CHALMERS
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Charging behavior and energy use for 15 electric vehicles in two-car households in the Gothenburg region

Master's thesis in Sustainable Energy Systems

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Abstract

Conventional vehicles burning fossil fuels are emitting CO_2 emissions contributing to climate change. Therefore, electric vehicles are becoming more and more an area of interest due to the need of lowering the CO_2 emissions from transportation. This development goes hand in hand with the rising awareness of greenhouse gas (GHG) emissions. The Swedish government has set a goal to have a fossil independent vehicle fleet by 2030, and since analysis made by the IEA indicates that the number of electric vehicles (EVs) are growing in the country and globally, EVs will probably play a big role going there. Moreover, almost all major car producers have EV models and are investing in further research.

In this thesis we have analyzed driving and charging data for 15 EVs, all of them were Volkswagen e-golf vehicles situated in Gothenburg, Sweden. The data sets have been collected during the two time periods 1st of October to 22nd of January, and 11th of Febrauray to 30th of May by the division of physical resource at Chalmers university of technology. Our analysis focuses on driving and charging behaviour, including calculations of the energy consumption from both driving and charging the EVs. In order to analyze the behaviours of the test drivers using the EVs, we have looked into how the EVs have been driven through following parameters: number of trips; distance; as well as how, where and how much they have been charged.

The results show clearly that the different EV test drivers, included in this study, have different driving behaviours, which, for example, resulted in a broad range of energy consumptions when driving. We also saw that there were variations in energy consumption over periods of time, indicating that the drivers were able to handle seasonal variations differently. It could be concluded that the charging load curves for the EVs showed strong tendencies towards charging in the afternoon, directly at upon home coming. Furthermore, we also saw that all of EVs 1-5 and six of EVs 6-15 were charged simultaneously during the maximum day of energy demand. In addition to this it can be concluded that the analysis of possible shifting of charging showed a big potential for cost savings of about 30 to 50 % during both test periods.

Keywords: data, Gothenburg, driving behavior, VW e-golf, smart grids, V2G, shifting of charging, load curve.

Acknowledgements

We would like to thank our examiner Sten Karlsson, supervisors Niklas Jakobsson and Maria Taljegård for guiding us through this thesis and for all educational discussions along the way. All of you certainly have been very helpful and kind.

Finally, we would like to thank our families, friends and fellow students, who accompanied and supported us during our education and the process of this Master thesis.

Oskar Bohlin, Gothenburg, May 2017
Laura-Marie Kaese, Gothenburg, May 2017

Contents

1
Introduction

The Paris agreement, which is the outcome of the climate conference in Paris (COP21), states that the increase in global mean temperature should be kept well below 2 °C [1]. In order to achieve a CO2 emissions reduction corresponding to less than 2 °C temperature increase compared to pre-industrial levels [2], an increased amount of fossil free power production and transportation modes will be needed. Although Sweden is aiming for a fossil independent vehicle fleet by 2030 the transportation sector in Sweden represented 45.3 % of the national total emissions in 2011. Therefore meeting this goal will require political incentives facilitating for alternative fuels and drive trains. An analysis done by the international energy agency (IEA) suggests that electric vehicles (EVs) are increasing steadily, both in a Swedish and global perspective. Sweden is part of the electric vehicle initiative (EVI), which is a multi-government policy forum that includes countries with the fastest growing number of EVs. For instance, the number of newly registered battery electric vehicles (BEVs) in Sweden have increased from 1240 in 2014 to 2960 in 2015 [3], [4].

As a consequence of a substantial increase of EVs, extra pressure can be expected to be put on the electricity system, where energy peaks probably will be more significant in the afternoons than they have been before. Therefore additional knowledge regarding charging and driving behaviour will be of great importance for electricity operators maintaining grid stability, for politicians to facilitate the implementation of adequate subsidies and incentives, as well as for consumers affected by potential price fluctuations [5]. Analyzing driving patterns of EVs also helps find out more about potential customers, needed battery size etc., which are essential information for up-scaling of EVs in the market. Furthermore, the data could also provide information regarding flexibility in the power system through the concept of vehicle to grid (V2G), where the EVs can act as providers of electricity when not being charged [6]. Charging and driving patterns can be provided by mapping and measuring when, where and how much a number of the EVs are being driven and charged.

1.1 Purpose and objectives

The main objectives of this thesis are to analyze and process charging and driving data of 15 EVs in order to identify charging and driving behaviour, as well as energy use. In more detail we look into how the cars are charged and driven which will include the parameters: number of conducted trips and charging events; distance driven; SoC% level before and after charging; as well as when and where the EVs are being charged during the day. Furthermore, we also cover how much energy that is consumed, both when driving and charging the EVs. The EVs are all Volkswagen e-golf cars, with an original battery capacity of 24.2 kWh, which are situated at different locations in the Gothenburg region, Sweden. The locations in which charging can take place are separated into three categories: home charging; the test drivers workplace; or somewhere else where there is a possibility to charge. GPS systems were installed in the EVs to provide position data, whereas other data has been provided either through the home charging stations, battery or both.

Charging and driving behaviour, as well as energy consumption can be used for calculation of potential economical and environmental benefits. Furthermore, the behaviours are useful when modelling the effects of scaling up the number of EVs in the Swedish power system, as well as for examining if the EVs can be used as flexibility providers in a V2G system. In that respect, the analysis of charging duration, when and where charging occurs, as well as energy consumption are of great importance.

1.2 Background

1.2.1 What is an EV?

An electric vehicle is a car which has one or more electric motors, fuelled by electrical energy stored in batteries or other energy storage devices. The idea of an EV is actually not a new one. The first electric cars have been already produced in the 1880s, but mainly due to the low gasoline price, cars with internal combustion engine became the major technology. Cars with an internal combustion engine are three times less efficient than electric cars [12]. During the energy crisis in the 1970s and 1980s, EVs had a small period of success, but they could not enter the mass market.

Therefore, it happens that one can say the market for EVs has mainly developed over the last decade and is therefore a relatively new (mass) market, trying to provide a more sustainable and clean technology for transportation. To promote the purchase of a new Battery Electric (BEV), or Plug-in Hybrid Electric vehicles (PHEV) a lot of countries, like the Netherlands and Norway, have introduced special tax schemes. The Norwegian government combined tax schemes with free parking and permits to use bus lanes to give incentive to its population to change to electric cars and thereby creating a traffic causing less noise, air pollution, GHG emissions and congestion [13].

1.2.2 What different types of EV are there on the market?

There are basically four major technologies using electricity as a fuel for driving: BEV, PHEV, Hybrid Electric (HEV) and Fuel Cell Electric Vehicles (FCEV).

The most common EV type is the Battery Electric Vehicle (BEV). BEVs have no internal combustion engine, and therefore no direct emissions while driving. The batteries can be charged at home, or public places that often support fast charging. BEV batteries have a higher storing capacity compared to PHEV batteries, which is because PHEVs have an internal combustion and electrical engine.

Plug-in Hybrid Electric Vehicles (PHEVs) can be charged by plug-in, regenerative breaking, which converts kinetic energy into electricity (in conventional cars this energy gets lost), and their internal combustion engine, or be run entirely by electricity. Due to the internal combustion engine as a back-up it is a very good possibility for longer travels.

HEVs basically save energy from regenerative breaking in a battery, but are not possible to be charged by plug-in to an electric outlet [8].

Fuel Cell Electric Vehicles (FCEVs) are combining stored hydrogen, which can be refueled within five minutes at the gas station, with oxygen from the air to produce electricity and run an electricity-only motor. This technology does not have any tailpipe emissions, whereas production emissions of hydrogen should not be ignored. Emission from hydrogen produced by natural gas are comparable to Electricity production emissions by natural gas, but produced by renewable energies like solar it is nearly emission-free [7].
The development of the electric car stock in the European Union (EU) has been stated by the International Energy Agency (IEA) and can be seen in figure 1.1. PHEVs were not present in the market before 2010. However are the new registration for BEVs (328,770 in 2015) in the EU higher than for PHEVs (221,810 in 2015). Even though increasing registration numbers can be noted for every year, the market share of EVs is still just 1 % in the EU [9].

Table 1.1: *Worldwide electric car stock (BEV and PHEV cars) in thousands by the IEA*

	2015	**2014**	**2013**	**2012**	**2011**	**2010**
BEV & PHEV cars worldwide	1,256,900	706,77	383,09	179,230	60,650	12,480

International Energy Agency (IEA) stated that in 2015 a total electrical vehicle stock of 14,530 vehicles existed in Sweden, whereof 4,770 where BEV and 9,760 PHEV: In contrast to this 210,330 BEVs and 193,770 PHEVs were registered in the United States, which sums up to an Electric vehicle stock of 404,090 vehicles. PHEVs which have been introduced in 2011 to the market are now the best seller in Sweden; but in the US BEVs are still leading regarding new registrations [9]. The market share of electric cars, including BEVs and PHEVs, has been 2.4 % in Sweden and 0.7 % in the US [9].

