THESIS WORK

Master of Science in Energy Technology

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Price-based charging scheduling optimization for battery electric vehicles

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Declaration

I declare that I have developed and written the enclosed Master Thesis completely by myself and have not used sources or means without declaration in the text. Any thoughts from others or literal quotations are clearly marked. The Master Thesis was not used in the same or in a similar version to achieve an academic grading or is being published elsewhere.

Karlsruhe, 29/03/2019

Place, Date

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Abstract

The high emissions of greenhouse gases and the impact generated on the environment by human behavior during the last few years has led many governments to decide to promote the use of electric cars for passenger transport, as well as the replacement of conventional energy sources by renewable ones. These radical changes have a high impact on the installed energy infrastructure, especially if electric vehicles are charged in an uncontrolled mode because this could generate peaks of consumption saturating the electricity grid, as they require a high-power load. However, if the same vehicles could be charged in a controlled manner this would bring several advantages, such as shifting load to times when there is less consumption thus decreasing the power required during consuming peaks, or charging them during times when the price of electricity is low, thus generating savings in energy costs. In this master's thesis, a model was developed to find a schedule for charging electric vehicles that reduce these costs, later analyzing the economic benefits that this entails.

Kurzfassung

Die hohen Treibhausgasemissionen und die Auswirkungen des menschlichen Verhaltens auf die Umwelt in den letzten Jahren haben viele Regierungen veranlasst, die Verwendung von Elektroautos im Personenverkehr sowie den Ersatz konventioneller durch erneuerbare Energiequellen zu fördern. Diese radikalen Veränderungen haben einen hohen Einfluss auf die bereits installierte Energieinfrastruktur, insbesondere die Elektrofahrzeuge. Wenn diese unkontrolliert aufgeladen werden, könnten Verbrauchsspitzen entstehen, die das Stromnetz überfordern, da Elektroautos in diesem Fall eine sehr hohe Stromleistung benötigen. Wenn jedoch dieselben Fahrzeuge kontrolliert aufgeladen werden könnten, würde dies verschiedene Vorteile mit sich bringen, wie z.B. die Verlagerung der Stromnutzung auf Zeiten mit geringerem Verbrauch, wodurch der Leistungsbedarf in Spitzenzeiten verringert wird, oder die Aufladung in Zeiten mit niedrigem Strompreis, was zu Einsparungen bei den Energiekosten führt. In dieser Masterarbeit wurde ein Modell entwickelt, das einen Zeitplan für die Ladung von Elektrofahrzeugen vorsieht und gleichzeitig zu einer Reduzierung der Kosten führt und später den damit verbundenen wirtschaftlichen Nutzen analysiert.

Abstracto

Las altas emisiones de gases de efecto invernadero y el impacto generado en el medio ambiente por el comportamiento humano durante los últimos ha generado que muchos gobiernos decidan promover el uso de automóviles eléctricos para el transporte de pasajeros, así como también el reemplazo de las fuentes de energía convencionales por las renovables. Estos cambios radicales tienen alto impacto en la infraestructura energética ya instalada, especialmente los vehículos eléctricos ya que si los mismos son cargados de forma no-controlada podrían generar picos de consumo saturando la red eléctrica, ya que requieren de una alta potencia de carga. Sin embargo, si los mismos vehículos pudieran cargarse de forma controlada esto traería consigo diversas ventajas, como desplazar la carga para momentos donde haya menor consumo disminuyendo así la potencia requerida durante los picos, o cargarlos durante momentos en que el precio de la electricidad es bajo, generando de esta forma ahorros en gastos energéticos. En esta tesis de maestría, se desarrollo un modelo que encuentra un cronograma de carga de vehículos eléctricos para disminuir dichos gastos, analizando posteriormente los beneficios económicos que ello conlleva.

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1 Introduction

1.1 Background

Since the Kyoto Protocol was signed in 1997 by the UN participating countries, in which global warming was acknowledge and accepted, the nations involved are trying to reduce CO_2 emissions. Several years later in 2015 in Paris 195 state parties agreed on limiting the increase on the world's temperature on 1.5 °C per year, confirming the direction of policy makers to continue reducing greenhouse gas emissions (BMU, 2018, p. 18). In Germany, one of the highest CO_2 emitters, in the year 2018, 60.6% of the transport sector emissions were produced by passenger vehicles, and it is one of the aims of the Climate Action Plan 2050 of the Federal Government to reduce these emissions (BMU, 2018, p. 39). And to accomplish this objective, electrifying part of the transport sector might seem a reasonable solution, but the integration of renewables it is also an important factor to consider. Eventually, if the energy used to drive electric and plug-in hybrid vehicles is produced by carbon-based power plants, it will not help to reduce the emissions. The energy sector is also responsible for green-house gases emissions and therefore, measures in this subject are being taken also by the policy makers in Germany to accomplish the political objectives set by the energy transition ("*Energiewende*"), shutting down lignite and coal power plants and replacing this generation with renewable energy sources (RES) (Hayn, Bertsch, & Fichtner, 2014, p. 30), which are expected to represent at least the 35% of the electricity consumption in the year 2020 (BMU, 2018, p. 24).

Since 2005 the market of electric vehicles (EV) has been expanding around the world, with a notorious increase in the past few years. Only in the year 2017 regarding the EVs sales, in China almost 580.000 were sold, in Norway, the leader in market share, 39% of all the vehicles sold were EVs, and in Germany the sales were doubled respect to 2016 as described in Figure 1 (IEA, 2018, p. 21).

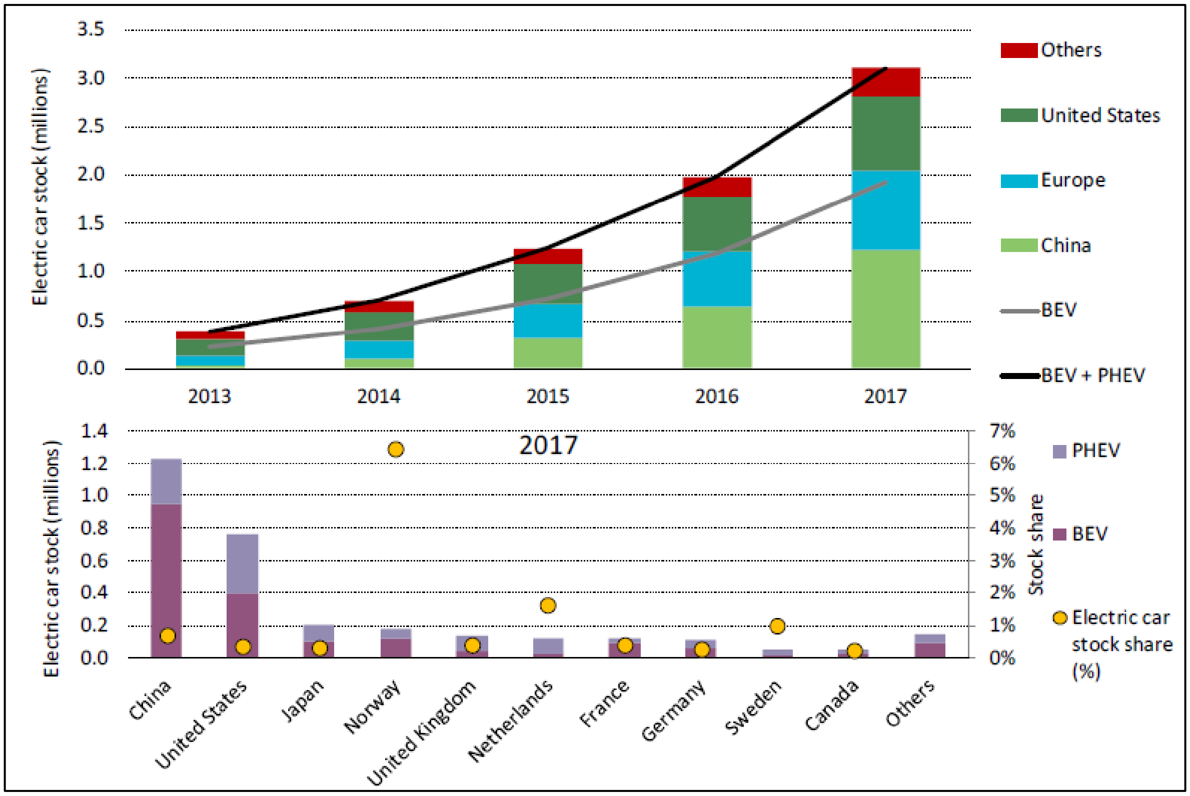

Fig. 1. *Passenger electric car stock in major regions and the top-ten EVI (Electric Vehicles Initiative) countries. Source: (IEA, 2018, p. 19)*

Subsequently, this change of the share of EVs will bring new challenges, but especially regarding the electrical grid, the responsible of delivering the driving energy for all these vehicles. Charging simultaneously several EVs will change significantly the load profile for a certain residential area, as discussed in (Jochem, Kaschub, & Fichtner, 2011) and shown in Figure 2.

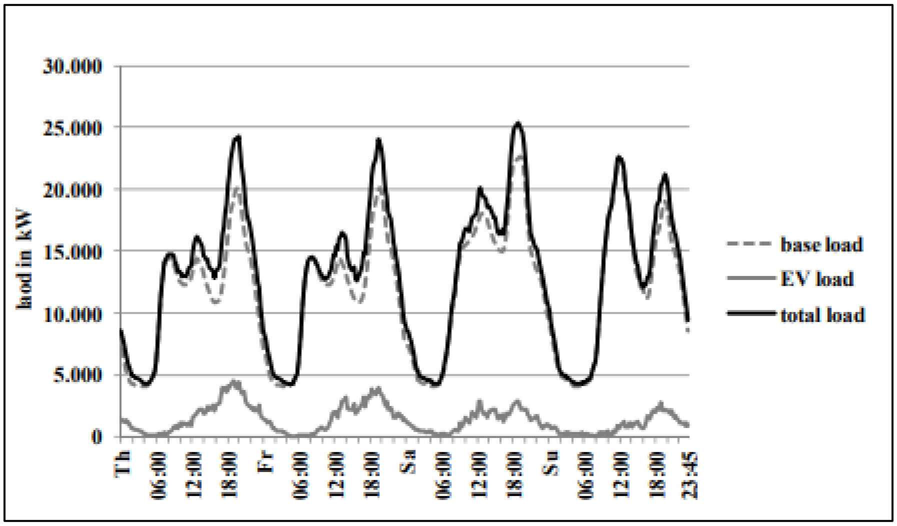

Fig. 2. *Load profile of an urban district with uncontrolled electric vehicles charging.*
Source: (Jochem, Kaschub, & Fichtner, 2011)

Moreover, not only will the charging process of an EV increase the household net energy requirements but will also rise the peak loads during peak hours, when users usually charge their vehicles. Controlling the charging process of the vehicle so that it can be scheduled for hours in which power demand is lower can actually help to reduce the impact of the EVs in the electrical grid.

1.2 Motivation and scope

The goal of this master thesis is to analyse, comprehend and understand the full potential of controlling and scheduling the charging process of battery electric vehicles, based on the intraday electricity prices and the benefits, advantages and drawbacks it may produce. For this, a linear optimization model is going to be developed to find an optimal charging schedule for a single vehicle, based on data of real vehicle drivers and the spot electricity prices for the Schleswig-Holstein region in northern Germany for the year 2015, which purpose is to minimize the expenditures on energy for driving these vehicles, eventually reducing operation costs, and consequently improving the total cost of ownership (TCO) for an EV. The results of the optimization for a single vehicle could be later on aggregated to find the charging load for a whole fleet when using controlled charging methods. In addition, controlled charging could be used as a demand response (DR) measure in the future, to load the grid when its required or as an option for load shifting potential (LSP), to reduce the electricity demand during peak hours.

1.3 Research questions

Although some publications in this same direction describe a similar approach, there are no studies that describe with detail the model aforementioned and there is no tool to simulate the model for further analysis of results. Therefore, the following research questions are answered in this master thesis:

> **RQ1:** How can a mathematical model that optimizes the charging schedule of an EV that minimizes the expenditures on energy and meets the trip requirements of the driver be described and formulated?
>
> **RQ2:** Can this model be simulated to find the optimal schedule for a single vehicle?
>
> **RQ3:** How significant are the savings when charging in a controlled versus uncontrolled mode for a single vehicle and for a fleet?

To answer the first two research questions, and after the research presented in section 2, the model is going to be described in section 3, where the mathematical model is presented, and the software implementation explained. In section 4, results for the optimization are shown to answer the third research question. To conclude, in sections 5 the model is going to be furtherly discussed, and in section 6 conclusions to the research outlined.

2 Literature research

In this chapter of the master thesis the reasons to study the benefits of controlled charging of an EV are going to be presented, mentioning other studies with different approaches to analyse a solution for the important changes the electrical grid will suffer by the emerging electromobility.

Using electric motors to drive means of transport has been working since the first half of the 19th century, after the discovery of electricity. In May 1834 Moritz Hermann Jacobi built the first electric motor in Königsberg, Prussia (today Kaliningrad, Poland) (Doppelbauer, 2018), and sometime later (1884) Thomas Parker, prominent British pioneer, built what can be considered the first electric car, in the same era in which Karl Benz was inventing his first "*Motorwagen*" in 1885 in Mannheim, Germany (Guarnieri, 2012).

But later, in the beginning of the 20th century, due to the success of the internal combustion engine vehicle (ICEV), boom of oil production and consequent falling prices and growing accessibility of petrol stations, ICEV prevailed, and electric powered vehicles were forgotten (Palinski, 2017, p. 3). Of course, that didn't mean that electromobility had no future, since train, trolleys, trams and other means of transport continued using electric motors to drive, although there are some basic differences with battery electric vehicles.

2.1 Charging electric and hybrid vehicles

Electric vehicles are, by definition, vehicles which are driven by electric motors, using electric energy. This energy can be stored in the vehicle or can be obtained from an electrical grid. When cars include a battery, they are generally considered as a Battery Electric Vehicle (BEV) or just Electric Vehicle (EV) and this battery needs to be connected to the electrical grid to obtain electrical energy, that will be later used for driving. But there are also hybrid cars which are cars that are driven by both electric motors and internal combustion engines. This kind of cars may or may not include a battery, therefore the ones which do include a battery and need to be connected to be charged are called Plug in Hybrid Electric Vehicles (PHEV), and if they don’t just Hybrid Electric Vehicle (HEV).

Nowadays charging electric vehicles it is a key factor because it is considered as one of the disadvantages of the EV when compared with ICEV, since the second one only needs a few minutes to fill its tank, and although there are today several different modes of charging an EV, including a fast charging mode, still it is very difficult to do in the same time as a regular car takes to fill the tank of petrol or diesel.

Throughout the past three decades there had been several developments in technology for charging EVs, the so-called Electric vehicle supply equipment (EVSE) and the International Energy Agency (IEA) uses three main characteristics to differentiate chargers from one another (IEA, 2018, p. 39):

- Level: the power output range of the EVSE outlet.
- Type: the socket and connector used for charging.
- Mode: the communication protocol between the vehicle and the charger.

The following table shows the most prevalent charging standards by level and type, since they vary according to different regions around the globe. Direct current (DC) seems to be the most promising technology, although it requires higher investments cause its technology is more complex.

		Conventional plugs	Slow chargers		Fast chargers		
Level		Level 1	Level 2		Level 3		
Current		AC	AC		AC, triphase	DC	
Power		≤ 3.7 kW	> 3.7 kW and ≤ 22 kW	≤ 22 kW	> 22 kW and ≤ 43.5 kW	Currently < 200 kW	
Type	**China**	Type I	GB/T 20234 AC			GB/T 20234 DC	
	Japan	Type B	SAE J1772 Type 1	Tesla		Accepts all IEC 62196-3 standards	Tesla and CHAdeMO (IEC 62196-3 Type 4)
	Europe	Type C/F/G	IEC 62196-2 Type 2		IEC 62196-2 Type 2	CCS Combo 2 (IEC 62196-3)	
	North America	Type B; SAE J1772 Type 1	SAE J1772 Type 1	Tesla	(Under development) SAE J3068	CCS Combo 1 (SAE J1772 & IEC 62196-3)	
	Australia	Type 1	IEC 62196-2 Type 2			Accepts all IEC 62196-3 standards	
	Korea	Type A/C	IEC 62196-2 Type 2			CCS Combo 1 (IEC 62196-3)	
	India	Type C/D/M	(Draft) IEC 60309 industrial socket (two wheelers) and IEC 62196-2 Type 2 (other vehicles)		(Draft) IEC 62196-2 Type 2	(Draft) GB/T 20234 DC (< 20 kW) and CCS Combo 2 (IEC 62196-3) (≥ 20 kW)	(Draft) CHAdeMO allowed

Table 1. Overview of the EVSE characteristics in the main regions
Source: (IEA, 2018, p. 40)

With these new technologies charging an 85-kWh battery with a 480 V_{DC} Tesla supercharger may take up to 75 minutes. Nevertheless, as the charging time tends to reduce to make the BEV competitive with the ICEV, consuming power on peaks hours tends to increase, and this may lead to a mismatch between electricity demand and supply and eventually considerable changes in the electricity market: if the demand cannot be fully satisfied by the generation, a loss-of-load event occurs, also known as "*generation capacity deficit*", and the market will set the price synthetically (Ensslen et al., 2018, p. 112).

