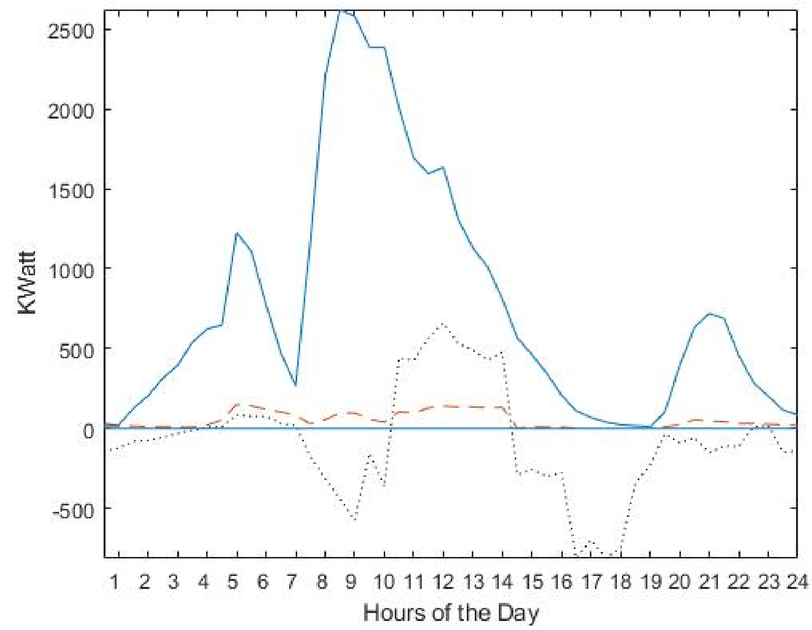
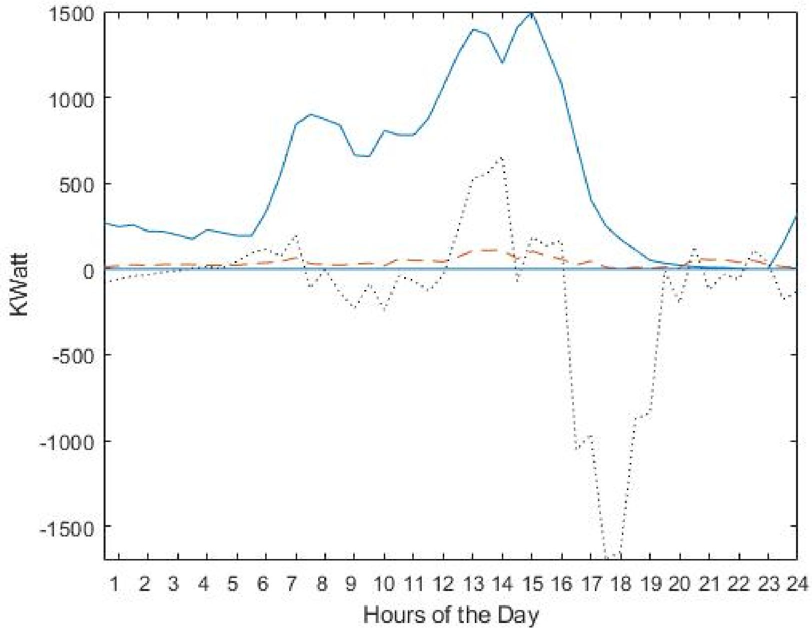


Figure 5.11: Results for charging at home

Overall, the charging load is lower for all the 3 algorithms than in the previous results, while having similar forms and the spaces that the V2G algorithm supports the grid with power are more narrow. The lower capacity of the batteries won't allow them to fully charge and then discharge on the grid as much as the batteries with double capacity. This can be noticed in all four Figures



(a) Charging load at work



(b) Charging load at shop

Figure 5.12: Results for charging at work and shop

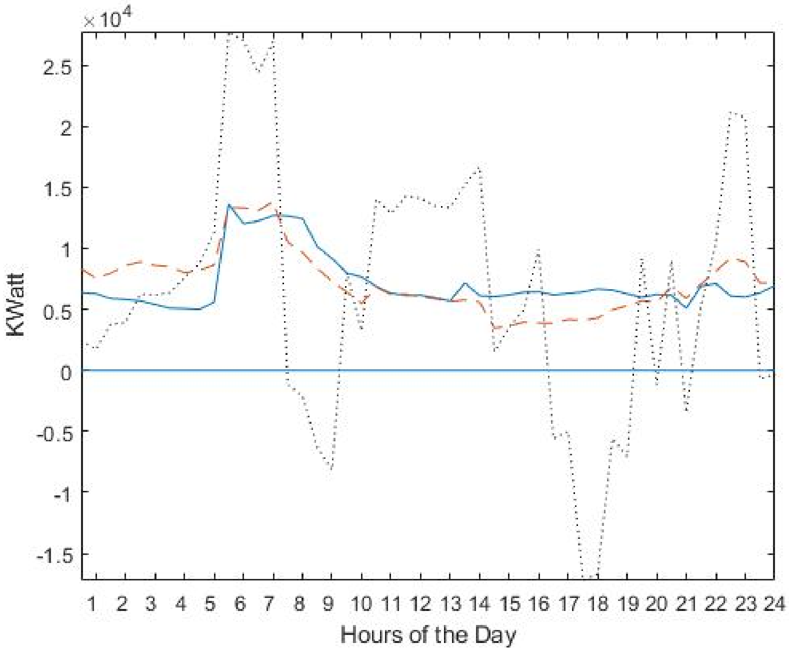


Figure 5.13: Total load

6

Conclusions

Two new algorithms were created, based on algorithms of Section 3. As input, real world driving data are used, which are then processed with a mathematical model in order to get the State of Charge (SOC), Distance to Home (DTH), Parking Duration (PD) values. After, these 3 and Electricity Price (EP) become the inputs to two different fuzzy engines and the output is the average probability of charging for every hour of the day for 2 different algorithms. Then, with the help of an optimization function, the grid load due to Plug-in Electric Vehicle (PEV) charging is calculated.

6.1 | Achieved Aims and Objectives

From the energy provider's perspective, the main aim was to ease the grid more of the huge load due to PEV charging. The proposed algorithms not only lowered the load at off-home locations for the same amount of cars, but also they rearranged the charging of the vehicles, so that they mostly charge during low peak hours and mostly at home. We should not forget to mention that the second algorithm supports the grid with power from the PEV batteries during peak load hours. And higher capacity batteries can support the grid with bigger amounts of energy than smaller ones on the same vehicles doing the same travels.

From the driver's point of view, the charging of his car will cost less; the vehicle will be charged with only the energy it needs to return home and won't be fully charged without reason at off-home locations. Furthermore, there is a possibility that the driver earns some money during peak hours, if there is the option to sell power to the grid.

6.2 | Critique and Limitations

The target distance of the car is what will give the algorithms an estimation of the energy that the car should have after it disconnects from the charger. And the estimation of the distance is limited to the ability of the driver to foretell all the future trips before the car can reconnect to a charging station. Therefore, there is a small possibility that the car will run out of electrical power.

Furthermore, the second algorithm proposed can discharge the PEV battery to the grid. Since the battery life is connected to the full charge or discharge cycles, charging and discharging a vehicle continuously can result in smaller battery life.

6.3 | Future Work

I plan on publishing a paper based on the algorithms of this thesis :)

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