One of the main barriers for buying an EV is the lack of charging infrastructure. Therefore the EU introduced an aggressive support program in 2015 to improve the infrastructure of charging points and thereby built up a system which enables long distance traveling by EVs. In 2015 there have been 161,802 slow charging points and 27,707 fast charging points publicly accessible [9] in the EU.

Sweden applies tax breaks that resulted in higher purchase incentives for PHEVs (Mock and Yang, 2014) [9]. The global electric car share in 2015 was above 700,000 for BEVs and above 500,000 for PHEVs [9].

Table 1.2: *Non-exhaustive electric vehicles with battery type, driving range (under normal non-optimized driving conditions), and maximum optimized driving range [19]. Abbreviations used: Li-manganese (LMO), Nickel-manganese-cobalt (NMC), Li-aluminum (NCA)*

Model	**Battery**	**Driving Range**
Mitsubishi iMiEV	16kWh; Li-ion	85km (128km)
SmartFortwo ED	16.5kWh; Li-ion	90km (136km)
BMW i3	22kWh (18.8kWh usable), LMO/NMC	135km (130-160km)
Nissan Leaf	30kWh; Li-manganese	160km (250km)
Tesla S 85	90kWh, Li-ion	360km (424km)

BEV batteries have a higher storage capacity than PHEV batteries, which results in a higher possible driving range, while never producing tailpipe emissions. Most BEVs can go 95 to 130 km with one battery charge, which fits the weekday driving distance of 69 % of US citizens [7].

The daily driving distance in the Nordic country ranges between 32 km in Sweden up to 42.8 km in Finland, which can as well be fully met with the battery charge of a common EV model [15]. But it is important to consider that there can be many days per month which have a daily driving range above the battery charge limit of a common EV model.

1.2.3 What are the different charging types?

There are two different charging types: home and public charging. Then there is also several different charging technologies that can allow charging at different power levels and thereby charge at different speeds both at home and in public places. The different charging technologies are divided into four categories (level 1, level 2, level 3 and level 4). Furthermore it can be said that faster charging can be used for the beginning of the battery charging process (1-80 % SoC) but not towards the end (> 80 % SoC). Above 80 % SoC [10] it therefore makes little sense to charge due to a insufficient time-charging-ratio. Some public charging stations even cut you off at this percentage [10].

There are big differences between type 1 and type 2 (level 1: up to 1.9 kW, level 2: 7.2 to 19.2 kW [23] using AC electricity) charging, which is proposed by the EU Commission to be the standard, compared to the fast DC charging (up to 120 kW) by Tesla Motors [24]. Using Teslas technology, a 85 kWh battery could be charged in half an hour compared to 12-24 hours by type 1, based on a research article by the University of Uppsala. But the authors, Knutsen and Willén, point out that regular use of fast charging points can have a negative effect on the battery life performance.

One point which is essential to keep in mind, is that every EV has an upper level for the supported rate of energy transfer. This upper level is defined with 3.6 / 7.2 kW for the Volkswagen e-golf, which has been used as a test vehicle in this study. Other cars, like the Tesla Model S have a higher supported rate, at 10 / 20 kW [10]. Therefore it is important to keep in mind that level 3 and level 4 charging stations can be just use by a minority of the EVs on the market right now.

Level 1 and level 2 charging

PHEVs on the market right now are not able to use fast charging. A Tesla can add approximately double as many ”miles of charge” within 30 minutes than an e-golf by Volkswagen, which has been used in this study. Fast chargers are not that common yet. Level 2 chargers, which use 220 V, have already built up a good infrastructure network in Europe. The same can be said for level 1 chargers, which use 110 V, in North America [10]. Charging stations which can be installed at home follow the level 1 and level 2 standard.

It is possible to charge the battery of an EV in 4-8 hours by using 240 V (Level 2). A PHEV battery can be charged with an output of 120V (Level 1) in 8-12 hours, which is perfect for overnight charging. Level 2 is common in the EU, whereas Level 1 only exists in the US. The difference in charging time is based on the different battery sizes. The most common electric car types including information on battery and driving range information is presented in table 1.2.

Level 3 and level 4 charging

To provide faster charging of the EV battery level 3 (DC fast charger) and level 4 (Tesla Supercharger) chargers have been introduced. In contrast to level 1 and level 2, which provide AC electricity, level 3 chargers provide DC electricity. This becomes possible due to by-passing the on-board charging of the EV [10]. Fast charging is defined by a rate of energy transfer >40 kW. There are several different fast charging technologies, two of them will be introduced in the following.

SAE Combo charging standard, also known as CCS (abbreviation for Combined Charging system). CCS is mainly used by German and US car producers. This standards has a max power output of 62.5 kW.

CHAdeMO (abbreviation for "CHArge de MOve"), which is also called DC fast charger, has a max power output of 50 kW. It was most common until European and American car producers teamed up for promoting the CCS standard. This standard has also been adopted by the EU as main standard due to car lobbying. In addition to that has Teslas supercharger a max power output of 120kW and is the fastest possibility on the market as of today to charge an EV.

1.2.4 Why is charging behaviour interesting?

Charging behaviour is of interest for several reasons like over night charging, special night tariffs etc, as home charging is most common in the EV community. About 98 % of the Americans prefer over night charging (including work charging at work days) [16]. There is a strong preference for home charging, for example in the Netherlands [18].
Some Energy providers have special EV electricity bills, called dynamic pricing or "time of use" (TOU) electricity rate to use charging on low demand times to prevent stress on the system due to over-demand (morning and evening). Portland General Electric is one of the electricity operators who provide such a tariff to their customers [17].

Some EVs have fast charging capability, which is available for level 3 and level 4 chargers. Some public chargers are for free, installed by governmental agencies. By mapping and registering the charging impact on the electricity system it could be seen, if future problems might be able to prevent by the introduction of EVs on a high scale.

1.3 Previous studies

International outcomes of previously conducted studies regarding driving and charging behaviour of electric vehicles will be presented in the following section.
All previous studies presented in this section used EVs out in the field, to obtain real world data. Nevertheless all testing periods were different regarding time span and included test cars.
For obtaining the data different methods have been used in previous studies, whereas it can be stated that the basic idea behind it is similar.
The biggest field study included in the literature research consists of 125 million miles of driving by 8300 cars in 22 US regions over three years, conducted by the Idaho National Laboratory [16]. The study calls itself the "largest plug-in electric vehicle infrastructure demonstration in the world". The obtained data included charging data from PHEVs.
Whereas the smallest study found was done by the University of Utrecht gathered data from 965,414 charging transactions of Dutch EVs during January 2013 and April 2014 [18]. The study was performed on a national level and included data from 67% of the EVs registered in the Netherlands in 2014. In 2014 46,111 EVs have been on the streets, which results in XX EVs participating in the study [22]. For doing so measurements and interviews with 16 Dutch EV drivers have been used to collect subjective and objective measurements.

1.3.1 Electric vehicles as part of a Renewable Energy System

An analysis performed by the US Department of Energy's (DOE) Smart Grid Investment Grant (SGIG) program looked at the possibility of EVs to be used as a potential source to smoothen power peaks in a renewable energy system (RES), which has huge shares of fluctuating and hardly predictable technologies like wind and PV power, in the near future. Furthermore the introduction of EVs on a high scale can be seen to provide demand side flexibility, as a part of an distributed energy system, which is required for the implementation of a smart grid.The study showed that with a 25 % per year growth in usage at public charging stations, utility investments could have a seven-year payback, which would be a financially attractive business case for some utilities [14].

PEVs are likely to play an important role in energy and environmental sustainability, such as by helping to reduce greenhouse gas emissions and dependence on foreign oil. Some of those benefits may be enhanced through demand response (for example, shifting PEV charging from on-peak hours to off-peak hours). A lot of studies (e.g.: [[14],[16],[17]]) have been conducted in the US on the topic of EVs. These came to the conclusion that most home charging has been done overnight during off-peak periods. One of the main results from this is that the customers experience high bill savings due to special off-peak electricity contracts [17]. Therefore about 76 % of charging in the US is performed during off-peak [14].

To achieve such financial savings for the consumers and taking stress from the energy system by shifting the charging cycles of the EVs from the peak to off-peak times, it is proposed by Spoelstra, from the Univerity of Utrecht, [18] to educate EV drivers, ideally already before the purchase of the electric car, to built a behaviour, which is in line with these findings.