The charging process of a BEV it is a very complex process that involves several parameters, such as electrical specifications of the charger, technical characteristics of the battery's technology, age and reuse cycles of the battery, but they are of no interest in this thesis. Yet, it is relevant to mention that the charging process can be controlled or uncontrolled. For an uncontrolled charging process the battery begins to charge at maximum power as soon as it is connected and will continue to charge until the battery has reached its maximum state of charge (first at constant current, then constant voltage). In contrast, a controlled charging process is the one in which the process may or not may be continuous, but instead it is deliberately paused or delayed by a human or a machine, and power can be adjusted from 0 Watts to maximum power. This charging method can also be sometimes referred as "smart charging".

2.2 Power generation: renewables and electricity market.

However, considerably higher charging times is not the only issue to address. Unlike other goods and services, electricity has a unique condition: supply must meet demand at all time (or generation must meet consumption) otherwise the networks stability can be compromised as well as the grid infrastructure could be jeopardized (Flath, Ilg, Gottwalt, Schmeck, & Weinhardt, 2014, p. 619). Since the *Energiewende* (energy transition) goals were set (Hayn et al., 2014, p. 30), Germany is trying to change its energy matrix, increasing the share of renewable energy sources (RES) like wind and photovoltaic and reducing the participation of nuclear and carbon-based power plants. But there is a natural characteristic that differentiates these types of technologies: on one side wind and photovoltaic are intermittent, their generation depends on weather and climate conditions which cannot be controlled, and its generation is decentralized. On the other side, carbon and nuclear power plants are used as base power since they are more reliable and their generation it is usually centralized and injected into a high voltage grid. So as more renewables come in, and more base power plants are put out of service, the electric network becomes more unstable and intermittent in generation, making it less reliable. Therefore, it is even more difficult to make consumption (demand) meet generation (supply) since it is more unpredictable. Furthermore, Germany has policies which give priority to dispatch RES energy over fossil fuels energy when demand is satisfied (Khoshrou, Pauwels, & Dorsman, 2017, p. 4).

The modifications to the electrical grid mentioned influence the electricity spot market. An electricity spot market is a place or platform where short term electricity contracts are agreed to trade electric energy for the next days. Electricity generators or sellers must set the quantities of energy they are willing to offer and its price, and distributors or buyers should set the amount of energy they will be needing for the next day, and how much are they willing to pay. In Germanys electricity market there are two spot markets: the day-ahead market where bids are offered hourly for the next day, and the intraday market where bids can be offered hourly and every 15 minutes. The main difference between these both markets, besides the time basis, is that on the day-ahead market bids must be made a day before, and for the intraday market they can be done 45 minutes before.

More importantly, since the renewables share in the energy matrix is rising, this has been affecting these markets. According to (Khoshrou et al., 2017), the impact of RES on the day ahead market can be appreciated when analysing data from 2011 to 2016, showing a clear correlation between the price day profile of the sunlight hours and the energy produced by the photovoltaic systems, especially during the summer when it can be seen that peak prices shift away from the day-light hours. The increase of the occurrences of negative and low prices can also show how the renewables, especially wind energy, are affecting price because they have been happening more often for the past last years. (Flath et al., 2014) explains this correlation: "*As wind turbines and solar power have almost zero marginal cost* *of generation, they displace peaking plants with higher marginal costs. Therefore, availability of generation from renewable sources reduces the wholesale price.*" (Flath et al., 2014, p. 621)

2.3 Power consumption: load profiles, load shifting and demand response

In the following section the power consumption is going to be discussed, focusing on how will the increase of market share of EV influence of the loading profile, although making focus on the residential load, which in the case of Europe is not the most representative part, just the 29% (Hayn et al., 2014, p. 30), but it is of the interest of this thesis. In addition, concepts such as Load Shifting and Demand Response are going to be introduced.

If a typical household consumption profile is analysed, it can be observed that the consumption peaks occur mostly during the morning and evening hours. The most power demanding appliances such as the fridge, dishwasher, washing machines, heating devices and hair dryers are usually being used during these periods, causing these peaks, but when compared in power and energy requirements with an electric vehicle charger they seem insignificant, especially when considering the 11 kW charger, which can easily double the household electricity consumption (Jochem et al., 2011, p. 5). As analysed by (Hayn et al., 2014, p. 37) assuming that a single driver could drive 15.000 km per year with an efficiency of 20 kWh/100 kilometres, one single EV would require 3.000 kWh per year, the equivalent of the annual electricity consumption for a German average household.

This means, the load profile for the typical household can change drastically when an EV is charged, and when the charging process is uncontrolled this may happen during the consumption peaks, making the worst case possible, increasing the maximum power consumption of the household, consequently impacting also on the low voltage grid (0.4 kV). The same analysis was made in (Paetz, Kaschub, Jochem, & Fichtner, p. 4) for a 500 households profile assuming a high penetration of EV in the market share and obtaining as a result an increase of the load peak of 231%, during evening hours (see figure 3).

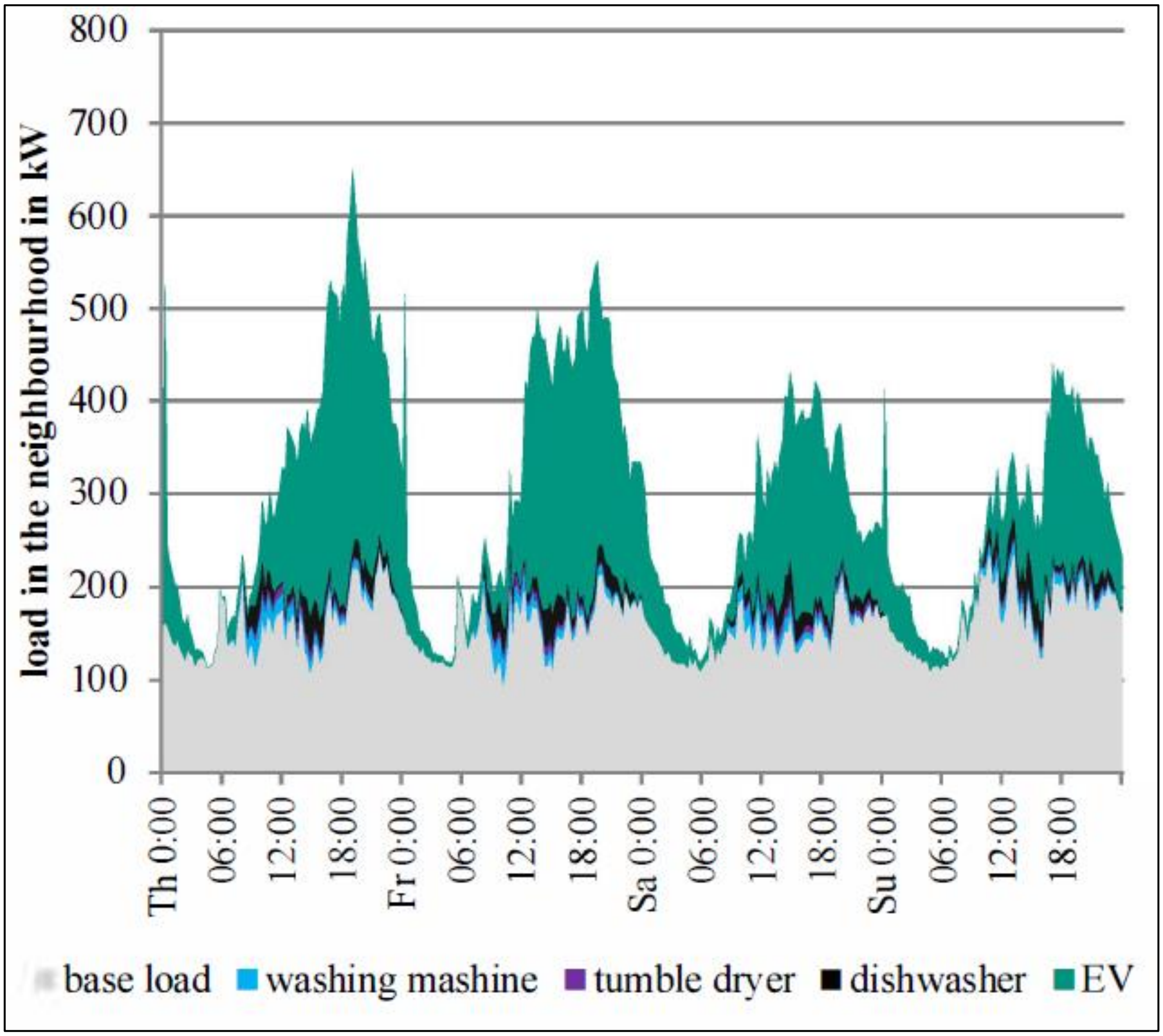

***Fig. 3.** Effect of uncontrolled charging of an EV on a 500 aggregated load profiles of households in summer (assuming high penetration of EVs).*
Source: (Paetz, Kaschub, Jochem, & Fichtner, p. 4)

This issue was also addressed in (Jochem et al., 2011) and the solution proposed is to control the charging process so it doesn't match with the already existing high peaks, but by charging the vehicle during times of lower consumption. By doing this, the load generated by the EV charging process would be shifted to a consumption valley, for example, during the night hours where consumption in households is really low. Battery electric vehicles turn out to be a very good option for load shifting because of their long parking hours (Paetz et al., p. 1), whether it is at home or at the workplace and a great demand of power and energy. As stated in (Babrowski, Heinrichs, Jochem, & Fichtner, 2014) EV have a great load shifting potential (LSP), and could be used as a demand response (DR) measure. For LSP is understood the potentiality of shifting load from consumption peaks to low power demand valleys, as described in figure 4.

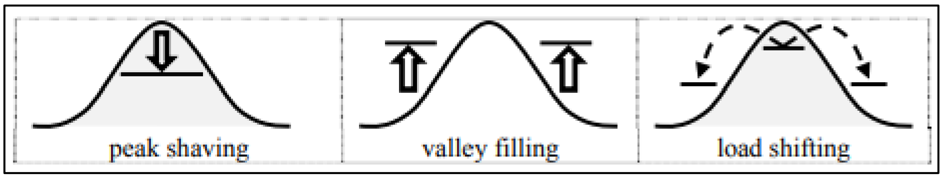

Fig. 4. *Load shifting concept.*
Source: Jochem et al 2013 (026)

This is quite relevant because, as mentioned in the previous section, the energetic matrix will be going through several significant changes that will compromise its stability and will be needing this balancing measures, and a demand response measure like sending low price signals to encourage users to charge the EV in load demand hours could be really helpful in this way. However (Babrowski et al., 2014, p. 284) stated that this measure should be carefully coordinated to prevent an undesired effect of having simultaneous EV charging at the same time in the same location. This problem was identified at (Ensslen et al., 2018) when all the users received the same price signal and all the charging was scheduled for the same low-price period, generating a spike of consumption load, what it is known as "*avalanche effect*" (Ensslen et al., 2018, pp. 112–113), a significant and sudden increase of the charging load.

2.4 Relevant studies

For the research corresponding to this master's thesis, different publications have been studied related to the optimization of charging electric vehicles. First of all, it is worth mentioning the work of (Ensslen et al., 2018) "Incentivizing smart charging" which describes and evaluates the benefits of implementing an electricity tariff or business model that will incentive EV users to charge their vehicles with a controlled mode, and consequently provide load flexibilities to charging managers, focusing on France and Germany. This study analyses also the acceptance of the user of the electric vehicle, their minimum range requirements, the social barriers, as well as the business model of the aggregator or charging manager and their revenues. Another essential point to mention is that, as it is intended to do in this master thesis, the objective of the charging manager is to minimize the costs and uses the day-ahead market prices information to find the optimum schedule of the charging events. For the 5 different scenarios presented, the results of the average load profiles for scenarios 1, instantaneous or uncontrolled charging, and scenario 4, scheduled charging at home and work, are interesting for the study of this master thesis because the same comparison is intended to be done. As a general conclusion, from this work it can be stated that controlled charging methods can generate savings to the charging managers, as it is intended to be shown in the model that will be developed.

In second and third place, the contributions of (Sundstřom & Binding, 2010) and (Hu, You, Oestergaard, Lind, & Qiu Wei, 2011) as they describe an optimization model also based on the price of electricity, although with some differences between them, but are the works that came closest to what this thesis work aims to study. Both have the objective of minimizing the costs of charging an electric car, but the first of them with a specific focus on the behaviour of the battery (linear or quadratic approximation) and also taking into account a "constraint" for generation, while the second has an approach from the point of view of "aggregator/fleet manager/fleet operator". This manager, who has information on the future trips of users and the price of electricity for the next 24 hours, finds the schedule to charge the entire fleet while minimizing energy costs. To do so, it must assume that the power of the charger is constant, that it knows the state of charge (SOC) of the battery at the time of starting the simulation/optimization and underestimates the costs for deeply discharging the battery (Depth of Discharge) that decrease the useful life of the battery (Hu et al., 2011, p. 3). These two works propose quite similar mathematical models, clear and concise, but none of them details the development of the equations to obtain the corresponding matrices and vectors to be able to implement any model or other.

$$
\begin{aligned}
&\min_{\mathbf{p}_b} \; t_s \mathbf{c}^T \mathbf{p}_b \\
&\text{subject to} \\
&\quad \mathbf{A}_s \mathbf{p}_b \geq \mathbf{b}_s \\
&\quad \mathbf{A}_g \mathbf{p}_b \leq \mathbf{b}_g \\
&\quad \mathbf{A}_b \mathbf{p}_b \leq \mathbf{b}_b \\
&\quad \mathbf{b}_l \leq \mathbf{p}_b \leq \mathbf{b}_u,
\end{aligned}
$$

Fig. 5. *Mathematical model proposed by (Sundstr̆om & Binding, 2010).*

$$
\begin{aligned}
&minC^T E \\
&\text{subject to} \\
&\begin{cases}
A_t E \geq B_e \\
A_t E \leq B_b \\
A_t E \geq B_{set} \\
0 \leq E \leq E_{max}
\end{cases}
\end{aligned}
$$

Fig. 6. *Mathematical model proposed by (Hu, You, Oestergaard, Lind, & Qiu Wei, 2011)*

In the model described by (Sundstr̆om & Binding, 2010) (figure 5) $\mathbf{p_b}$ is the decision variable, $\mathbf{c^T}$ is the costs vector, $\mathbf{t_s}$ is the time slot and the function to minimize is $t_s c^T p_b$, subject to three constraints: a stop-over inequality constraint, which means the vehicle must have enough energy in the battery to drive the following trip, a generation inequality constraint, to assure that there is energy being generated to charge the vehicle, and the battery inequality constraint which is defined to set the upper limit of the battery capacity. Finally, the last equation sets the boundaries for charging power $\mathbf{p_b}$ (Sundstr̆om & Binding, 2010)

On the other side, the model proposed by (Hu et al., 2011) described in figure 6 uses energy instead of power as a decision variable, simply by multiplying the charging power vector times the time variable. Again, they use $\mathbf{C^T}$ as costs vector, and the function to minimize is $C^T E$, being ***E*** the decision variable vector. This function is subject also to three constraints just like in the previous model.

2.5 Conclusions

The EV market will continue to grow over the next few years and the share of RES in the energy matrix will increase, and this will bring with it many challenges to face. The grid instability generated by RES can produce a mismatch between supply and demand of electric energy, and this can be aggravated by the simultaneous charging of electric cars, affecting the grids reliability and security. On the other hand, this same problem that EV generate could serve as a solution to give stability to the network and generate consumption when needed, if the charging events for these EV's can be schedule to low demand consumption valleys. If these solutions can be implemented, not only it benefits the grid but also reduces price volatility in the wholesale electricity markets (Ensslen et al., 2018, p. 112) and also could save money, since electricity prices are usually higher during consumption peaks, shifting the charging process to a valley would make it more cost effective.

Several studies have been conducted regarding the subject of finding the optimal schedule to minimize the expenditures, with different approaches and different outcomes. Although all of them propose the same idea of finding the optimal schedule by minimizing charging expenditures, none of them described how to formulate the model in details, as this master thesis pretends to do in Section 3, showing how to obtain matrices and vectors needed to find this optimal schedule, and by this, answering the first research question.

3 Modelling

Finding an optimal schedule for charging an EV that minimizes charging expenditures can be interpreted as a mathematical problem and in order to answer the first research question (RQ1), a mathematical model was elaborated as a linear optimization to find the charging schedule which minimizes the costs on driving energy but fulfils the trip requirements of the vehicle's user. Later, this same model that it is going to be described in the following sections was the model used and programmed in MATLAB R2018b and using an optimization solver tool from IBM called CPLEX to solve the linear optimization problem.

The idea of this software is to find for each driving profile a cost-efficient schedule for charging the vehicles battery but considering also the driving necessities of the user and its availability to charge the vehicle. In a previous Bachelor Thesis in this institute, another model was developed to find these representative driving profiles using data from the German Mobility Panel (MOP) (Heinz, 2018). These driving profiles would be calculated depending on the driving behaviour, departing and arriving time, and the driving time and distance for every trip. Afterwards, the obtained charging schedules are going to be aggregated to find an aggregated loaded profile for this charging mode (smart charging) for this vehicle's fleet.

3.1 Input data and assumptions

In order to find this optimal solution, certain data is necessary from the vehicle's driver, such as, for example, to know when the vehicle is being used, how many kilometres it travels daily, when it is available to be charged, where it can be charged and with what power. All this data has been collected by the German Mobility Panel and later processed by Daniel Heinz in his work "Creating and Evaluating Representative Mobility and Load Profiles for Electric Vehicles in Germany" (Heinz, 2018), and from the model developed in this work, the data can be extracted as standard driving profiles. A driving profile contains the data that is needed to find the optimal charging schedule, and each of the 2120 standard profiles are structured in a table as follows:

1) Time (t-1)
2) Time (t)
3) Position (t-1)
4) Position (t)
5) Consumed energy [kWh]
6) Available power of the charging point [kW]
7) Available energy of the charging point [kWh]
8) Electric energy consumed by driving according to maximum strategy [kWh]
9) Electric energy consumed by driving according to minimum strategy [kWh]
10) Charging power used according to maximum strategy [kW]
11) Charging power used according to minimum strategy [kW]
12) Charged energy according to maximum strategy [kWh]
13) Charged energy according to minimum strategy [kWh]
14) State of charge at end of interval according to maximum strategy [kWh]
15) State of charge at end of interval according to minimum strategy [kWh]
16) SOC at the end of the interval according to maximum strategy [%]
17) SOC at the end of the interval according to the minimum strategy [%]
18) BEVID (Battery Electric Vehicle Identifier)
19) Weight Factor

All of these values can be obtained from the model for a period of one week, and with a chosen time interval, which in this case was 15 minutes, finally obtaining 672 time intervals. In addition to the time interval that was chosen, and in order to obtain the driving profiles it is necessary to set other variables as well, such as the vehicles specifications (battery capacity and driving efficiency), the locations where the EV can be charged, and the maximal power of the charger. Although these parameters can be changed in the future, for this simulation it was decided to configure them in the following way:

- Battery capacity: 22 kWh
- Driving efficiency: 15 kWh/100 km
- Charging locations: home and workplace
- Maximum charging power: 3.7 kW

The International Electrotechnical Commission (IEC) standard 61851-1 specifies a set of modes for EV charging. These encompass 16 A 1-phase charging (3.7 kW).

Once these parameters were set, the driving profiles can be extracted from the model as a MATLAB file, and the following variables were used in this optimization:

- Position (t) – (4)
- Consumed energy [kWh] – (5)
- Available power of the charging point [kW] – (6)
- Charging power used according to maximum strategy [kW] – (9)
- State of charge at end of interval according to maximum strategy [kWh] – (14)
- State of charge at end of interval according to minimum strategy [kWh] – (15)
- BEVID (Battery Electric Vehicle Identifier) – (18)
- Weight Factor – (19)

The weight factor will be needed when aggregating variables such as power or charging costs, since not every profile has the same representativity.

Before describing the mathematical model, it is important to introduce the charging strategies that are going to be used as boundaries in the optimization problem. These limits are the data already processed in variables (14) and (15) as SOC according to maximum and minimum strategies respectively.

Charging as soon as possible strategy (ASAP) or maximum strategy

When charging mobile devices or vehicles which have a battery for energy storage, the most usual way to do it is to charge it as soon there is an available a charging site. This means that as soon as the vehicle arrives to a charging point, whether it's a parking lot or a garages house, the user will plug the BEV and start charging it at maximal available power, even though he or she is not planning to use the BEV soon. The BEV battery is going to be charged until the battery's capacity is completely full of energy or until the user must leave to do the next trip, whatever occurs first. This method is the so called "as soon as possible" (ASAP) and the $SOC(t)$ curve generated from charging the BEV this way will be called $SOC_{max}(t)$.

Charging as late as possible strategy (ALAP) or minimum strategy

In contrast, we can find another way of charging mobile devices/vehicles which is called "as late as possible", and this means that instead of charging the BEV battery instantaneously as the charging spot is reached the user will wait some time before to begin with the charging process. In this case, only the energy that is needed to drive the following trip is going to be charged into the battery. So, if the user needs to drive 10 km and the vehicles needs 22 kWh to drive 100 km, the user will charge only 2.2 kWh to the BEV battery. And to do this it will set the charging process to begin some time t before the departure time, being t = 2.2 kWh/charging power. Although it is assumed that the vehicle has enough energy to drive the whole trip before departing, when this method is considered, there is a threshold value of minimum amount of energy that will be always available in case of emergency. In this thesis this value was set to 5% of the nominal battery capacity. This method is the so called "as late as possible" (ASAP) and the $SOC(t)$ curve generated from charging the BEV this way will be called $SOC_{min}(t)$.

Finally, since the optimization is based in minimizing costs, intraday electricity prices series from Schwelsig Holstein for the year 2015 were used. This data was obtained from EPEX Spot (EPEX, 2015) and it contains the intraday electricity price for this region in a 15 minutes resolution, for a whole year, resulting in 35040 registers.

Certainly, with this information the model could be developed, however it is necessary to comment some of the assumptions that will be made. As described before, this model assumes all vehicles to have the same battery capacity, the same driving efficiency, all drivers are able to charge their EV's at their home and their workplaces, always with the same maximum power which is 3.7 kW. This value was determined by the International Electrotechnical Commission (IEC) in its standard 61851-1, where it specifies a set of modes for EV charging (Flath et al., 2014, p. 622). Regarding the battery's charging process, it is going to be modelled as a linear process when it is not actually like this, since there are no significant effects by using this model instead of a quadratic one, as concluded by (Sundstřom & Binding, 2010, p. 6), "*In this paper the impact of using a linear versus a quadratic approximation of the EV batteries to plan the charging has been shown. The observation is made that the resulting violations of the battery boundaries when applying the charging schedule based on the linear approximation are relatively small, i.e., less than 2% of the usable capacity. The benefit of using the quadratic formulation does not justify the increase in computation time".* Also, in this work, losses when charging EV are not considered, so charging efficiency is assumed to be 1.

Since the time resolution for the prices series is 15 minutes, the same time interval was chosen for the driving profiles, and so the charging process must be also discretized this way, which means that a charging process occurs in 15 minutes times intervals.

Finally, since the aim of this optimization is to reduce to its minimum the expenditures on charging EV, it is assumed that the electrical grid operator (or charging manager) can control the charging process of the vehicle's fleet and can obtain a price forecast for a week.

3.2 Mathematical model

In the following section the mathematical model used to find the optimum solution for every profile is going to be described. But before defining the target function and its constraints there are some concepts that should be introduced. The term State of Charge is often used when referring to the amount of energy stored in the BEV battery, and we will be using the abbreviation SOC from now on. The following equation (3.2.1) represents how is the SOC of a BEV battery calculated based on the previous SOC and the energy that is aggregated and the energy that is subtracted from it:

$$SOC(t) = SOC(t-1) + p(t).\Delta t - e(t) \qquad (3.2.1)$$

- $SOC(\mathrm{t})$ is the actual state of charge of the vehicle's battery in kWh
- $SOC(\mathrm{t}\text{-}1)$ is the state of charge for the previous time period in kWh
- $p(\mathrm{t})$ is the power being charged to the battery during time period t in kW
- Δt is the time period, measured in hours
- $e(\mathrm{t})$ is the energy driven by the car during time period t in kWh, always positive

All the terms in this equation are energy and measured in kWh. Of course, it is not possible for a vehicle to be driving and charging at the same time period, but this equation its representative and helpful for our purpose.

Although $SOC(\mathrm{t})$ it's a continuous function, and for further purposes, equation (3.2.1) will be also expressed with sub-indices, representing sub-index i each time slot and being n the last time slot in the problem's domain:

$$SOC_i = SOC_{i-1} + p_i.\Delta t - e_i \qquad \forall\ i\ \in \{1,2,3,\dots,\mathrm{n}\} \qquad (3.2.2)$$

Therefore, the state of charge for the first time step can be calculated by:

$$SOC_1 = SOC_0 + p_1.\Delta t - e_1 \qquad (3.2.3)$$

And the following interval:

$$SOC_2 = SOC_1 + p_2.\Delta t - e_2 \tag{3.2.4}$$

But if we replace equation (3.3.3) into equation (3.3.4) we would get the following equation:

$$SOC_2 = (SOC_0 + p_1.\Delta t - e_1) + \ p_2.\Delta t - \ e_2 \tag{3.2.5}$$

So, if we consider any state of charge at any moment, it can be calculated using the following expression:

$$SOC_n = SOC_0 + \sum_{i=1}^{n} p_i.\Delta t - \sum_{i=1}^{n} e_i \tag{3.2.6}$$

This way we will only use the following parameters: SOC_0 and e, and variable p.

3.2.1 Target function

The objective of this optimization method is to find a charging schedule for the electric vehicle that minimizes the expenditures on charging energy, but that also fulfils with the energy requirements to drive the following trips. This means that the BEV should have enough energy in the battery before departing, and that this energy should be enough to get the BEV to the next charging site. Considering this, the proposed target function for every BEV driving profile is:

$$\min\ \bar{C}^{\,T}\bar{X}\,\Delta t \tag{3.2.7}$$

where:

- C represents the price series vector [€/kWh]

$$\bar{C} = \{c_1, c_2, c_3, \ . \ . \ ., c_n\} \tag{3.2.8}$$

- X represents the vehicle charging power [kW]

$$\bar{X} = \{p_1,\ p_2, p_3, \dots, p_n\} \tag{3.2.9}$$

- Δt is the time slot [h] (scalar)

3.2.2 Constraints

In the previous sections the concepts for charging modes ASAP and ALAP were introduced because it will help us define the constraints for this optimization problem. Both modes of charging are the limits of the charging possibilities that the electrical grid operator or charging manager has to charge the vehicle so the driver can get enough energy to drive the next trip. It is not possible to charge it faster than ASAP (because that would have meant that ASAP method was not correctly defined) and it is also not possible to charge later than ALAP because the BEV wouldn't get enough energy to drive the next trip. Therefore, we could now state the actual state of charge of the BEV should be always between these both limits that we have already defined as $SOC_{max}(t)$ and $SOC_{min}(t)$, as shown in figure 7 and equation (3.2.10).

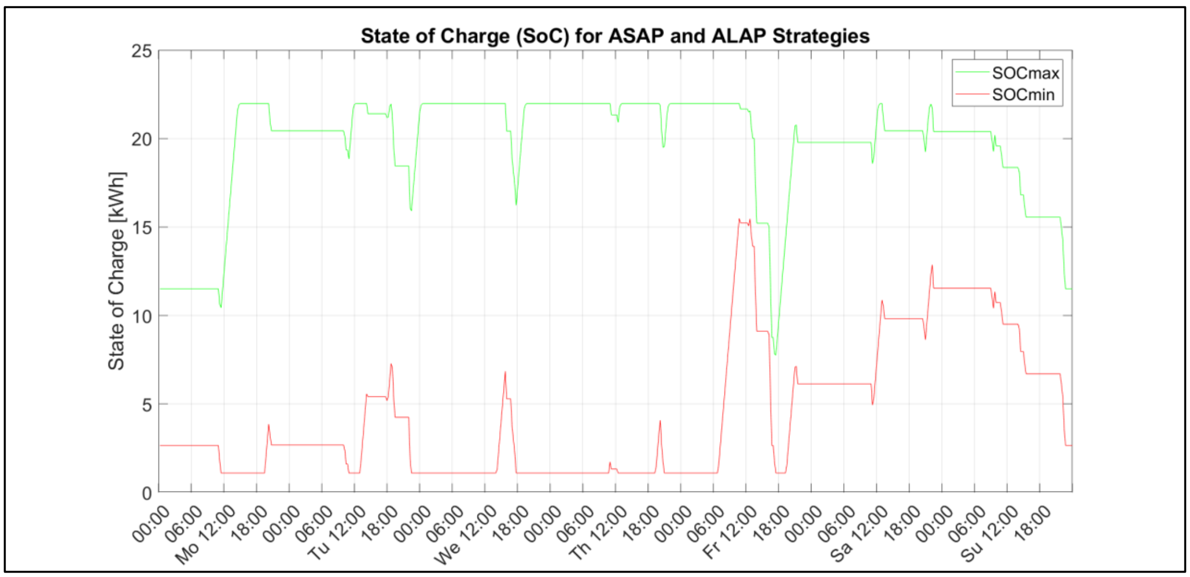

Fig. 7. *SOC curves for ASAP (SOC_{max}) and ALAP (SOC_{min}).*
Own source.

$$SOC_{min}(t) \leq SOC(t) \leq SOC_{max}(t) \qquad \forall\, t \tag{3.2.10}$$

<u>Constraint 1:</u> the BEV should have enough State of Charge to drive the next trip (SOC_{min})

$$SOC_{min}(t) \leq SOC(t) \qquad \forall\, t \tag{3.2.11}$$

with

$$\overline{SOC}_{min} = \{SOC_{min,1}, SOC_{min,2}, SOC_{min,3}, \dots, SOC_{min,n}\} \tag{3.2.12}$$

Definition (3.2.12) represents the SOC_{min} vector with the values for every time slot which are imported as data.