1.3.2 The Nordic region

Looking at the Scandinavian countries the "State Grid Electric Power Institute" found out, in cooperation with the Technical University of Denmark, that the daily driving distance ranges from 32 km in Sweden to 46.8 km in Finland. A majority of the EVs in Scandinavia have a driving distances are below 40 km per day. In particular 64 % of the vehicles in Denmark and Finland, as well as 73 % of Norway and Sweden. These distances can be supported by all EVs available on the market. Tesla cars and future batteries have higher ranges. During the weekends are 75 % of all driving distances less than 40 km in Denmark, Norway and Sweden, with 66 % in Finland [15].

To ease out the peaks and prevent fluctuations in the Nordic region charging should be mostly done during off-peaks, which would include home charging overnight and public charging and semi public charging at work places between 10:00 and 15:00 with solar power [15].

1.3.3 Range anxiety

The researchers Knutsen and Willén from the University of Uppsala hav been focusing on how to decrease range anxiety of today´s EV drivers, which has been defined by Chris Moore from ”The Washington Post” [11] as ”the state of fear drivers experience from knowing that their battery could run out of charge and strand them far from a recharging station”.

Knutsen and Willén came to the conclusion that more charging stations and faster charging are essential in the early adoption phase in the present infrastructure of the fleet state of EVs, rather than increasing the battery size or decreasing the minimum state of charge (least amount of power left in the battery). By investing in an increased coverage of charging stations, the easiest solution to implement has been favored, as changes in battery size and fast charging stations are still quite expensive changes.

These conclusions, made by Knutsen and Willén, have been drawn from today´s perspective. By continuous development of batteries a finely woven EV charging infrastructure might become less necessary and a bad investment.

1.3.4 Charging behaviour

We need to distinguish between home charging, public charging (car parks, shopping malls) and semi-public charging (work place). With most people preferring home charging according to University of Utrecht [18].

The study conducted by the Idaho National Laboratory is based on data, which has been acquired during a three year period and includes almost 125 million miles of driving and 6 million charging events. This is one of the biggest data collections on EVs in the US, conducted until now. The purpose was to find out information about the demand for charging stations and the charging behaviour of EV drivers..
Nearly all charging events, investigated in this study show that, 98 %, have been performed at home and work during the week. Most people, or at least 77 %, did most of their away-from-home changing at three or fewer locations, and much of the away-from-home charging can be identified as workplace charging (semi-public charging during the days) [16].

According to Banez-Chicharro, who published a study on "Smart Vehicle to Grid Interface Project: Electromobility Management System Architecture and Field Test Results" in 2009, and Kristoffersen, who focused on "Optimized charging of electric drive vehicles in a market environment" in 2013, charging occurs more often during the day. Furthermore by using private, as well as public and semi-public charging stations for charging the stress on the electricity system can be lowered and peak problems reduced.

In a Dutch study, Spoelstra found out that most of the EV drivers, never used a public charging station, or just once during the time of the research. Just about half of the drivers, 46 %, only used one charging station (home charging), whereas 41 % used two to five different charging locations, which might most likely be home charging combined with work charging, as public charging is not that popular in the Netherlands [18].

Spoelstra performed a study focusing on the EV drivers charging behavior in the Netherlands and came to the conclusion that more than 62 % of EV drivers were able to accomplish their daily driving needs on one fully charged battery.

1.3.5 Specific energy use

Using average data for energy use by EVs is not a good option, as the specific energy use can range a lot based on different factors like road categories (e.g. urban or cross-country travels), climate conditions (e.g. winter and summer, as well as different climate regions, e.g. Scandinavia compared to South East Asia), or EV driver behaviour (e.g. progressive breaking). In the following paragraphs, the outcomes of studies which investigated these differences will be communicated.

A German study, by the Institute for Energy and environment (IFEU), investigated the electricity consumption of BEVs and PHEVs separately for different road categories. Hereby, they included the categories urban, extra-urban and motorway [26]. Looking at the BEVs it can be seen that the energy use for urban and extra-urban is nearly equal (urban: 20.4 kWh/100km, extra-urban: 20.8 kWh/100km). The highest energy consumption occurs for BEVs on motorways, which is equal to 24.9 kWh/100km [26]. In comparison to this, PHEVs have an overall lower energy consumption. The highest energy use appears in urban areas with 17.8 kWh/100km. The energy use on extra-urban roads is 33% lower, compared to the urban energy use, with 10.7 kWh/100km. The lowest energy consumption for PHEVs regarding road categories can be found for motorways, with a value at 3.2 kWh/100km [26].

A Nordic study aims for testing electric vehicles in Nordic conditions to give the consumer a realistic range estimate for EVs.
The range of an EV gets diminished by 27 % when the temperature is -20 °C compared to +23 °C. By using additionally battery powered cabin heating this range reduction can increase up to -76 % [25].

The British organisation "Energy saving trust" came to the conclusion that energy use is depending on drivers behaviour. By being part of the organisation´s EV Eco-driving training, the participants reduced their electricity consumption on average by 16 % which resulted in a 20 % higher driving range [27].

2
Data and method

Charging data from home charging stations and driving data in sets of 15 EVs containing several parameters for a number of trips have been processed and analyzed in this study. The collection of data has been conducted by the Division of Physical Resource Theory at Chalmers University of Technology during two time periods: one from 1st of October 2015 to 22nd of January 2016, including ten of the EVs denoted EV 6-15; and the other from 11th of February 2016 to 30th of May, where the other five EVs denoted EV 1-5 are included. Each data set is two dimensional in which rows represents home charging events or trips whereas the columns represents each parameter, respectively. The trips were registered from when the EVs were put in motion to when they were stopped. Though, stops shorter than five minutes were not registered as actual stops so that one continuous trip could contain stops shorter than five minutes. Home charging data has been collected from the home charging stations, whereas the trip data was collected through a common GPS system together with sampling from an on-board-data (OBD) system. The home charging stations and other equipment gave the parameters presented in table 2.1.

Table 2.1: *Specification of from where each parameter is extracted.*

Parameters from home charging stations	**Parameters from GPS and OBD system**
length of time	length of time
charging duration	latitude coordinate of vehicle at start and end of trip
charging energy (kWh)	longitude coordinate of vehicle at start and end of trip
vehicle ID	average velocity
	vehicle ID
	trip distance
	pause before and after trip
	battery SoC%* level at start and end of trip
	outdoor temperature at start and end of trip

* SoC% levels with an accuracy of 0.4 %

The major strengths of the data are that it is extracted from real life charging and driving, as well as that the EVs are of the same type and situated in the same region. This allows for a fully comparable analysis of the charging and driving behaviour connected to respective EV. Though, the fact that only 15 EVs are included possibly makes cumulative analyzes less reliable. The EVs used by the test drivers were all VW e-golf cars, which is a BEV with a battery capacity of 24.2 kWh. See figure 2.1 below for an illustration of the battery system and electric drive of the e-golf.

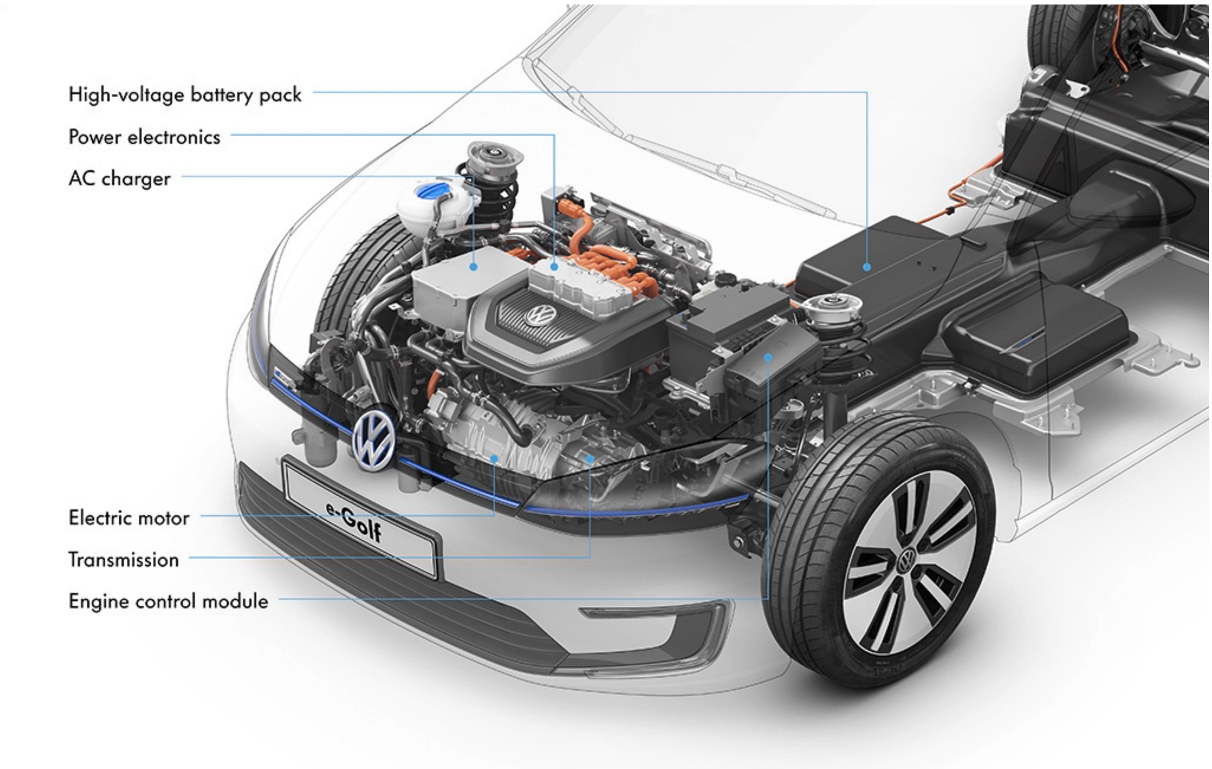


Figure 2.1: *Specification of components of the VW e-Golf battery system and electric drive [21].*