Combining equations (3.2.1) and (3.2.11) we get:

$$SOC(t) = SOC(t-1) + p(t).\Delta t - e(t) \geq SOC_{min}(t) \qquad \forall\, t \tag{3.2.13}$$

$$SOC_i = SOC_{i-1} + p_i.\Delta t - e_i \geq SOC_{min,i} \qquad \forall\, i \in \{1,2,3,\dots,\mathrm{n}\} \tag{3.2.14}$$

Combining equations (3.2.6) and (3.2.14) we would get the following system of equations:

$$\left\{\begin{matrix} SOC_1 = & SOC_0 + p_1.\Delta t - e_1 & \geq SOC_{min,1} \\ SOC_2 = & SOC_0 + p_1.\Delta t - e_1 + p_2.\Delta t - e_2 & \geq SOC_{min,2} \\ SOC_3 = & SOC_0 + p_1.\Delta t - e_1 + p_2.\Delta t - e_2 + p_3.\Delta t - e_3 & \geq SOC_{min,3} \end{matrix}\right\} \tag{3.2.15}$$

$$\left\{\begin{matrix} SOC_1 = & SOC_0 & +p_1.\Delta t & -e_1 & 0 & 0 & 0 & 0 & \geq SOC_{min,1} \\ SOC_2 = & SOC_0 & +p_1.\Delta t & -e_1 & +p_2.\Delta t & -e_2 & 0 & 0 & \geq SOC_{min,2} \\ SOC_3 = & SOC_0 & +p_1.\Delta t & -e_1 & +p_2.\Delta t & -e_2 & +p_3.\Delta t & -e_3 & \geq SOC_{min,3} \end{matrix}\right\}$$

Multiplying by -1 and rearranging:

$$\begin{pmatrix} -p_1.\Delta t & 0 & 0 & \leq & -SOC_{min,1} & +SOC_0 & -e_1 & 0 & 0 \\ -p_1.\Delta t & -p_2.\Delta t & 0 & \leq & -SOC_{min,2} & +SOC_0 & -e_1 & -e_2 & 0 \\ -p_1.\Delta t & -p_2.\Delta t & -p_3.\Delta t & \leq & -SOC_{min,3} & +SOC_0 & -e_1 & -e_2 & -e_3 \end{pmatrix} \tag{3.2.16}$$

<u>Constraint 2:</u> the actual State of Charge can never be bigger than the battery capacity (SOC_{max})

$$SOC(t) \leq SOC_{max}(t) \qquad \forall\, t \tag{3.2.17}$$

with

$$\overline{SOC}_{max} = \{SOC_{max,1}, SOC_{max,2}, SOC_{max,3}, \dots, SOC_{max,n}\} \tag{3.2.18}$$

Combining equations (3.2.1) and (3.2.17) we get:

$$SOC(t) = SOC(t-1) + p(t).\Delta t - e(t) \ \leq SOC_{max}(t) \qquad \forall\, t \tag{3.2.19}$$

$$SOC_i = \ SOC_{i-1} + p_i.\Delta t \ - \ e_i \ \leq SOC_{max,i} \qquad \forall\, i \ \in \{1,2,3,\dots,\mathrm{n}\} \tag{3.2.20}$$

Combining equations (3.2.6) and (3.2.14) we would get the following system of equations:

$$\left\{\begin{matrix} SOC_1 = & SOC_0 + \ p_1.\Delta t - \ e_1 & \leq SOC_{max,1} \\ SOC_2 = & SOC_0 + p_1.\Delta t - \ e_1 + \ p_2.\Delta t - \ e_2 & \leq SOC_{max,2} \\ SOC_3 = & SOC_0 + p_1.\Delta t - \ e_1 + \ p_2.\Delta t - \ e_2 + \ p_3.\Delta t - \ e_3 & \leq SOC_{max,3} \end{matrix}\right\} \tag{3.2.21}$$

$$\left\{\begin{matrix} SOC_1 = & SOC_0 & +p_1.\Delta t & -e_1 & 0 & 0 & 0 & 0 & \leq SOC_{max,1} \\ SOC_2 = & SOC_0 & +p_1.\Delta t & -e_1 & +p_2.\Delta t & -e_2 & 0 & 0 & \leq SOC_{max,2} \\ SOC_3 = & SOC_0 & +p_1.\Delta t & -e_1 & +p_2.\Delta t & -e_2 & +p_3.\Delta t & -e_3 & \leq SOC_{max,3} \end{matrix}\right\}$$

After rearranging:

$$\begin{pmatrix} p_1.\Delta t & 0 & 0 & \leq & SOC_{max,1} & -SOC_0 & +e_1 & 0 & 0 \\ p_1.\Delta t & p_2.\Delta t & 0 & \leq & SOC_{max,2} & -SOC_0 & +e_1 & +e_2 & 0 \\ p_1.\Delta t & p_2.\Delta t & p_3.\Delta t & \leq & SOC_{max,3} & -SOC_0 & +e_1 & +e_2 & +e_3 \end{pmatrix} \tag{3.2.22}$$

<u>Constraint 3:</u> this constraint states that the SOC of the battery at the end of the optimization period should be the same as it was at the beginning.

$$SOC_0 = SOC_1 = SOC_n \tag{3.2.23}$$

By definition of equation (3.2.6) the term for SOC at the end of the period can be replaced:

$$SOC_0 = SOC_n = SOC_0 + \sum_{i=1}^{n} p_i.\Delta t - \sum_{i=1}^{n} e_i \tag{3.2.24}$$

And after subtracting the initial state of charge term from both sides of the equation we get:

$$\sum_{i=1}^{n} p_i.\Delta t = \sum_{i=1}^{n} e_i \tag{3.3.25}$$

Meaning that for optimization period, the sum of charged energy should be equal to the sum of driven energy:

$$p_1.\Delta t + p_2.\Delta t + p_3.\Delta t + \cdots + p_n.\Delta t = e_1 + e_2 + e_3 + \cdots + e_n \tag{3.2.26}$$

Note that equation (3.2.26) is only valid when considering the whole period and is not valid for temporal instances.

Boundaries: For decision variable X there are boundaries to be set, depending on the time availability to charge the vehicle, the maximum power available.

Vector $\boldsymbol{d}$ is the charging availability vector:

$$\bar{d} = \{d_1, d_2, d_3, \dots, d_i, \dots, d_n\} \qquad \forall\, i \in \{1,2,3, \dots, \mathrm{n}\} \tag{3.2.27}$$

where

$$d_i = \begin{cases} 0; & when\ charging\ is\ not\ posible \\ 1; & when\ charging\ is\ posible \end{cases} \tag{3.2.28}$$

To find vector $\boldsymbol{\bar{P}max}$ we will do the following operation:

$$\boldsymbol{\bar{P}max} = \hat{P}max.\bar{d} \tag{3.2.29}$$

where the scalar $\hat{P}max$ is the maximum available power to charge the BEV.

Finally setting lower and upper boundaries vectors for decision variable X:

$$0 < \bar{X} < P_{max,i} \;\; \forall\, i \in \{1,2,3, \dots, \mathrm{n}\} \tag{3.2.30}$$

$$\bar{X} = \{p_1, p_2, p_3, \dots, p_n\} \tag{3.2.31}$$

$$\overline{lb} = \{0,0,0, \dots, 0\} \tag{3.2.32}$$

$$\overline{ub} = \{p_{max,1}, p_{max,2}, p_{max,3}, \dots, p_{max,n}\} \tag{3.2.33}$$

So, our system will try to find a solution where:

$$\overline{lb} < \bar{X} < \overline{ub} \tag{3.2.34}$$

3.3 MATLAB & CPLEX Model Implementation

Section 3.3 will describe how the optimization was solver, which solver tool was used and how it was the solution implemented.

3.3.1 Linear programming and CPLEX

For the optimization done in this master thesis a mathematical solver was used and invoked from the main function in MATLAB. This solver developed by IBM, called CPLEX, specifies some prerequisites to use the solver. For the most basic mathematical programming formulation, which is known as Linear Programming (LP) and the one used in this model, the following parameters should be defined:

- a function to maximize or minimize:

$$\max \text{ (or min) } \bar{f}\,\bar{X} \tag{3.3.1}$$

- subject to

$$\bar{A}_{eq}\,\bar{X} = \bar{b}_{eq} \tag{3.3.2}$$

$$\bar{A}_{ineq}\,\bar{X} \leq \bar{b}_{ineq} \tag{3.3.3}$$

- with these bounds

$$\overline{lb} \leq \bar{X} \leq \overline{ub} \tag{3.3.4}$$

where A_{eq} and A_{ineq} are matrices, f, b_{eq}, b_{ineq}, lb and ub are vectors such that the upper bounds ul and lower bounds lb may be positive infinity, negative infinity, or any real number.

Finally, when the mathematical model is written and adapted to CPLEX prerequisites it can be introduced into MATLAB for proper solving. Basically, find the variables, matrices and vectors as described on the next section.

3.3.2 Objective function coefficients, matrices and vectors

Objective function coefficients

If we look at equation (3.2.7) we can easily state that our objective function is:

$$\min\ \bar{C}^{\,T}\bar{X}\,\Delta t \qquad (3.2.7)$$

being in this particular case

$$\bar{f} = \bar{C}^{\,T}\,\Delta t \qquad (3.3.5)$$

Matrices $\boldsymbol{A_{ineq}}$ and $\boldsymbol{b_{ineq}}$

Constraints 1 and 2 which set the lower and upper limits of the vehicle's SOC are inequalities which can be written in the form of equation (3.3.3). For Constraint 1 we will start with equation (3.2.16):

$$\begin{pmatrix} -p_1.\Delta t & 0 & 0 & \leq & -SOC_{min,1} & +SOC_0 & -e_1 & 0 & 0 \\ -p_1.\Delta t & -p_2.\Delta t & 0 & \leq & -SOC_{min,2} & +SOC_0 & -e_1 & -e_2 & 0 \\ -p_1.\Delta t & -p_2.\Delta t & -p_3.\Delta t & \leq & -SOC_{min,3} & +SOC_0 & -e_1 & -e_2 & -e_3 \end{pmatrix} \qquad (3.2.16)$$

$$\begin{pmatrix} -\Delta t & 0 & 0 \\ -\Delta t & -\Delta t & 0 \\ -\Delta t & -\Delta t & -\Delta t \end{pmatrix}.\begin{pmatrix} p_1 \\ p_2 \\ p_3 \end{pmatrix} \leq \begin{pmatrix} -SOC_{min,1} & +SOC_0 & -e_1 & 0 & 0 \\ -SOC_{min,2} & +SOC_0 & -e_1 & -e_2 & 0 \\ -SOC_{min,3} & +SOC_0 & -e_1 & -e_2 & -e_3 \end{pmatrix} \qquad (3.3.6)$$

$$-\Delta t.\begin{pmatrix} 1 & 0 & 0 \\ 1 & 1 & 0 \\ 1 & 1 & 1 \end{pmatrix}.\begin{pmatrix} p_1 \\ p_2 \\ p_3 \end{pmatrix} \leq \left[\begin{pmatrix} -SOC_{min,1} & +SOC_0 \\ -SOC_{min,2} & +SOC_0 \\ -SOC_{min,3} & +SOC_0 \end{pmatrix} - \begin{pmatrix} 1 & 0 & 0 \\ 1 & 1 & 0 \\ 1 & 1 & 1 \end{pmatrix}.\begin{pmatrix} e_1 \\ e_2 \\ e_3 \end{pmatrix}\right] \qquad (3.3.6)$$

And for Constraint 2 we will be using equation (3.2.22):

$$\begin{pmatrix} p_1.\Delta t & 0 & 0 & \leq & SOC_{max,1} & -SOC_0 & +e_1 & 0 & 0 \\ p_1.\Delta t & p_2.\Delta t & 0 & \leq & SOC_{max,2} & -SOC_0 & +e_1 & +e_2 & 0 \\ p_1.\Delta t & p_2.\Delta t & p_3.\Delta t & \leq & SOC_{max,3} & -SOC_0 & +e_1 & +e_2 & +e_3 \end{pmatrix} \quad (3.2.22)$$

$$\begin{pmatrix} \Delta t & 0 & 0 \\ \Delta t & \Delta t & 0 \\ \Delta t & \Delta t & \Delta t \end{pmatrix} . \begin{pmatrix} p_1 \\ p_2 \\ p_3 \end{pmatrix} \leq \begin{pmatrix} SOC_{max,1} & -SOC_0 & +e_1 & 0 & 0 \\ SOC_{max,2} & -SOC_0 & +e_1 & +e_2 & 0 \\ SOC_{max,3} & -SOC_0 & +e_1 & +e_2 & +e_3 \end{pmatrix} \quad (3.3.7)$$

$$\Delta t. \begin{pmatrix} 1 & 0 & 0 \\ 1 & 1 & 0 \\ 1 & 1 & 1 \end{pmatrix} . \begin{pmatrix} p_1 \\ p_2 \\ p_3 \end{pmatrix} \leq \left[\begin{pmatrix} SOC_{max,1} & -SOC_0 \\ SOC_{max,2} & -SOC_0 \\ SOC_{max,3} & -SOC_0 \end{pmatrix} + \begin{pmatrix} 1 & 0 & 0 \\ 1 & 1 & 0 \\ 1 & 1 & 1 \end{pmatrix} . \begin{pmatrix} e_1 \\ e_2 \\ e_3 \end{pmatrix} \right] \quad (3.3.8)$$

Since Constraints 1 and 2 are both inequations they should be summed up into one equation system, combining equations (3.3.6) and (3.3.8):

$$\Delta t. \begin{pmatrix} -1 & 0 & 0 \\ 1 & 0 & 0 \\ -1 & -1 & 0 \\ 1 & 1 & 0 \\ -1 & -1 & -1 \\ 1 & 1 & 1 \end{pmatrix} . \begin{pmatrix} p_1 \\ p_2 \\ p_3 \end{pmatrix} \leq \left[\begin{pmatrix} -SOC_{min,1} & +SOC_0 \\ SOC_{max,1} & -SOC_0 \\ -SOC_{min,2} & +SOC_0 \\ SOC_{max,2} & -SOC_0 \\ -SOC_{min,3} & +SOC_0 \\ SOC_{max,3} & -SOC_0 \end{pmatrix} + \begin{pmatrix} -1 & 0 & 0 \\ 1 & 0 & 0 \\ -1 & -1 & 0 \\ 1 & 1 & 0 \\ -1 & -1 & -1 \\ 1 & 1 & 1 \end{pmatrix} . \begin{pmatrix} e_1 \\ e_2 \\ e_3 \end{pmatrix} \right]$$

which is equivalent for the inequation required:

$$\bar{A}_{ineq}\,\bar{X} \leq \bar{b}_{ineq} \quad (3.3.3)$$

Matrices $\boldsymbol{A_{eq}}$ and $\boldsymbol{b_{eq}}$

Using the same procedure, we will find these matrices from Constraint 3, which instead of an inequation represents an equation. From equation (3.2.26)

$$p_1.\Delta t + p_2.\Delta t + p_3.\Delta t + \cdots + p_n.\Delta t = e_1 + e_2 + e_3 + \cdots + e_n \qquad (3.2.26)$$

we can define a system to find $\boldsymbol{A_{eq}}$ and $\boldsymbol{b_{eq}}$:

$$(\Delta t \quad \Delta t \quad \Delta t).\begin{pmatrix} p_1 \\ p_2 \\ p_3 \end{pmatrix} = (e_1 + e_2 + e_3) \qquad (3.3.9)$$

$$\overline{A}_{eq}\ \overline{X} = \overline{b}_{eq} \qquad (3.3.2)$$

3.4 Linear optimization problem summary

Optimizations problems are usually presented as a function to find a maximum or minimum and its constraints. For this model, the system can then be defined by:

$$\min\ \bar{C}^{\,T}.\bar{X}.\Delta t \tag{3.2.7}$$

Subject to

$$\bar{A}_{eq}\,.\bar{X} = \bar{b}_{eq} \tag{3.3.2}$$

$$\bar{A}_{ineq}\,.\bar{X} \leq \bar{b}_{ineq} \tag{3.3.3}$$

$$\overline{lb} \leq \bar{X} \leq \overline{ub} \tag{3.3.4}$$

As it was mentioned in section 2.4, this analysis was done with the support of different scientific papers which addressed the same problem. Although these papers didn’t use the same terminology and didn’t explain with full details how to write the mathematical model, they did share a vision on how to solve the problem, using X as charging power or charging energy, multiplying power vector X [W] by the time slot Δt [h], obtaining energy [Wh] (Hu et al., 2011) and (Sundstřom & Binding, 2010), and using also constraints for the availability to drive the next trip and the maximum SOC of the battery.

3.5 Source code and hardware

The source code described in this master thesis was all written for this purpose, except for the function to solve the optimization, which was developed by IBM and will not be discussed in this work. The first milestone in the code development was to find an optimal charging schedule for one profile for a one-week period, since the input profiles data were provided also for a one-week period. This function it is called "*optimize_week*" and its purpose is to find the minimal cost charging schedule that would allow the driver to drive its required trips. It receives as an input a certain profile which is identified by its unique identifier, a one-week price series, and the initial SOC of the battery. With the identifier, the model would get from the data the curves for SOC_{max} and SOC_{max}, mentioned in sections 3.1.1 and 3.1.2. With all this information, this function can build matrices $\boldsymbol{A_{eq}}$, $\boldsymbol{A_{ineq}}$, $\boldsymbol{b_{eq}}$, $\boldsymbol{b_{ineq}}$, and vectors $\boldsymbol{f}$, $\boldsymbol{lb}$ $\boldsymbol{ub}$. Finally, using these variables as input parameters it invokes the function "*cplexlp*" and get as an output the charging vector **X** for this particular profile, this price-series and this initial SOC. The charging vector **X**, which is the solution the solver provides when the system is feasible, consists of a vector which indicates the charging power for every time slot in the simulated period, 0 when it is not charging and a value between 0 and 3.7 when it is.

Subsequently, the following milestone in the development of the code was to find this same solution for a one-year period, and it was simply resolved by iterating 52 times the "*optimize_week*" function, but considering two aspects: firstly, the SOC at the end of one week would be the SOC at the beginning of the next one, and secondly, since the price series input data was given for the whole year, a week within this year-vector should be selected and would change for every iteration. This second function it's called "*optimize_year*".