In our work we have used the parameters included in table 2.2. To be able to process data the numerical calculating program MATLAB has been used, where the data sets and their parameters have been imported and sorted into specific arrays. However, trips that contained errors were removed in the process of sorting the data. The errors that we eliminated were: trips with a gain in SoC%; unrealistic outdoor temperature (e.g. -272 °C); and empty data points. This data was removed in order to prevent errors in the calculations of, for instance energy consumption and daily mean outdoor temperature.

Table 2.2: *Parameters that have been used in this thesis.*

Parameters	
vehicle ID	length of time
latitude coordinate of vehicle at start and end of trip	battery SoC% level at start and end of trip
longitude coordinate of vehicle at start and end of trip	trip distance
charging duration	outdoor temperature
charging energy (kWh)	

We were able to see the charging behaviours through analysis of the following: number of charging events; charging location; SoC% when starting and ending charging; as well as hourly charging load curves over a time period of a day (00:00-23:59). Finding charging events in the home charging data was straight forward since each row in the data were a charging event. However, the SoC% difference in between trips had to be analyzed in order to find charging events in the trip data: if the SoC% difference was positive we assumed a charging event.

Regarding the charging locations we connected the coordinates of the EVs with the corresponding charging events, whereupon ”home”, ”work” and ”other” were chosen as categories for charging location. In order to find the "work" charging coordinates we analyzed if the EVs have been charged repeatedly at one place that could be identified as a workplace. The coordinates of "home" were given, whereas "other" included charging coordinates of any other place than the previous two. Finding SoC% levels were not so cumbersome using charging events, whereas load curves demanded more work. The basic idea to estimate load curves over a time period of 24 hours was to find during what time charging was needed. Starting with start time points of the charging events, given energy of charge (E_{charg}) and charging power (P_{charg}), the end time points ($t_{charg,end}$) were calculated with equation (2.1). A charging power of 3.4 kW was used for home charging, since it was the most common charging power at the home charging stations. For all away from home charging events a charging power of 2.2 kW was assumed.

$$t_{charg,end} = t_{charg,start} + \frac{E_{charg}}{P_{charg}} \tag{2.1}$$

A very important side note here is that calibration was needed between the charging events in home charging and trip data to be able to convert a change in SoC% to kWh for the charging energy in the trip data, which is due to the fact that there are losses during the charging process. For further specification of the calibration process see appendix A.1. With a calibration value for SoC% difference to kWh conversion for the charging events in the trip data all charging end time points were calculated. Specifically for calculation of charging end time points for charging events in the trip data, the energy of charge were now given by equation (2.2) instead of directly from the home charging data, since the SoC% values had to be converted to kWh. Here the calibrated value 31 kWh was used to convert from SoC% to kWh, in accordance with the result in the calibration process.

$$E_{charg} = E_{charg,SoC\%->kWh} = \Delta SoC\% * 31 \tag{2.2}$$

The next step in the process of generating load curves included to separate the power needed at every hour over a certain number of days in matrices, in which the rows represents the hours and columns the days. The matrices were used to plot both the average load curve over all days, as well as maximum load curves for a specific day where the power or energy were at their maximums. Observe that a constant charging rate has been assumed in all charging calculations, in table A.1 in section A.1 we confirm this assumption.

Regarding the driving behaviours we analyzed number of trips per day, total number of trips, distance per day, total distance driven and energy consumption. The per day values were possible to extract through looping of the date parameter accumulating the trip, distance and energy values separately for each day. Note here that trips that were ended past midnight were registered to the day before 00:00. The energy values were calculated with a battery capacity of 24.2 kWh, corresponding to a SoC% difference of 100, and in accordance with the assumptions of linear discharge and conversion from SoC% difference to kWh.

Regarding the shifting of the EV charging, values from the historic Nordpool data has been used [28] for the analysis. By comparing different strategies with the status quo potential cost savings related to dead-time, SOC values and start charging times have been calculated.

3

Results

This part will begin with the sections driving (3.1) and charging behaviour (3.2). The third section presented here is energy use (3.3), that includes the consumption of energy from driving, and the final section is presenting cost savings due to shifted charging time (3.4).

3.1 Driving behaviour

A major part of explaining charging behaviour is of course how individuals are driving since more driving means more charging, and from here on we will go into detail regarding driving behaviour. In figure 3.2 we show the number of trips, both in per day and total values. We see that there are several of the EVs test drivers that have taken over ten trips during their maximum day. These are also the ones with the highest average number of trips per day with the exception of EV 2 and EV 13, which have equal average values as EV 4, EV 9 and EV 14. With the exception of zero trips during a day, which is not included in figure 3.1, there are four vehicles that drive a minimum of two trips per day whereas the rest only are driving one. These values will be of further interest when analyzing distance driven, which will be covered next.

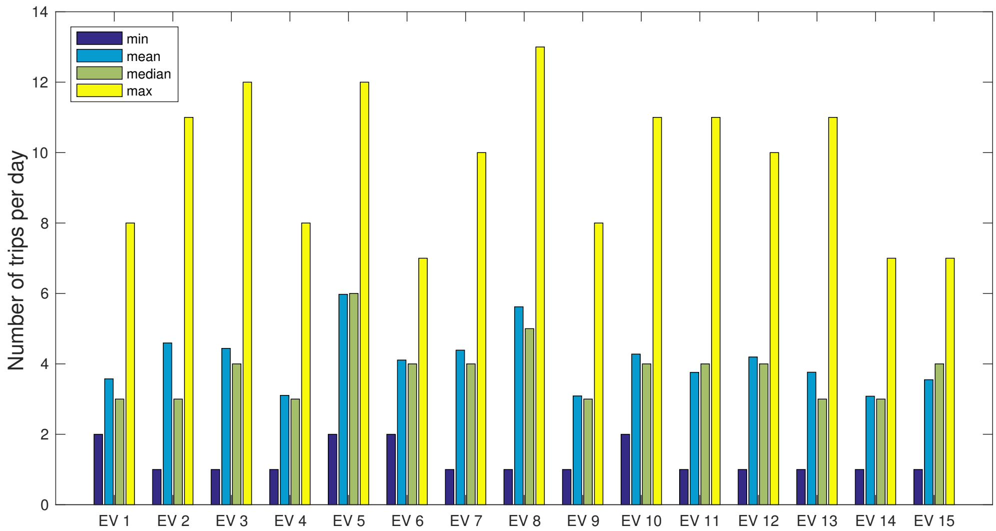


Figure 3.1: *Min, mean, median and max values for the number of trips taken per day when driving, excluding days of zero trips conducted.*

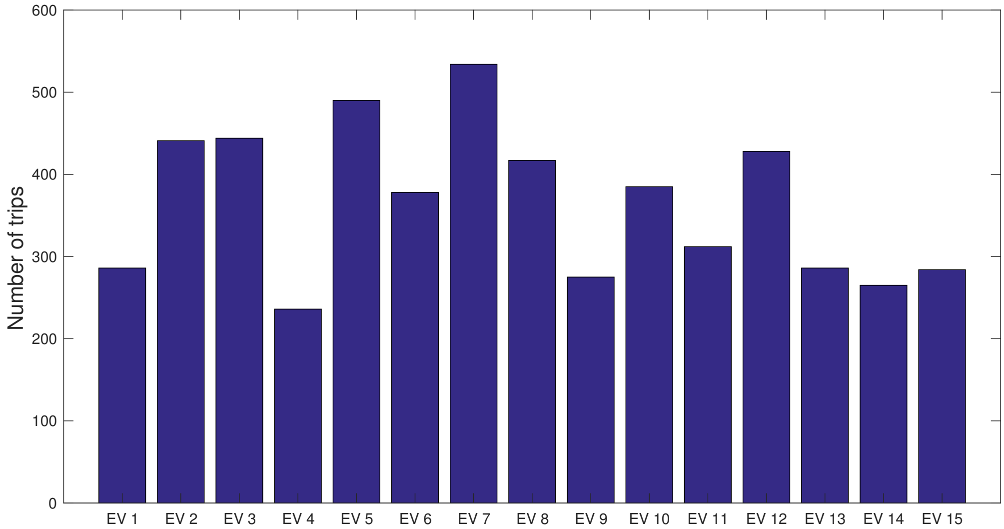


Figure 3.2: *Total number of trips taken for respective EV over the entire time periods.*

The distance per day when driving as well as total distance driven is illustrated in figure 3.3 and 3.4, respectively. An example of different behaviours is, for instance that the number of trips, both per day and in total for EV 15 are almost equal to the number trips conducted by EV 14. But EV 14 has been driven about 25 % more km's in total and 10 % more in average per day. The difference in total and average values between the two EVs is due to that the number of days that trips have been conducted vary, hence affecting the total value. Though, it is clear that those EVs (EV 2, EV 3 and EV 8) that have the highest average km per day also have the highest total values.