Finally, once the model was able to find the optimal solution for one profile the last step was to find the same solution for all the remaining profiles in the data set. And once again, this was done with an iteration among all the profiles, this is, 2120 times.

Since the source code for this master's thesis was developed as described in the previous paragraph, as a result of the development of the model and the source code, 4 scripts and 3 additional functions are presented. Each of these scripts serves to analyse the data in the following way, divided by amount of profiles and simulated time period:

- Script № 1: 1 profile – 1 week
- Script № 2: 1 profile – 1 year
- Script № 3: 2120 profiles – 1 week
- Script № 4: 2120 profiles – 1 year

Even though the scripts were written for those purposes, the number of profiles simulated can vary from 1 to 2120 in scripts 3 and 4, and the number of weeks simulated can vary from 1 to 52 in scripts 2 and 4. This was the best way to develop the code since the results shown and the variables analysed can change from script to script, and it is really advantageous to be able to change the number of profiles used or the week in the year which wants to be simulated. The results shown in the following section will follow the same structure as the scripts described. The code written as part of this master thesis can be founded in the institute's repository BW Sync and Share.

The hardware used to develop the model and for the further simulations was a Lenovo Thinkpad T460 with the following technical specifications:

- Processor: Intel ® Core ™ i5-6200 CPU @ 2.30 GHz
- Installed memory (RAM): 16,0 GB
- System type: 64-bit Operating System
- Operative System: Windows 7 Professional

4 Results

Before discussing the results obtained in the simulation, it is important to emphasize why not all the input data could be exploited. The profiles that were used represent the behavior of real users with ICEV, and some of these users made trips that could be considered long for a BEV, since the autonomies of current BEV are considerably lower than those of ICEV, i.e., those profiles with long trips cannot be used as valid profiles. During the process of simulation of the 2120 profiles used, some of them presented inconsistent values for some parameters, such as the battery capacity and therefore had to be discarded. Finally, of the profiles that had consistent data, some users had not driven any kilometers during the week the data was acquired, hence there is nothing to optimize and the result of the simulation is an empty vector. The corresponding detail of used profiles can be seen in Table 2.

	Number of profiles	%
Input Profiles	**2,120**	**100%**
Useful Profiles	**1,397**	**66%**
Non-useful Profiles	**723**	**34%**
Inconsistent input data	160	8%
Profiles that were not driving	411	19%
Non-feasible profiles	152	7%

Table 2. *Overview of the profiles used for the simulation.*
Own source.

Then again, there are also some cases of those profiles who, although their trips are not relatively long, do not have enough time during their stops to charge the battery, resulting in the simulation in an unfeasible profile. This means that the model cannot find such a solution that the car is charged to meet its travel requirements, even if it is spending more money on charging. These both cases were also mentioned in another publications such as (Flath et al., 2014, p. 622).

Certainly, these two cases and their occurrence depend on the size of the battery used for modeling, and in this case was chosen the value of 22 kWh. Finally, it is also worth mentioning that within the profiles used there are some users who have not used the car and therefore their record of kilometers traveled, and energy used to move is 0, resulting also in 0 € costs as a result.

4.1 One-week single vehicle optimization

As mentioned in the previous section, the first objective of the model was to solve the optimization problem for a short-term period, so it is relevant to show some results in the short term also. As an example, the results for profile number 6 are displayed (figures 8, 9 and 10), for different SOC initial values for a one week period optimization. As it can be seen in the following figures, this parameter is decisive to the determination of the charging vector and the corresponding SOC curve. The first graph shows the curves for the optimizations lower and upper boundaries (SOC_{max} for ASAP strategy and SOC_{min} for ALAP strategy), and the SOC curve for the resulting optimization or a controlled charging mode, also called smart charging (SMART strategy). For these three curves the behaviour it is the same: if the slope is positive, the SOC value is rising therefore the BEV battery is receiving energy, if the slope is negative the SOC value is decreasing which means the vehicle is driving and if there is no slope the SOC value remains the same, hence the vehicle is parked and not charging. On the second graph of this series, a bar plot shows when the BEV is charging, and the power used to charge it. The charging bars also represent energy, since power by time its energy, so when the slope is positive on the upper graph (energy vs. time), a bar should be on the same time slot on the lower graph (power vs. time).

Results for an initial SOC = 2.66 kWh

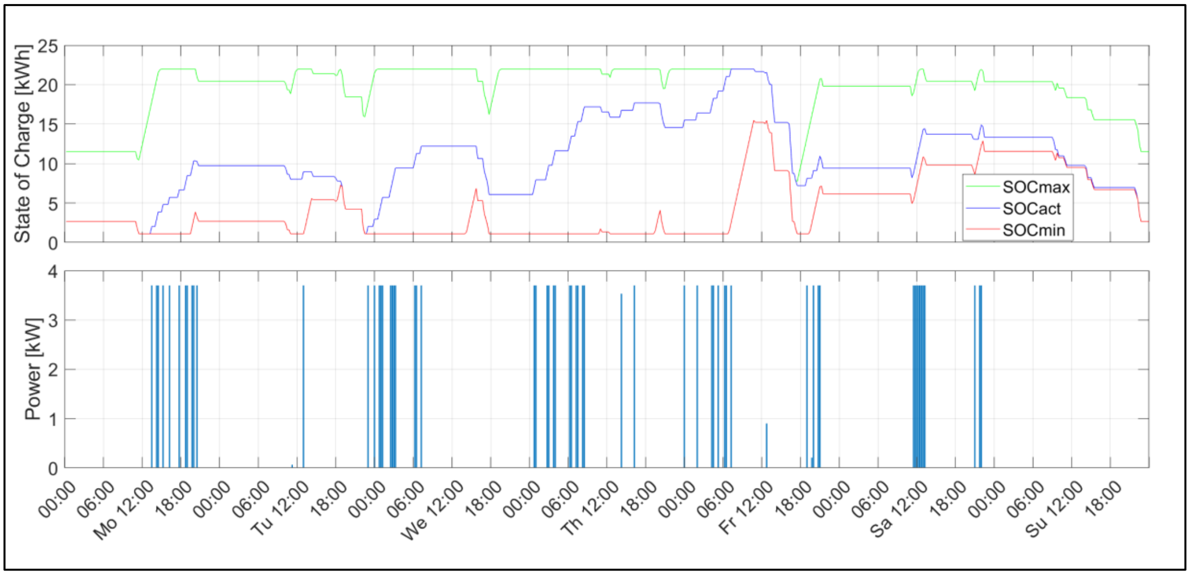

Fig. 8. *SOC curves for profile 6 and the corresponding charging bar plot for an SOC initial value of 2.66 kWh (12%). Own source.*

Results for an initial SOC = 7.09 kWh

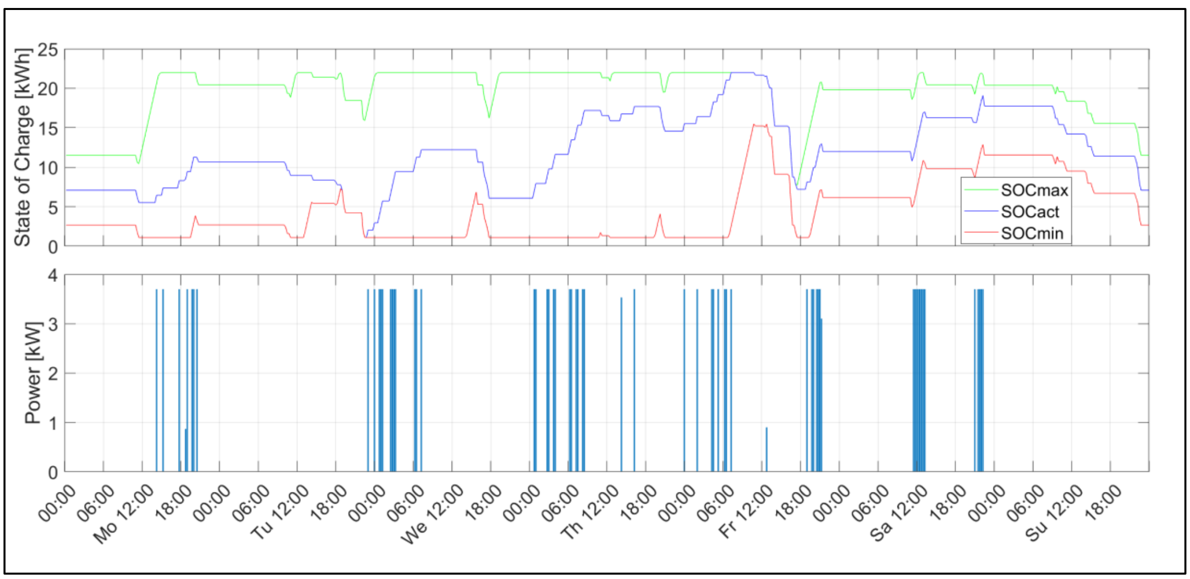

Fig. 9. *SOC curves for profile 6 and the corresponding charging bar plot for an SOC initial value of 7.09 kWh (32%). Own source.*

Results for an initial SOC = 11.51 kWh

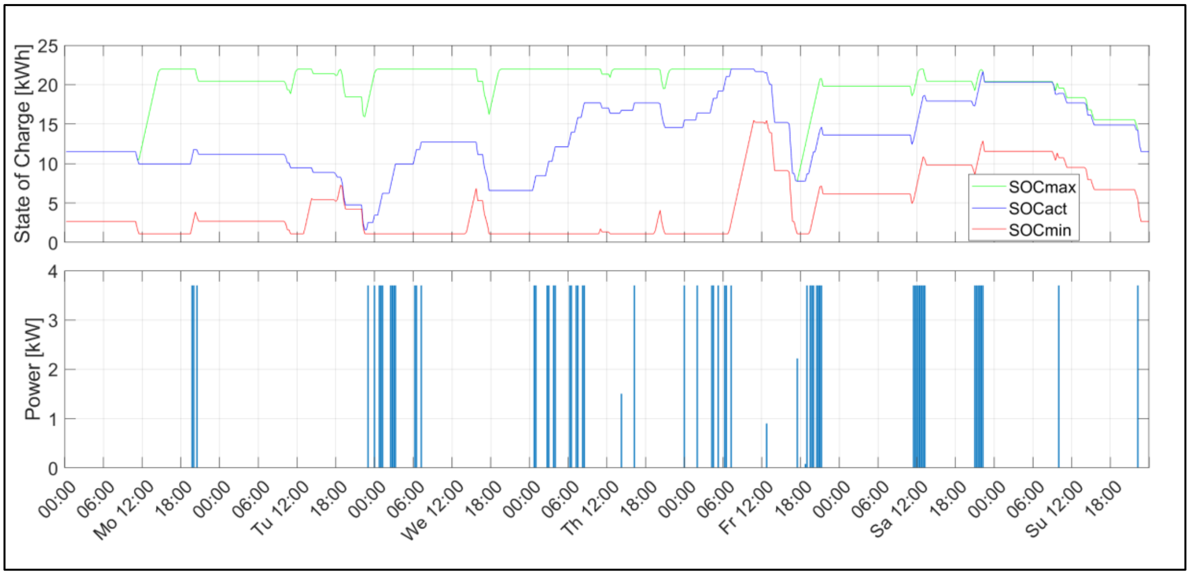

Fig. 10. *SOC curves for profile 6 and the corresponding charging bar plot for an SOC initial value of 11.51 kWh (52%). Own source.*

Simulation Parameters:			
Initial State of Charge [%]	12	32	52
Initial State of Charge [kWh]	2.66	7.09	11.51
Energy driven in simulated period [kWh]	57	57	57
Kilometers driven in simulated period [km]	378	378	378
Charging Manager Expenditures (single vehicle):			
SMART [€]	-0.15	0.03	0.25
ASAP [€]	1.50	1.50	1.50
Charging Manager Expenditure Savings (single vehicle):			
Net savings SMART vs ASAP [€]	1.65	1.47	1.25
Percentage savings SMART vs ASAP [%]	110	98	83

Table 3. *Parameters and results obtained from the 3 simulations. Own source.*

For this three cases the constraints for the optimization are the same: SOC curves and availability vector, but charging vector and corresponding expenditures results are different when intial conditions differ. As it can be seen on table 3, for lower initial SOC values greater are the savings for the charging manager. The results suggests that when the initial SOC of the BEV is low, the solver has more flexibility to allocate future charging events, and consequently find a schedule with lower prices. But beyond the differences of the results obtained for different initial condition values, the most significative result are the savings for the charging manager, which in this case oscillate between 83% and 110%, being for the last scenario negative net savings, i.e., the charging manager is getting paid for charging this particular vehicle. The savings expresed in the results are always comparing the SMART strategy versus the ASAP strategy, since SMART would represent the controlled charging mode and ASAP the uncontrolled charging mode.

In the following graph (figure 11) it is shown that the software allocates the charging events in the time slots where prices are low, and even some time slots where prices are negative. On the upper graph the price series for a week are shown in red marks, along with the available charging time slots for the BEV in grey. On the bottom graph, the blue bars show how every charging events were allocated, finding the minimum prices in the grey time windows. Lower prices can be found outside of the grey time windows, but during this time the vehicle is wheter driving or parked but no available for charging.

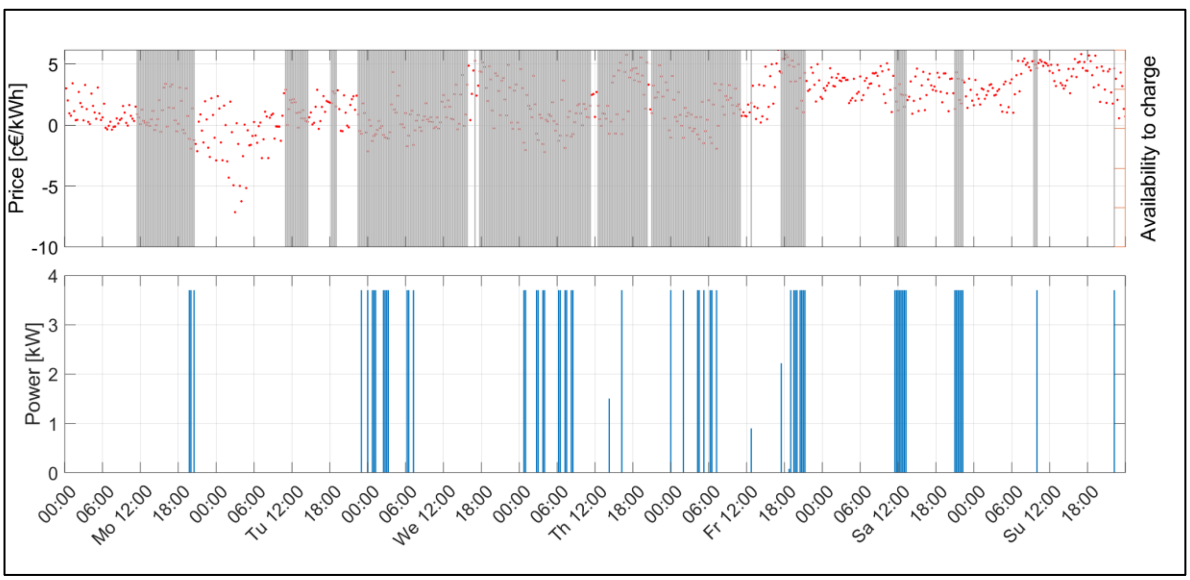

Fig. 11. *Allocating charging events. Own source.*

4.2 One-year single vehicle optimization

In the same way the software could find an optimal charging schedule for a single vehicle for a one-week time period, in this second analysis a whole year was simulated. To do this, as explained in the previous section, a script with 52 iterations was developed, and for each iteration a one week optimization was solved, but with one important consideration. By the end of each optimization, to accurately begin with the next one, the last value of the vehicle's SOC should be saved and used to begin the next simulation period as the initial SOC value. This way, the SOC for the simulated profile would have continuity between simulated weeks. In section 3.2.2 the constraints for the optimization problem were introduced, and Constraint 3 stated that the SOC at the end of the simulation period should be the same as it was at the beginning of the period, expressed by equation 3.2.23:

$$SOC_0 = SOC_1 = SOC_n \tag{3.2.23}$$

which later introduced the constraint-equation 3.3.2. Finally, to let the vehicle's SOC value freely fluctuate this constraint-equation was suppressed of the optimization problem. The first two weeks of the simulation of profile 6 are shown below (figures 12 and 13).