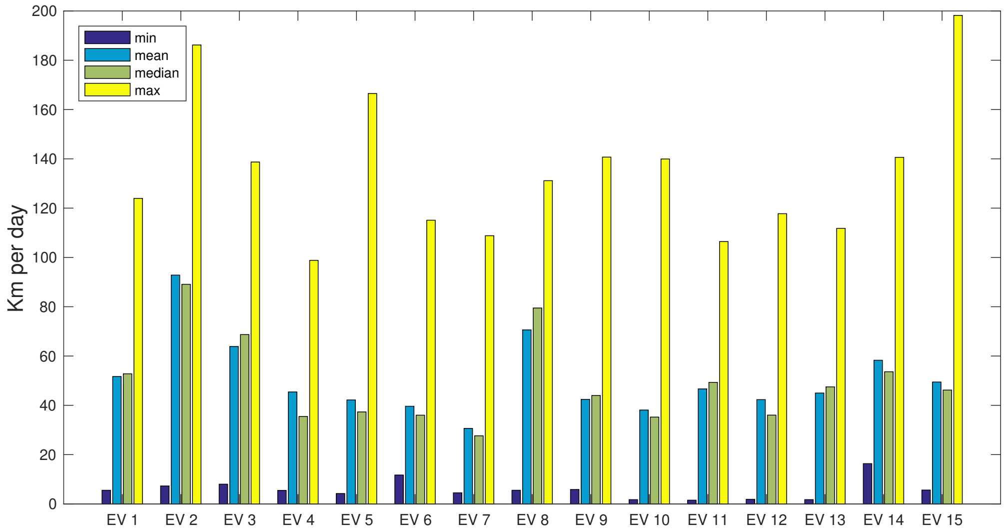


Figure 3.3: *Minimum, mean and maximum values for each EV's distance driven in km per day when driving, excluding days of zero km driven.*

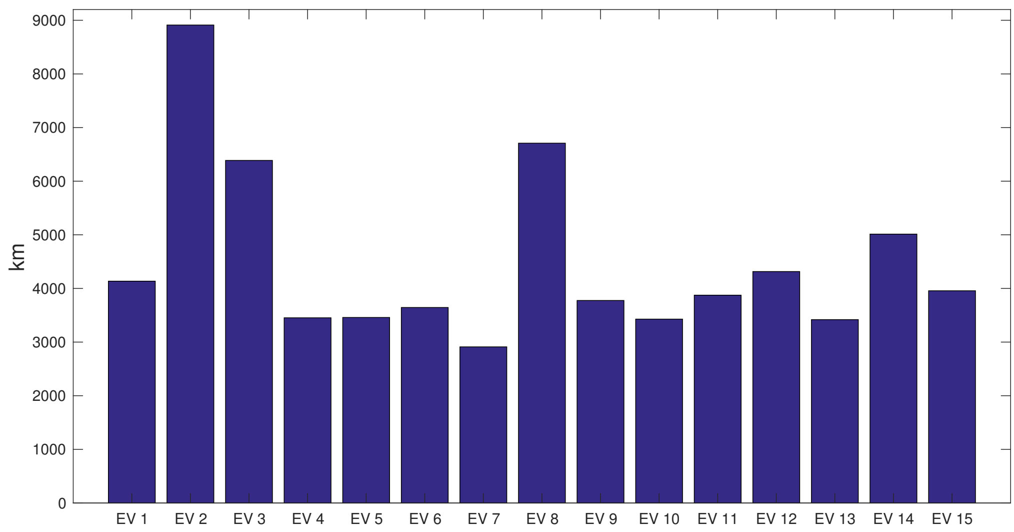


Figure 3.4: *Total distance driven for each EV in km over the entire time periods.*

Furthermore, regarding figure 3.3 one can see that EV 2 has the highest average distance per day when driving, which is about 90 km per day. This value is more than double than several of the other EVs, where the lowest one (EV 7) has been driven about 30 km per day on average. This shows quite a difference in driving behaviour between the EVs. In contrast to that, excluding the high extremes, about 80 % of the EVs have an average driving range between 30 and 60 km per day, which shows a similar driving behaviour for the majority of the EV test drivers. This behaviour can also be seen in figure 3.4.

3.2 Charging behaviour

An interesting and important part of the charging patterns is to evaluate how frequent the EVs are being charged.

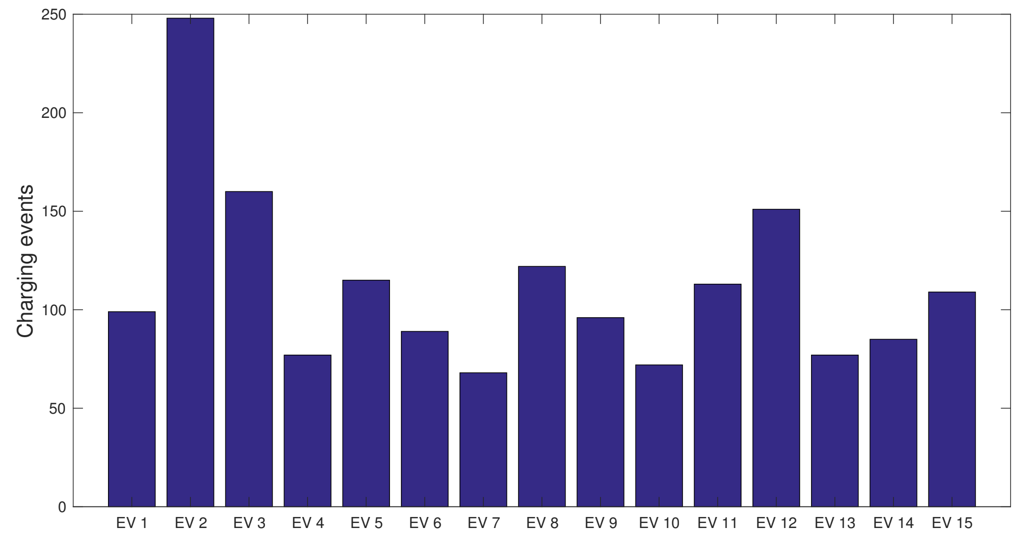


Figure 3.5: *Total number of charging events for respective EV over the entire time periods.*

The results in figure 3.5 are straight forward where EV 2 stands out with twice or more charging events compared to the majority of all other EVs. Moreover, except EV 2, all the EVs are distributed almost evenly in the interval from 50 to 150 charging events, which is confirmed by the calculated average value of 102 (EV 2 excluded).

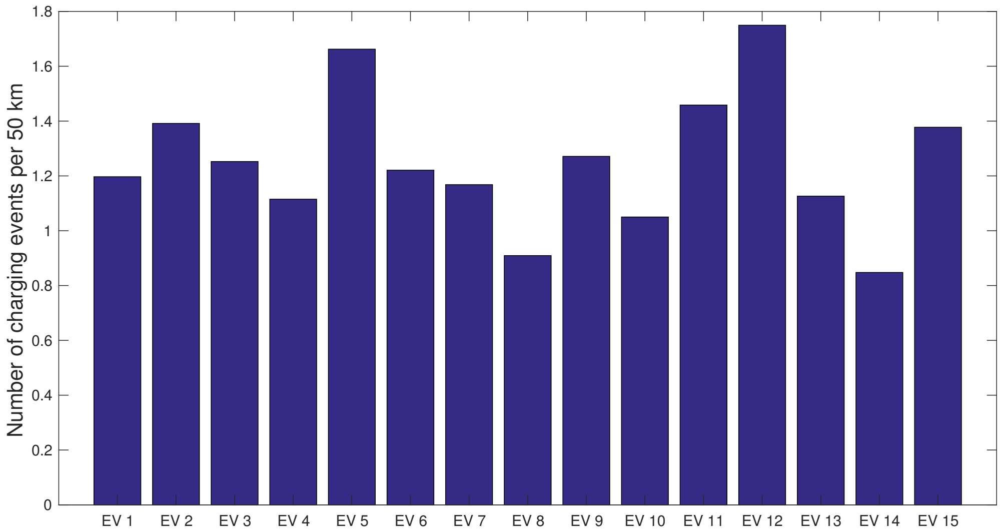


Figure 3.6: *Average number of charging events per 50 km driven for each EV.*

Since coordinates were given for each home charging event and trip we were able to see where each charging event occurred. In figure 3.7 the distribution of charging locations, separated in the three categories work, other and home, is presented for each EV. If the number of charging events at the workplace are zero it could be that it has been hard to localize any reasonable work place, the test drivers does not has possibility to charge there or simply did not even though they have the option. Most of the EVs have been charged to a large extent at home spanning from 68 to 99 % of their individual charging events. There is only one EV (EV 10) that has been charged less home than away. Specifically, EV 10 has been charged 89 % of the cases at the test driver's workplace. For four of the EVs (EV 1, EV 2, EV 8 and EV 10) it is clear that the workplace is used for a substantial amount of charging.

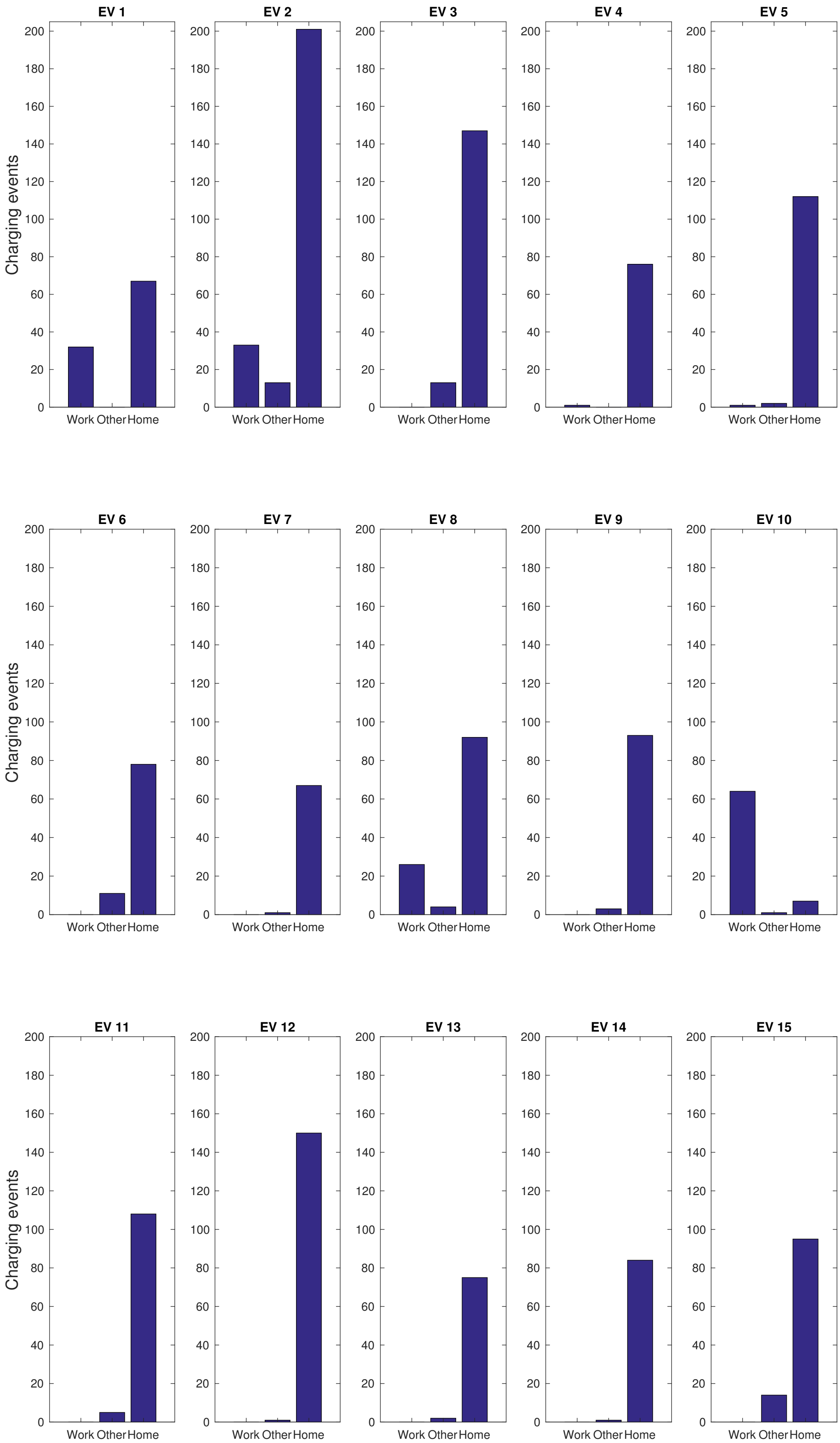
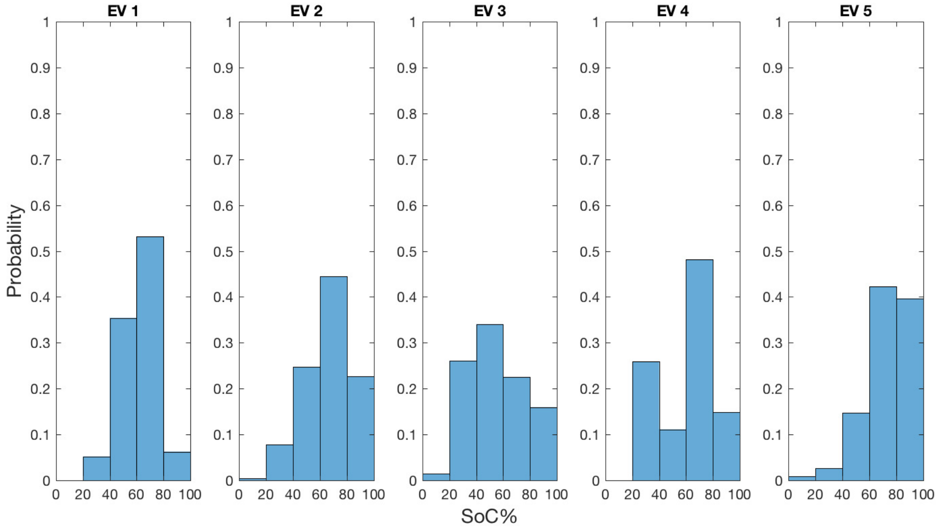
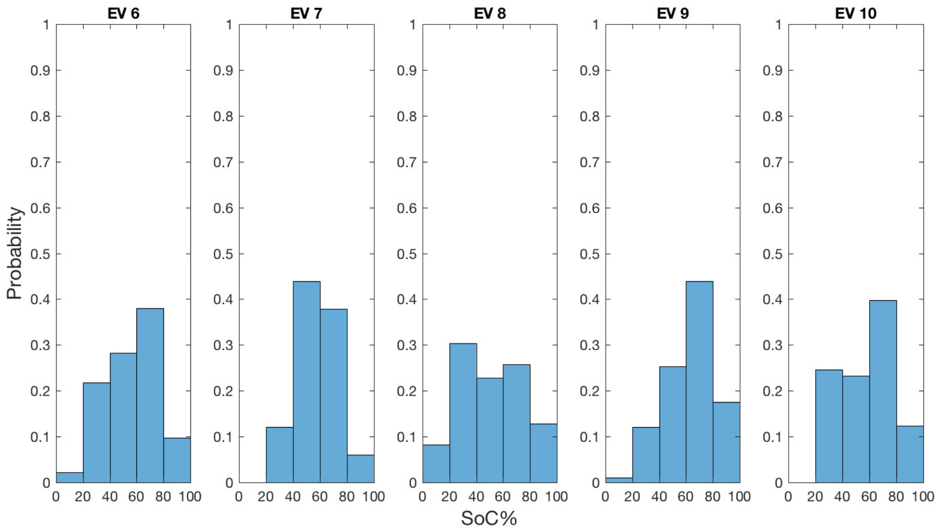


Figure 3.7: *Charging distribution for respective EV where three charging location alternatives have been included: At the workplace, home or any other location than the previous two.*

To gain a deeper understanding of the charging behaviour of EV test drivers, the SoC% levels are an important factor. Especially, the SoC% levels when starting and ending charging are interesting since these give information regarding the critical level of battery charge for the drivers. With the critical level we are able to see where each driver feels the need for charging in order to feel secure. Furthermore, these SoC% levels also points out the comfortable level of charging, i.e. if some drivers care for the battery more than others and are charging only in a certain interval. For those with the possibility to charge at the workplace it could also be that they charge because it potentially is for free. Hence, they will take the opportunity to charge even though a substantial amount of energy is left in the battery. The start and end SoC% values of charging for each EV are given in figures 3.8 and 3.9, where the probability of that charging occurs in 20 % intervals from 0 to 100 % is plotted. The probability for starting charging at 0-20 % is in general always below 0.1. We also see that most of the charging starts at levels in the interval of 20-80 %, even 40-80 % if excluding some of the EVs. Regarding the end charging levels the picture is clear; almost all charging ends at levels in the interval 80-100 %.