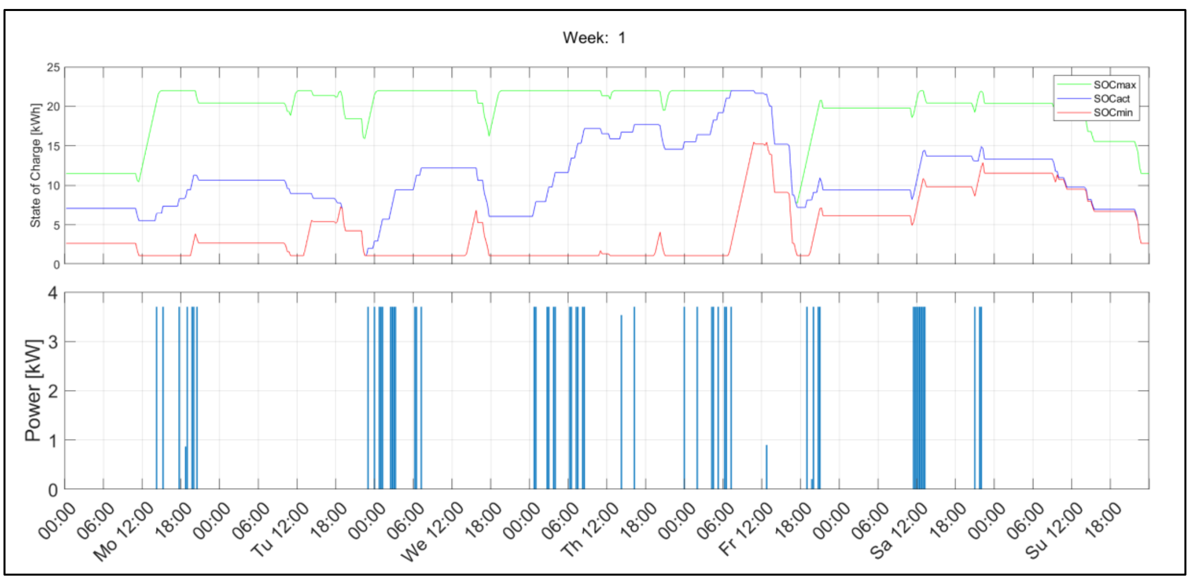

Fig. 12. *Week number 2 of optimization of profile 6. Own source.*

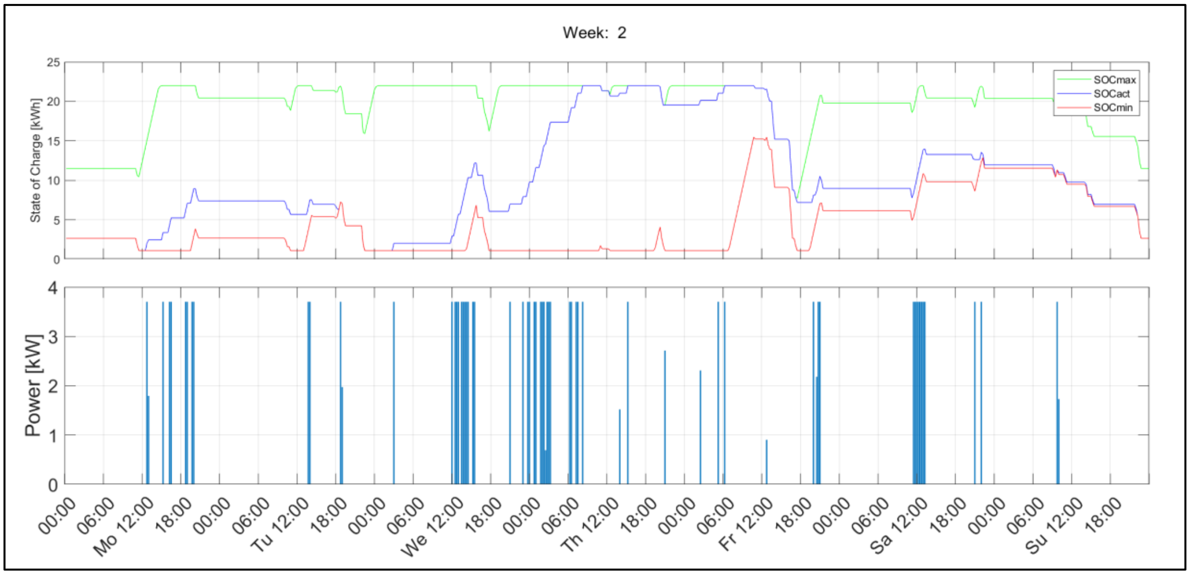

Fig. 13. *Week number 2 of optimization of profile 6. Own source.*

As the SOC graph on figure 13 shows, week number 2 begins with the SOC value of the end of simulation of week 1, which in this case is $SOC_{week\ 1,n} = SOC_{week\ 2,1} = 2.66\ kWh$. Although for reasons of simplicity only two simulations are shown here, when the whole year was simulated it could be clearly noticed from every simulation that the SOC always dropped to the minimum value by the end of the simulation period. When the solver notices that the vehicle does not require energy for driving, since it is trying to minimize expenditures, it will simply not allocate any more charging events, and only charge the minimum energy required to finish the remaining trips.

Regarding the economic savings for this particular profile for the year simulation, the results show that the charging manager could save up to 71% in charging energy expenditures with the controlled charging mode versus the uncontrolled mode (SMART vs. ASAP) (Table 4).

Simulation Parameters:	
Initial State of Charge [%]	32
Initial State of Charge [kWh]	7.09
Energy driven in simulated period [kWh]	2,947
Kilometers driven in simulated period [km]	19,648
Charging Manager Expenditures (single vehicle):	
SMART [€]	34.87
ASAP [€]	119.29
Charging Manager Expenditure Savings (single vehicle):	
Net savings SMART vs ASAP [€]	84.42
Percentage savings SMART vs ASAP [%]	71
Expenditures per km driven:	
SMART [c€/km]	0.20
ASAP [c€/km]	0.61

Table 4. *Parameters and results obtained from the simulation of profile 6 for a one-year period. Own source.*

4.3 One-week fleet optimization

After getting positive results for the single vehicle optimization, whether for a week or a year, the simulation could be further tested for more than one vehicle and eventually tested for all the profiles available. With the written script for this section, the week to be simulated could be chosen from the 2015 year period, by setting a value between 1 and 52, and with this possibility, the expenditure savings for the whole fleet can be compared between to different weeks of the year, which was the case.

Two specific weeks were selected: the one with the lowest price and the one with the highest price in the year.

- Week 14: on Saturday 11/04/2015 00:45 intraday price was 1 kWh = -0.117 €
- Week 26: on Friday 03/07/2015 09:30 intraday price was 1 kWh = 0.236 €

In figures 14 and 15 the price series for these both weeks are shown with their corresponding aggregated load profile for the 1397 vehicle's fleet. Again, it can be seen that charging events are allocated in time slots where prices decrease, responding accurately to these signals how the software it is intended to do, for instance figure 15 illustrates that when the price peaked on Friday 03/07/2015 at 09:30 in the morning, no charging events were scheduled. On the contrary, in figure 14, when the price decreased on Saturday 11/04/2015 00:45 several vehicles were scheduled to charge during this interval, generating a consumption peak. As a consequence, when comparing SMART charging mode with ASAP charging mode, the distribution of charging events it is rarely unequal as figures 15 and 16 depict. On the one side the ASAP strategy shows that the magnitude of the aggregated charging power events can oscillate between 0 and 1 MW, and these events are distributed from 06:00 in the mornings to midnight (00:00) almost in a continuous way, and with consuming peaks around 08:00 in the morning and 18:00 in the evening, and almost no consumption during the night hours, and this pattern may be caused by the behaviour of the drivers, i.e., charging the vehicle as soon as they get to their home or workplace. On other side the SMART strategy shows that the magnitude fluctuates between 0 and 5 MW, but its dispersion through time it is quite irregular, although some remarks can be made.

Week 14:

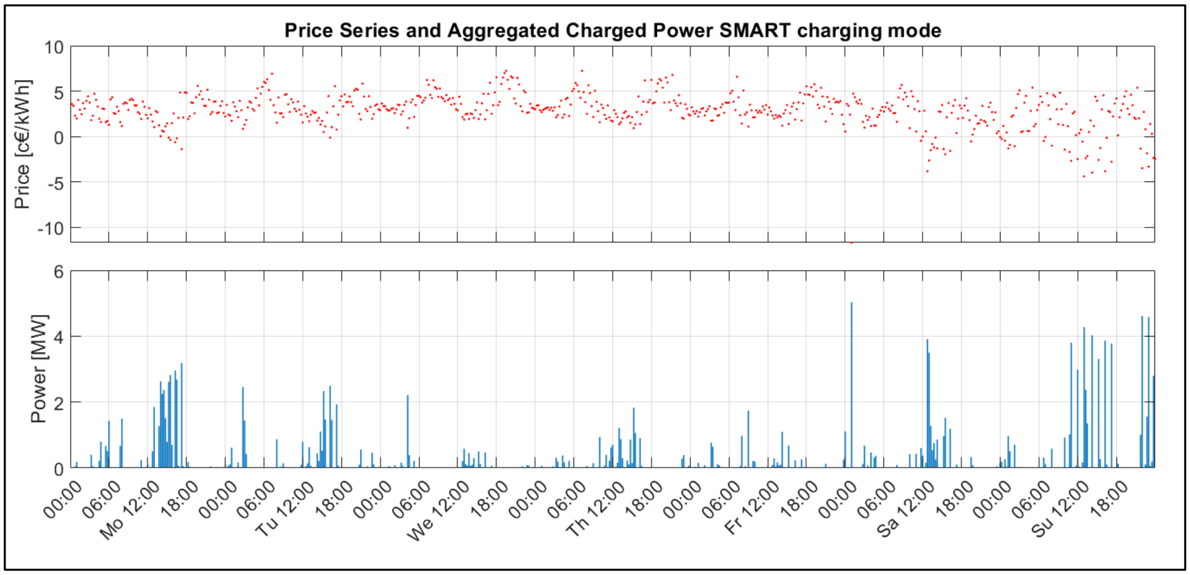

Fig. 14. *Prices series for week number 14 and aggregated load profile of 1397 vehicles fleet. Own source.*

Week 26:

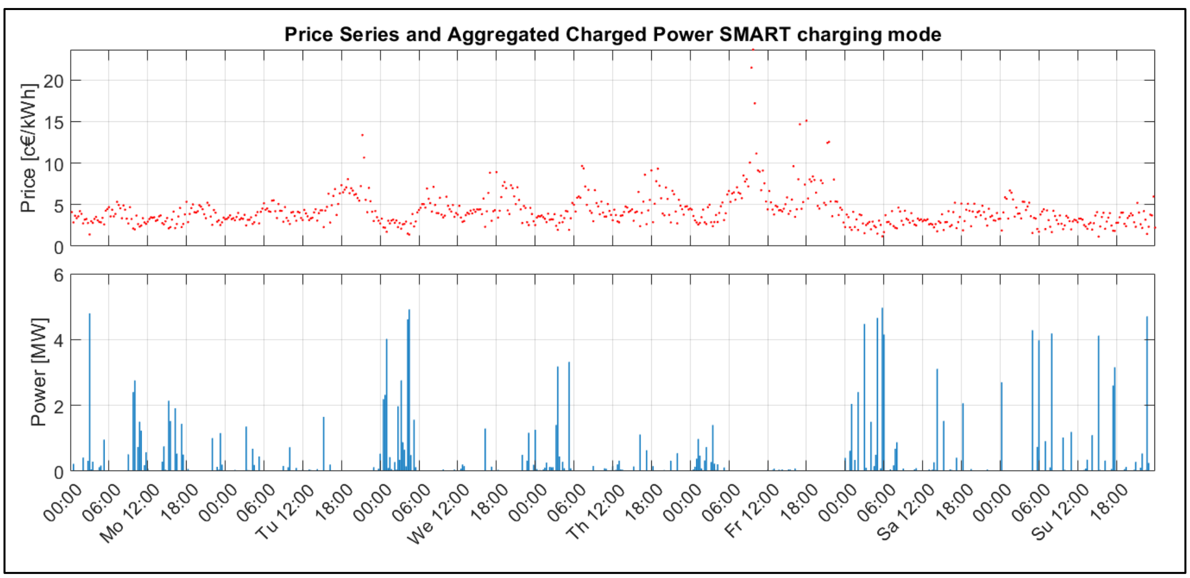

Fig. 15. *Prices series for week number 26 and aggregated load profile of 1397 vehicles fleet. Own source.*

This irregular distribution could be determined by the price instability and dispersion, even if it does show a pattern during the day in which prices are high during the morning and the evening, prices can vary rapidly from one moment to another in a big scale, causing a non-continuous charging process when SMART charging mode is used. Yet, the most relevant factor when comparing these two strategies is the magnitude of the charging power which in this case it is 5 times higher for SMART than for ASAP charging mode. When SMART strategy is used, all of the vehicles in this fleet are receiving the same price signals, and although their availability to charge may differ, it is highly likely that if the prices decrease and several vehicles are available to charge, they will be charged simultaneously, generating a peak consumption. This effect was already been noticed and identified in (Ensslen et al., 2018, pp. 112–113) as "*avalanche effect*" and also by (Flath et al., 2014, p. 620): "*our results show that EV charging coordination solely based on an exogenous price signals gives raise to large aggregate load spikes*". Further comments on the impacts and consequences of the SMART charging method will be discussed on Section 5.

From figures 16 and 17 it can also be observed that ASAP strategy load profile has consumption valleys during the night during which there is almost no consumption and a valley during the day between the morning and evening peaks. In contrast, SMART strategy does schedule charging events mostly during these two mentioned valleys. To illustrate this behaviour, these loading profile graphs were re-designed to present a clearer contrast between these two charging strategies, by aggregating the power by daily time slot and by discriminating the week day from the weekend day. The results are presented in figures 18 and 19 showing daily loading profiles and in figures 20 and 21 as percentage of number of charging events per time slot. From observing figure 18 we can affirm that during the week 14, great number of charging events occurred during the midday valley, assuming that during this week of the year prices were low from 12:00 to 16:00. On the other hand, for week 26 the charging events took place during the night hours, principally from 00:00 to 06:00 and even though a relationship with weather data has not been made, these differences between these two weeks could be adjudicated to weather and the influence of RES.