(a)



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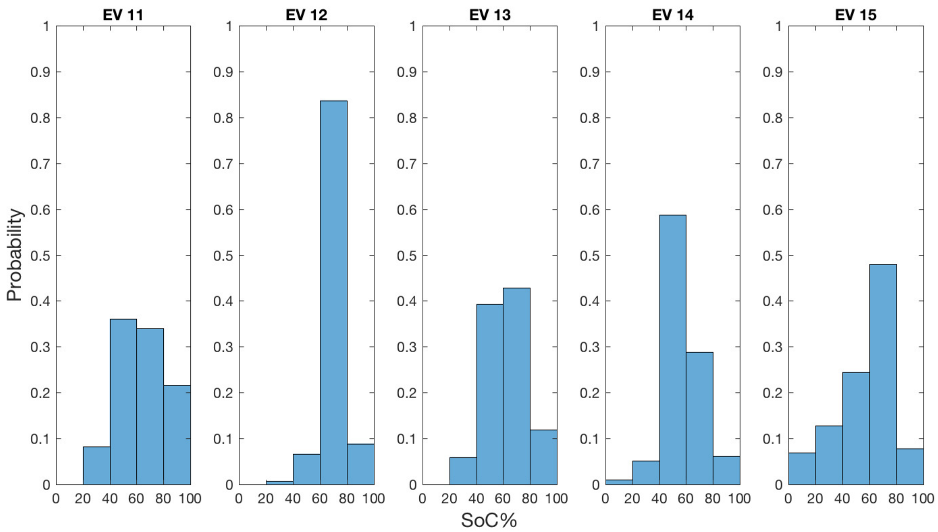
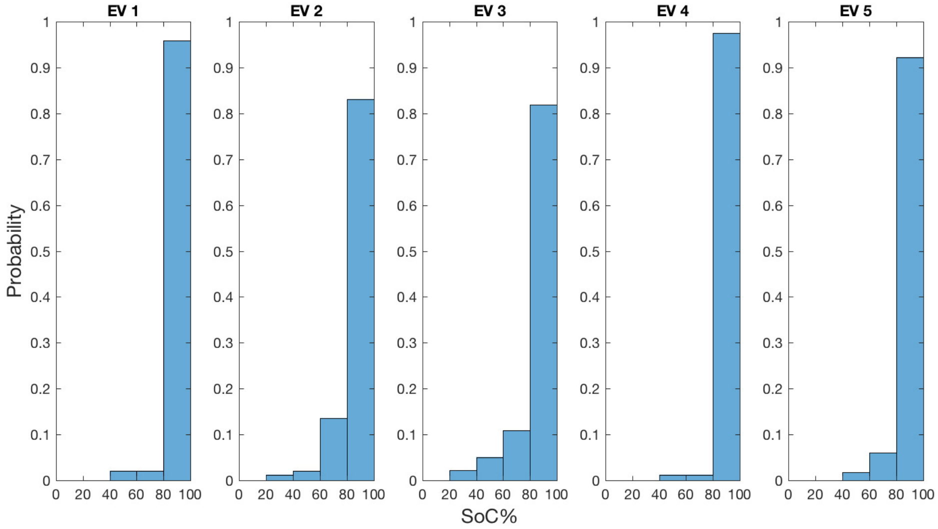
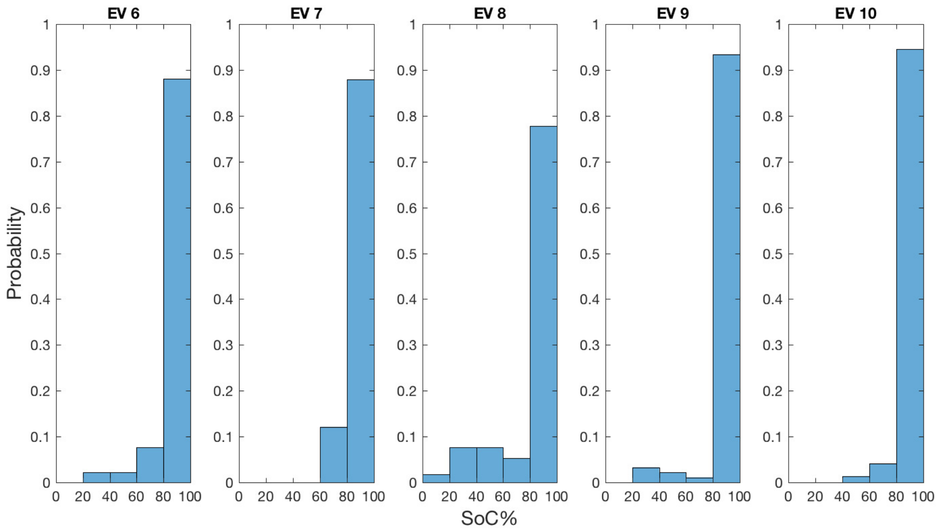


(c)

Figure 3.8: *Distribution of SoC% values when charging is started for all EVs.*



(a)



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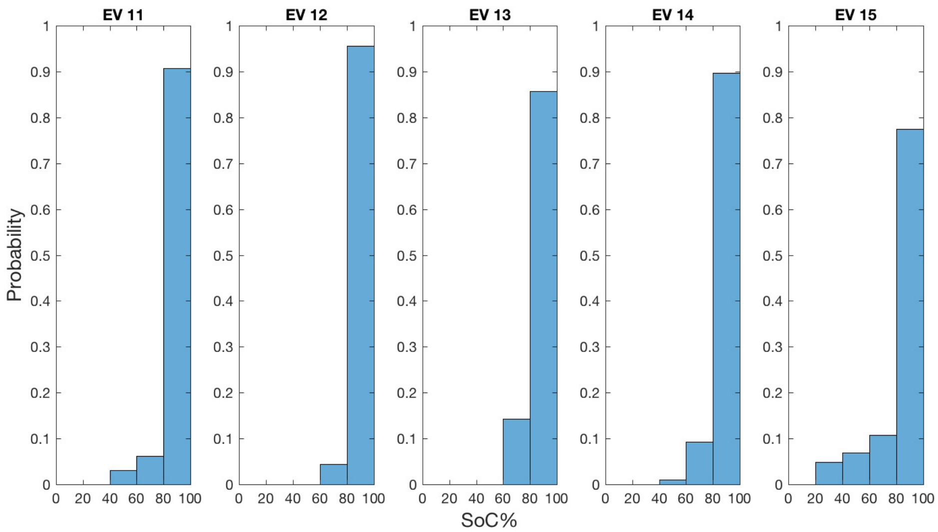
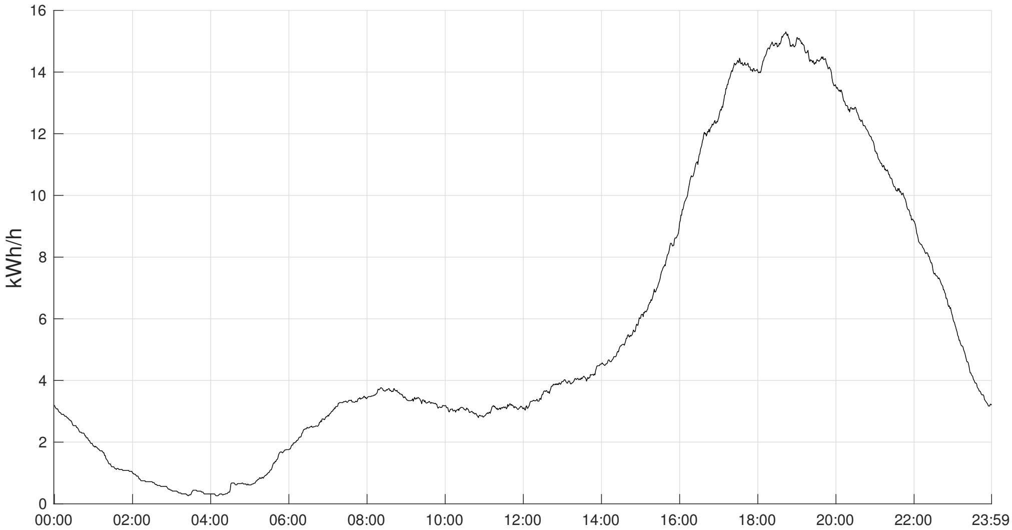