Week 14:

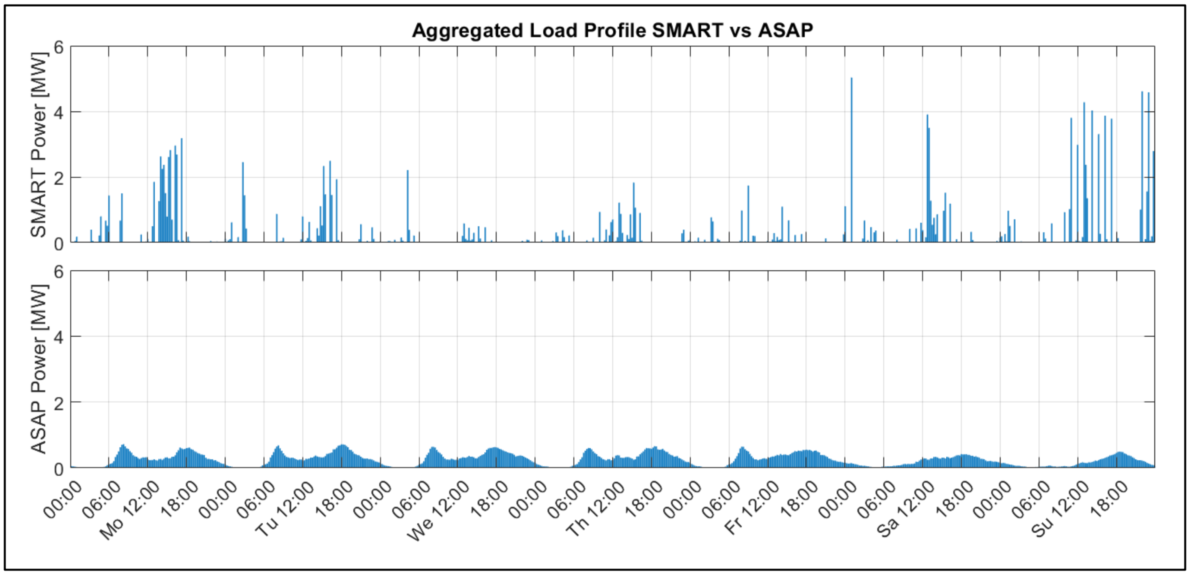

Fig. 16. *Aggregated load profiles for SMART strategy vs ASAP strategy for week 14. Own source.*

Week 26:

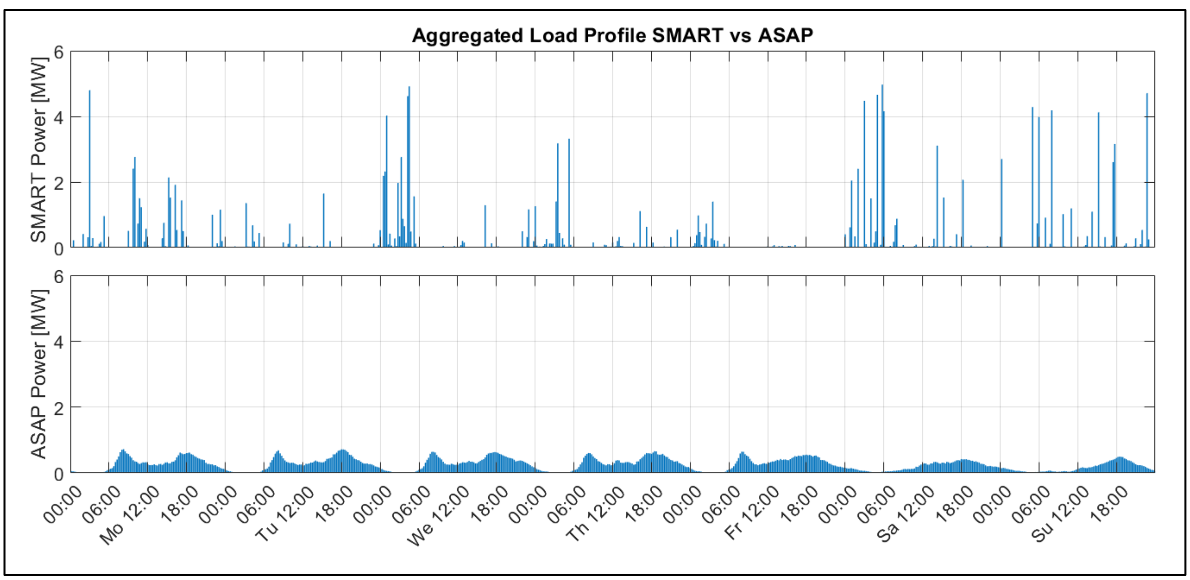

Fig. 17. *Aggregated load profiles for SMART strategy vs ASAP strategy for week 26. Own source.*

In relation to the difference between week day and weekend day, it can be enounced that during the weekend prices are more unstable or volatile and charging allocation could happen any time, with no particular pattern as it was founded for the week day.

<u>Week 14:</u>

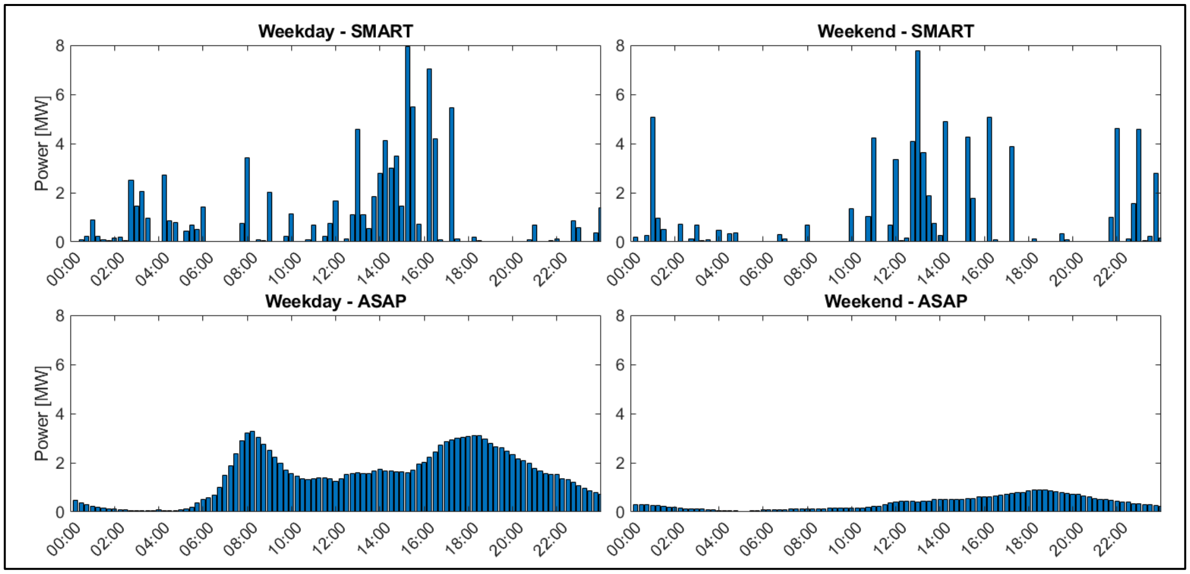

Fig. 18. *Aggregated load profiles for week 14, discriminating the weekday from the weekend, for SMART strategy vs ASAP strategy. Own source.*

<u>Week 26:</u>

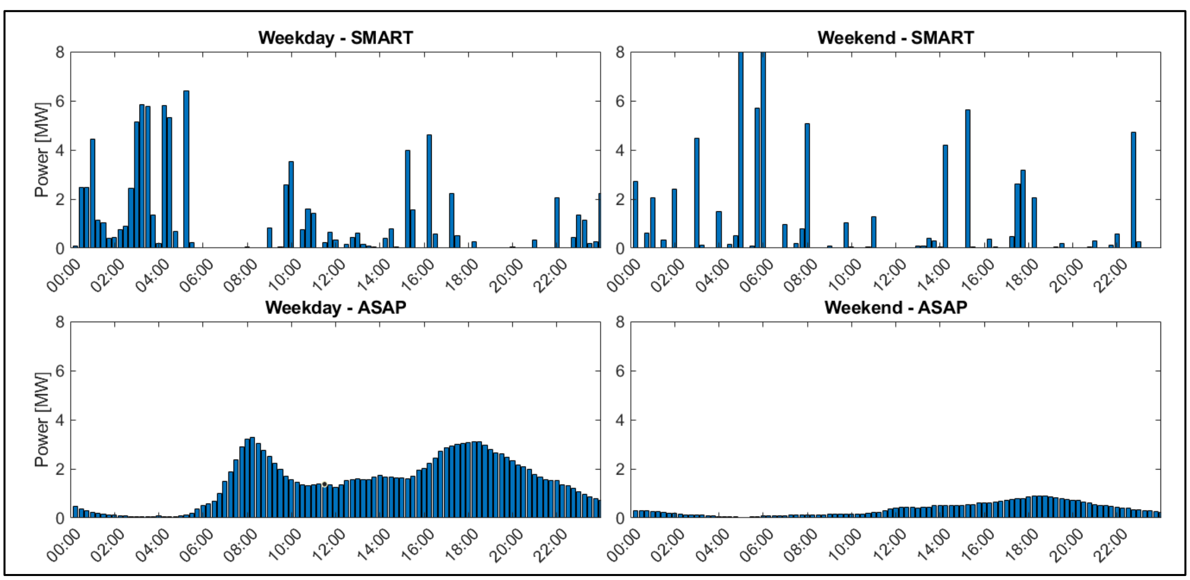

Fig. 19. *Aggregated load profiles for week 26, discriminating the weekday from the weekend, for SMART strategy vs ASAP strategy. Own source.*

Week 14:

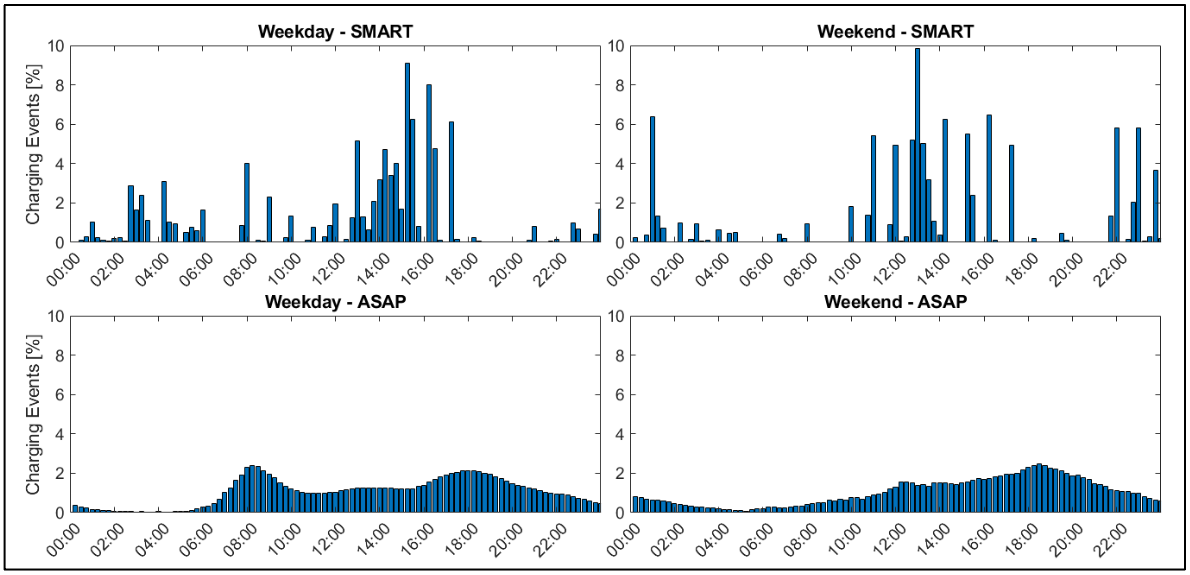

Fig. 20. *Charging events distribution for week 14, discriminating the weekday from the weekend, for SMART strategy vs ASAP strategy. Own source.*

Week 26:

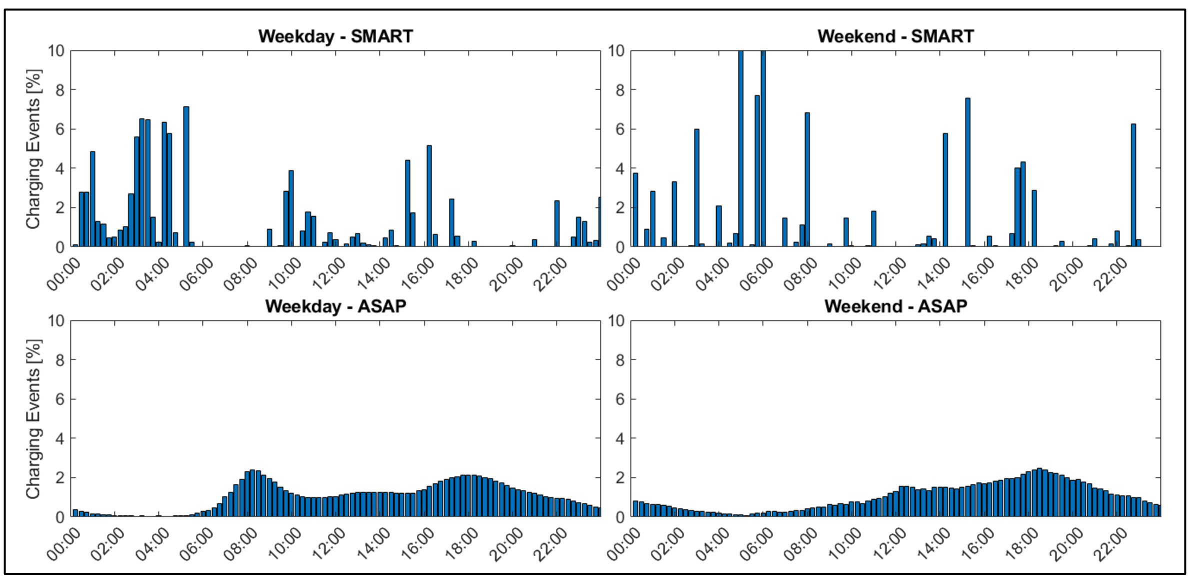

Fig. 21. *Charging events distribution for week 26, discriminating the weekday from the weekend, for SMART strategy vs ASAP strategy. Own source.*

Finally, and to address the research questions proposed in this master thesis, the economic savings for these two scenarios are going to be analysed, but in this opportunity as a fleet. In the following table (table 5) the results for the expenditures for this simulation are exposed.

Simulation Parameters:		
Week number simulated	14	26
Profiles simulated	1,397	1,397
Energy driven in simulated period for the fleet[kWh]	40,732	40,732
Kilometers driven in simulated period for the fleet [km]	271,546	271,546
Charging Manager Expenditures (CME) (fleet):		
SMART [€]	-372	830
ASAP [€]	1,367	2,104
Charging Manager Expenditure Savings (fleet):		
Net savings SMART vs ASAP [€]	1,739	1,274
Percentage savings SMART vs ASAP [%]	127%	61%
CME per km driven:		
SMART [c€/km]	-0.14	0.31
ASAP [c€/km]	0.50	0.77

Table 5. *Parameters and results obtained from the fleet simulation for weeks number 14 and 26. Own source.*

In this case it can be observed that for these two weeks the results were quite disparate. Firstly, for week 14 the total expenditures were negative, which means that the prices for this week have been low, and for week 26 they were positive, therefore, the prices have been generally higher than those of week 14, since for both simulations the kilometers traveled and the availability to charge each vehicle are the same. As for the net savings, the difference was greater for week 14, but it can be seen more clearly if the percentage variation is analyzed with respect to the ASAP charging mode, being more than double for week 14 with respect to week 26. Finally, to mention the performance indicator of kilometers traveled per euros spent, then again there is an important difference between both weeks for SMART mode (0.45 c€/km), but not so much for ASAP mode (0.27 c€/km). This indicator will be analyzed in more detail in the next results section.

4.4 One-year fleet optimization

In order to obtain a broader picture of the research relevant to this study and considering that the price of electricity can vary according to the climatic conditions of different seasons of the year, it was crucial to simulate a full year. Considering that the fleet is composed of 1397 profiles (without taking into account those that were not useful for this work), that the year is composed of 52 weeks and that each optimization solves one profile for one week, the corresponding script for this section solves 72,644 optimizations, so it is a process that can demand a considerable time, depending on the specifications and the computing power of the equipment used to simulate.

By observing table 6 we can discern that the savings were quite significant, since the expenses of the load manager for the ASAP charging mode were 79,356 € while for the SMART mode only 5,565 €, representing a saving of 73,791 € (93%). Although this data is conclusive and enough to state that one method is significantly cheaper than the other, it is also worth analyzing these same variables throughout the 52 weeks of the year.

Simulation Parameters:	
Weeks simulated	52
Profiles simulated	1,397
Fleet's driven distance [km]	14,140,618
Vehicle average driven distance [km]	10,122
Charging Manager Expenditures (CME) (fleet):	
SMART [€]	5,565
ASAP [€]	79,356
Charging Manager Expenditure Savings (fleet):	
Net savings SMART vs ASAP [€]	73,791
Percentage savings SMART vs ASAP [%]	93
CME per km driven:	
SMART [c€/km]	0.04
ASAP [c€/km]	0.56

Table 6. *Parameters and results obtained from the 1 year simulation for the 1397 vehicles fleet. Own source.*

For this purpose, the following graph is presented which illustrates the expenditures of the two methods for each of the simulated weeks. As can be seen from figure 22, the costs of the ASAP method range between approximately 700 and 2,000 € per week, while for the SMART method the same values range between -2,000 and 1,000 € per week, which means an amplitude of more than double. This confirms the idea that SMART spending can be unpredictable and highly variable.

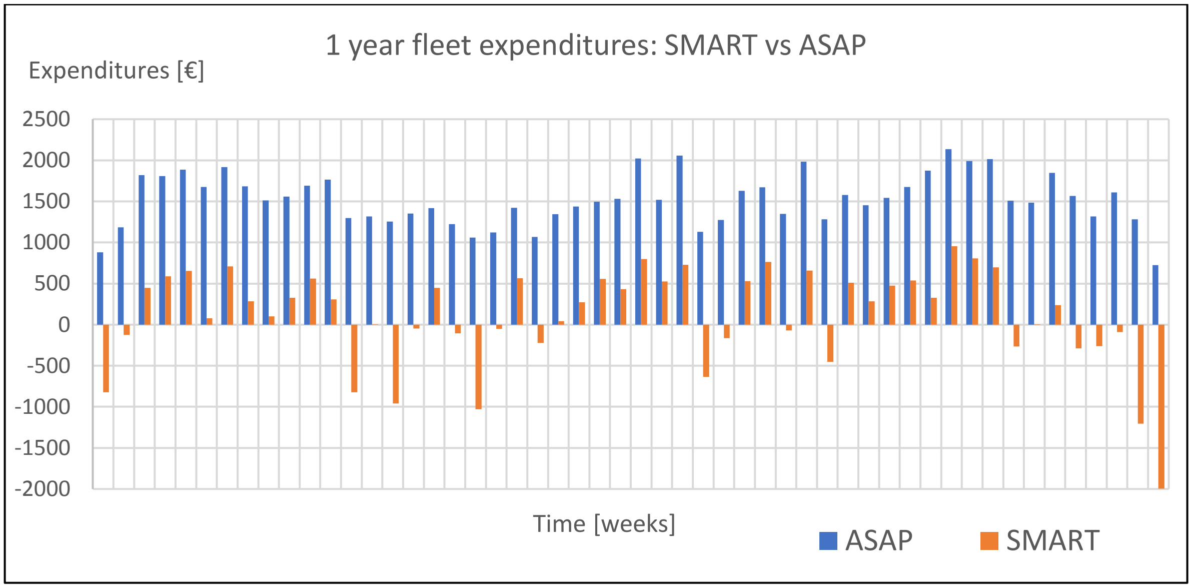

Fig. 22. *Charging manager expenditures for 1 year by two charging modes: ASAP and SMART. Own Source*

To further analyse this behaviour, the annual average performance indicator was calculated for all vehicles and their distribution. The average values can be seen in table 6, and the distributions graphs in figures 23 and 24, for ASAP and SMART respectively. The ASAP mode distribution graph suggests that, although driving profiles are very diverse because they drive different distances and their availability for charging the EV is not the same, their performances are quite similar. However, the graph of the SMART mode distribution does not suggest the same, but can vary quite a bit depending on the driving profile. This can be attributed to the fact that the savings produced by the SMART mode may be closely related to other variables such as the number of hours available for charging or the distance driven.

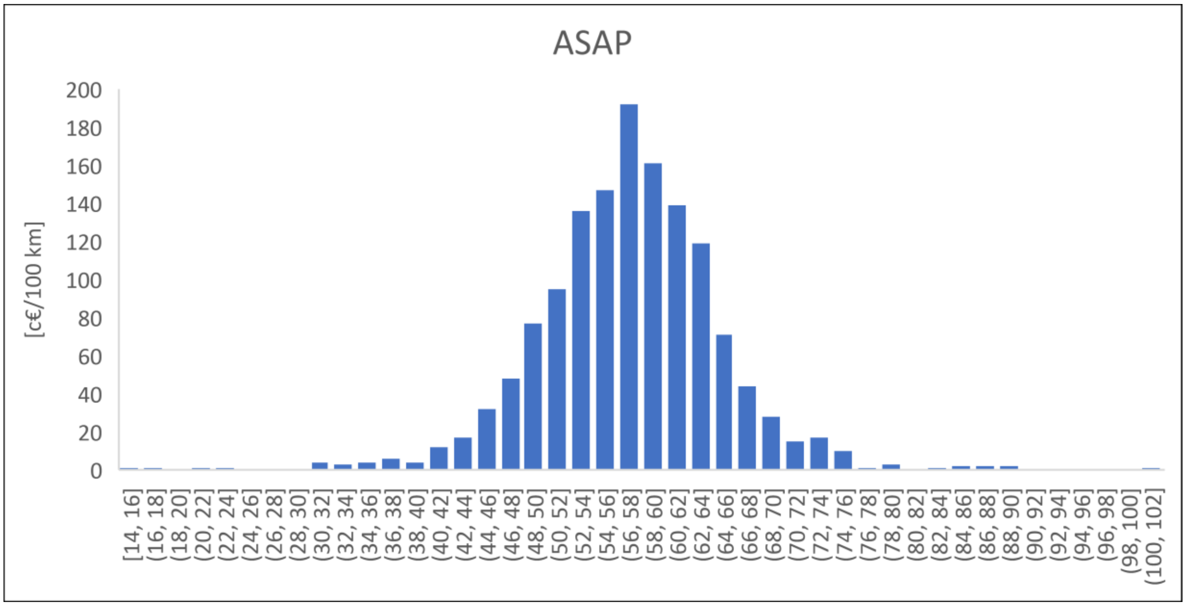

Fig. 23. *Performance indicator distribution for the n = 1397 samples for ASAP charging mode (1 year simulation). Own source.*

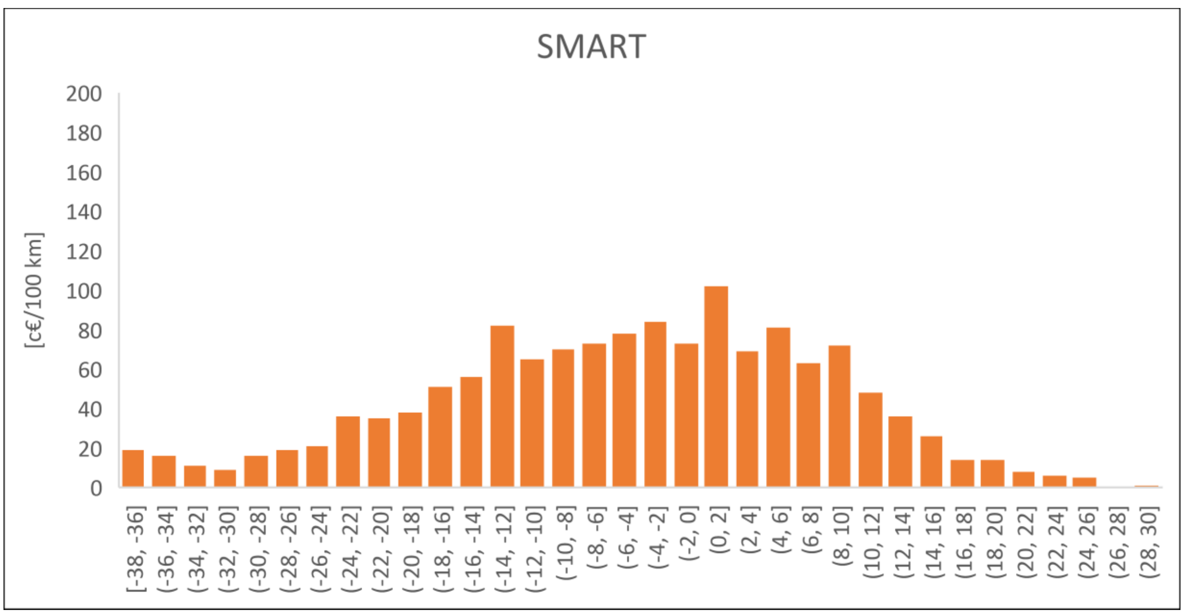

Fig. 24. *Performance indicator distribution for the n = 1397 samples for SMART charging mode (1 year simulation). Own source.*

4.5 Simulation times

Only as a record of the processing times for each of the simulations, a table with this information is shown below. The processing times in this table were obtained with the computer's specifications detailed in section 3.5.

Script Name	N° of profiles	N° of weeks	N° of optimizations	Elapsed time [s]	Elapsed time [m]
CSO_M02_V01	1	1	1	3.72	0
CSO_M02_V02	1	52	52	32	1
CSO_M02_V03	1,397	1	1,397	586	10
CSO_M02_V04	1,397	52	72,644	62,833	1,047

Table 7. *Processing times for the simulations. Own source.*

5 Discussion

This section will present some of the conclusions reached on the method used and the results obtained.

5.1 Method

To perform this optimization of the electric car charge scheduler, the method used was based on the literature that was researched, as mentioned in section 2.4., and despite having been very satisfactory for the purposes proposed for this master's work, some limitations can be mentioned and suggest some improvements that could be made in the future. To begin with, the model simplifies variables such as battery capacity, charging power and consumption efficiency, but actually these parameters differ greatly from vehicle to vehicle, and if considered, would have a significant impact on the results, as they depend on these variables.

Secondly, the model allocates charging events based solely on the price of electricity and with the only objective of minimizing costs, without considering consuming power. This approach is good, but not sufficient if one wants to reduce peak consumption and stabilize electricity demand. To achieve these objectives, optimization should also consider the overall consumption of the fleet and try not to exceed a certain threshold. In order to do this, one more constraint should be considered and included in the mathematical model. Furthermore, to develop a more complex model which not only optimizes the charging expenditures but also considers consuming power, it is suggested to distribute the fleet optimization to an optimization by nodes, where again each node has a price and a maximum available power capacity. Naturally, the vehicles when moving would be charging in different nodes. This model would find a solution that would help stabilize the electrical grid in residential areas, as stated (Flath et al., 2014, p. 620).

Moreover, if the model could consider the energy that it is curtailed to charge the EVs, it could get better economic results, since this energy can be considered to cost 0 € per kWh. Finally, the concept od vehicle to grid (V2G) could be also included in the model, by assuming that EV owners are willing to use their vehicles for energy storage for the moments in which there is mode supply of electric energy than demand and the prices are negative, so they would receive money to charge them. Later, they could choose to use this energy to drive, or sell it back to the grid when supply cannot meet demand and prices are high, receiving again revenues for storing energy.

5.2 Results

The results of this master's thesis model and simulation have been satisfactory, firstly because it has been possible to answer the research questions, and secondly because the model developed provides an initial approach and solution to address this issue. However, the results have also shown that the model has some shortcomings.

Firstly, as discussed in section 4.2, the optimization attempts to minimize energy expenditures, and thus by the end of the simulation period only the energy needed to finish driving the remaining trips, thus generating the SOC to reach its minimum level at the end of the interval (unless otherwise requested, with constraint 3). Although the solution founded by the model it is correct, it generates that the SOC of the battery is always next to minimum level.

Additionally, the software also usually shows charging scheduling solutions in which the charging process is not continuous but rather highly interrupted, and this could affect the performance of the batteries. Another constraint that could be added would be the one that limits the number of charge cycles to protect the battery’s life expectancy.

Yet, the most surprising result was the avalanche effect, which, although expected, the magnitude of the peak loads in SMART mode were considerably higher than the ones for ASAP mode, as discussed in the results section. Certainly, this is an important drawback of this model because although the charging manager expenditures are reduced it generates another problem. This effect could be diminished if the suggestions in section 5.1 were applied to the model, considering a constraint for the aggregated consumption power.

Finally, to analyses the results of the savings obtained using the SMART charging mode it can be affirmed that they are quite significant, but at the same time very volatile, so it is assumed that there is a close dependence on the intraday price of electricity and therefore just as the price is unpredictable so are the savings.

6 Conclusions

This work began describing the reasons behind the great interest of studying the future impact that electromobility will have in the coming years, like changing the households loading profiles and compromising the stability of the electricity grid. In order to address these problems, this master's thesis work sought to introduce the concept of controlled charging and describe how this concept might help to mitigate these issues, explaining for example how EV's could be used as a load shifting option. Later, a mathematical was described to optimize the charging schedule, assuming that the charging process can be controlled by the charging manager, and by this way it could minimize the energy charging costs for an EV fleet. But this model, although it did minimize the costs, neglected other aspects, which can be addressed in future investigations.

With the model developed a first approach has been introduced, with the possibility of extending this model to find more complex solutions, which include more than one variable and not only price. The mathematical model has proven to be useful for what has been developed and the simulation results obtained can give us an initial overview of the possibilities when of reducing expenditures on driving energy for EV's.

The first conclusion from the model described and proposed is that in fact when charging can be controlled by the charging manager and it is scheduled using price signals, costs on charging EV fleets can be reduced drastically, with an average of 93%, for this particular case i.e., these driving profiles and this prices series. Certainly, if the model is improved it could not only reduce expenses but also help to shift load from high consumption peaks to low demand valleys. But certain limitations were not considered when this model was proposed, and therefore no decision considering these limitations were introduced. In fact, not considering these limitations, showed us that using just price signals it is not enough. Since only price signals were used to find the optimal charging schedule, avalanche effects were clearly visible leading to the conclusion that more than one variable should be used to optimize the charging schedule and eventually help reducing the demand peaks.

Regarding the possible savings that controlled charging may produce, they can actually be quite high, but also very volatile and difficult to predict, but would certainly be more cost effective than charging with an uncontrolled mode.

7 References

Babrowski, S., Heinrichs, H., Jochem, P., & Fichtner, W. (2014). Load shift potential of electric vehicles in Europe. Journal of Power Sources, 255, 283–293. https://doi.org/10.1016/j.jpowsour.2014.01.019

BMU. (2018). Climate Action in Figures: Facts, Trends and Incentives for German Climate Policy. Retrieved from https://www.bmu.de/fileadmin/Daten_BMU/Pools/Broschueren/klimaschutz_in_zahlen_2018_en_bf.pdf

Doppelbauer, M. (2018). The invention of the electric motor. Retrieved from https://www.eti.kit.edu/english/1390.php

Ensslen, A., Ringler, P., Dörr, L., Jochem, P., Zimmermann, F., & Fichtner, W. (2018). Incentivizing smart charging: Modeling charging tariffs for electric vehicles in German and French electricity markets. Energy Research & Social Science, 42, 112–126. https://doi.org/10.1016/j.erss.2018.02.013

EPEX. (2015). EPEX Spot. Retrieved from https://www.epexspot.com/en/

Flath, C. M., Ilg, J. P., Gottwalt, S., Schmeck, H., & Weinhardt, C. (2014). Improving Electric Vehicle Charging Coordination Through Area Pricing. Transportation Science, 48(4), 619–634. https://doi.org/10.1287/trsc.2013.0467

Hayn, M., Bertsch, V., & Fichtner, W. (2014). Electricity load profiles in Europe: The importance of household segmentation. Energy Research & Social Science, 3, 30–45. https://doi.org/10.1016/j.erss.2014.07.002

Heinz, D. (2018). Erstellung und Auswertung repräsentativer Mobilitäts- und Ladeprofile fr Elektrofahrzeuge in Deutschland.

Hu, J., You, S., Oestergaard, J., Lind, M., & Qiu Wei, W. (2011). Optimal Charging Schedule of an Electric Vehicle Fleet. Retrieved from https://ieeexplore.ieee.org/document/6125547

IEA. (2018). Global EV Outlook 2018. Retrieved from https://webstore.iea.org/download/direct/1045?fileName=Global_EV_Outlook_2018.pdf

Jochem, P., Kaschub, T., & Fichtner, W. (2011). How to integrate electric vehicles in the future energy system?

Khoshrou, A., Pauwels, E. J., & Dorsman, A. B. (2017). The evolution of electricity price on the German day-ahead market before and after the energy switch.

Kohnji, M., Chau, S. C.-K., & Elbassioni, K. (2018). Scheduling Electric Vehicle Charging with Discrete Charging Options and AC Power Flow Constraints: Submitted to ACM Energy Conference 2018 at Karlsruhe. Patrick received it to blind review. Karlsruhe, Germany. Retrieved from http://doi.org/10.1145/3208903.3208934

Paetz, A.-G., Kaschub, T., Jochem, P., & Fichtner, W. Load-Shifting Potentials in Households Including Electric Mobility: - a Comparison of User Behaviour with Modelling Results. Retrieved from https://ieeexplore.ieee.org/document/6607324

Palinski, M. (2017). A Comparison of Electric Vehicles and Conventional Automobiles: Costs and Quality Perspective. Retrieved from http://urn.fi/URN:NBN:fi:amk-2017062413949

Sundstr̆om, O., & Binding, C. (2010). Optimization Methods to Plan the Charging of Electric Vehicle Fleets. Retrieved from https://www.zurich.ibm.com/pdf/csc/EDISON_ccpe_main.pdf

Wei, L., & Guan, Y. (2014). Optimal Control of Plug-In Hybrid Electric Vehicles with Market Impact and Risk Attitude. Transportation Science, 48(4), 467–482. https://doi.org/10.1287/trsc.2014.0532

Glossary

AC: Alternate Current

ALAP: As Late as Possible

ASAP: As Soon as Possible

BEV: Battery Electric Vehicle

CME: Charging Manager Expenditures

EV: Electric Vehicle

DC: Direct Current

RES: Renewable Energy Sources

SOC: State of Charge

SOCmax: State of Charge for ASAP strategy

SOCmin: State of Charge for ALAP strategy