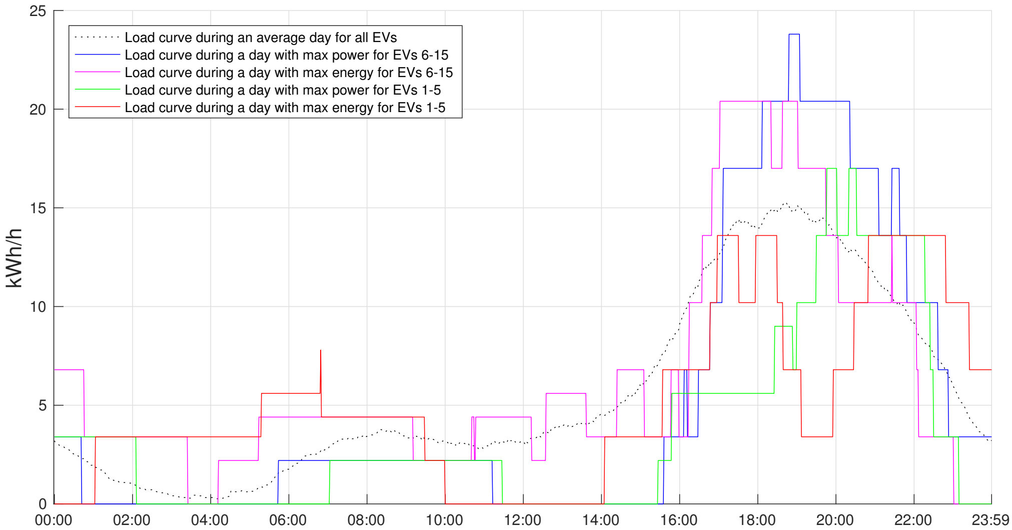
(c)

Figure 3.9: *Distribution of SoC% values when charging is ended for all EVs.*

In figure 3.10a the average charging load curves for respective EV have been accumulated spanning hourly from 00:00 to 23:59, whereas figure 3.10b illustrates charging load curves during the days when maximum energy and power are demanded. For the latter it is noteworthy that EVs 1-5 have been separated from EVs 6-15 since their respective data sets originates from different time periods, thus we can not know if the day of maximum power or energy demand in one of the sets would occur simultaneously as the corresponding day in the other set. However, this is not a problem when accumulating the EVs average values since they all have the same time base (00:00-23:59).



(a)



(b)

Figure 3.10: *(a) Average charging load curve in kWh/h accumulated from all EVs over all days. (b) Charging load curves in kWh/h during days of maximum energy and power demand. The black dotted line is the same load curve as in the (a) figure, blue is for max power connected to EVs 6-15, purple is for max energy also connected to EVs 6-15, green indicates the load curve of maximum power for EVs 1-5 and red the load curve of maximum energy for EVs 1-5. Both (a) and (b) includes a home and away charging power of 3.4 and 2.2 kW respectively.*

These charging load curves shows a strong tendency towards charging in the afternoon, with a maximum around 19:00. As seen before in figure 3.7 most EV test drivers charge their EV at home most of the times, and since they work during the day charging directly at upon homecoming seems logical. Furthermore, it is interesting to see that all of EVs 1-5 are plugged at the same time during maximum power demand (17 kW), whereas the maximum power demand (23.8 kW) for EVs 6-15 indicates that only seven of them are plugged in simultaneously. In figure 3.10a specifically there is a smaller peak around 08:00 which probably could be related to charging at the workplace. Note that 3.4 kW and 2.2 kW have been assumed as home and away charging power, even though there were a few away charging events where higher charging powers were used. Regarding the energy consumption when charging, we found that during the average day 120 kWh were consumed by all EVs. At the day of maximum consumed energy EVs 1-5 consumed 122 kWh, whereas EVs 6-15 consumed 153 kWh. Though, for the day of maximum power the energy consumption was calculated to 86 kWh for EVs 1-5 and 124 kWh for EVs 6-15.

3.3 Energy use

Figures 3.11 and 3.12 shows the energy consumption in the form of SoC% per day and accumulated numbers. Some SoC% values are above 100 % indicating that the vehicle has been charged at least once during the day, probably twice since it is not possible to make use of 100 % of the battery's capacity. Note here that all EVs use at least 70 % during their busiest day.

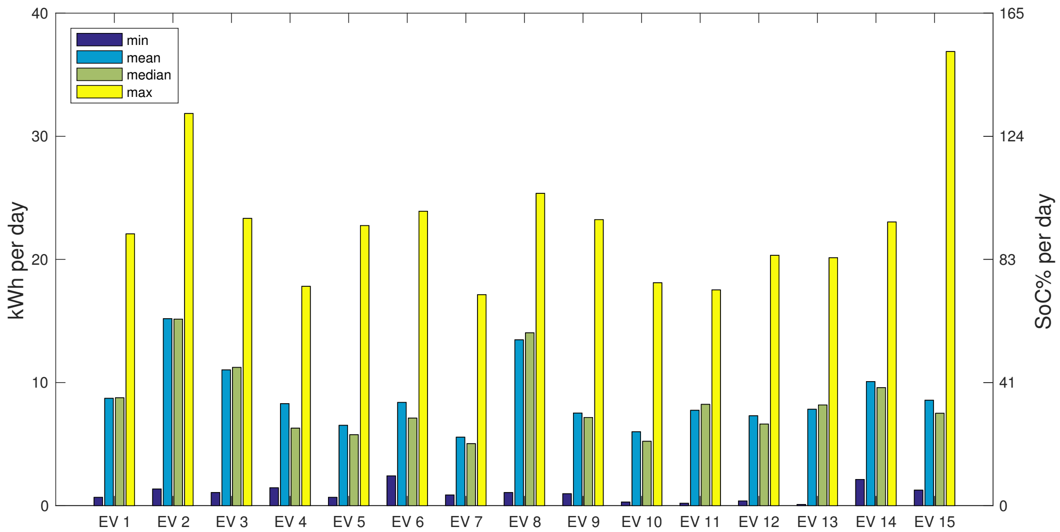


Figure 3.11: *Minimum, mean, median and maximum energy consumption from the battery in kWh per day for each EV. Both kWh and SoC% axes are included in the diagrams, these are linearly converted where 100 % is equal to 24.2 kWh.*

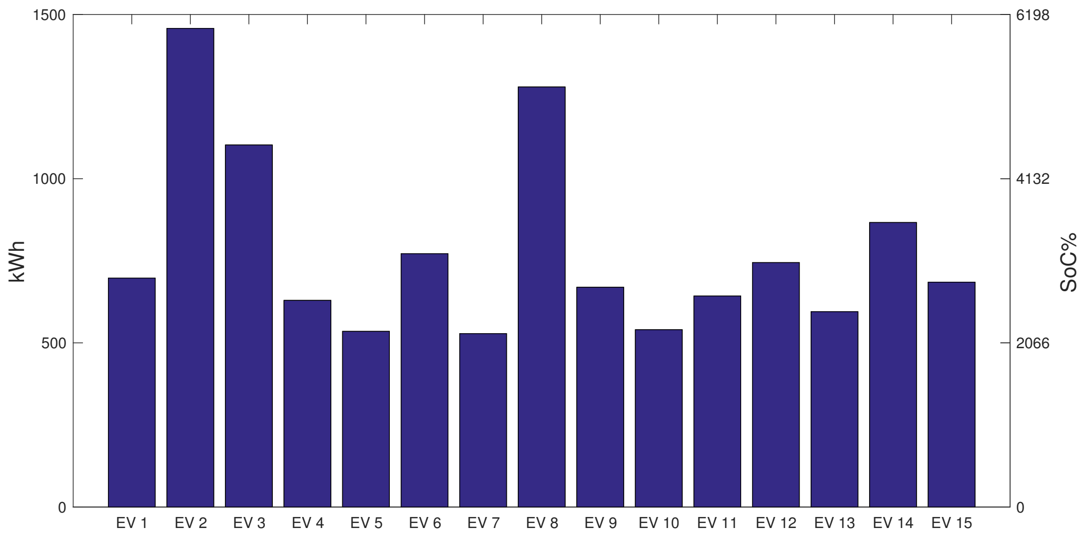
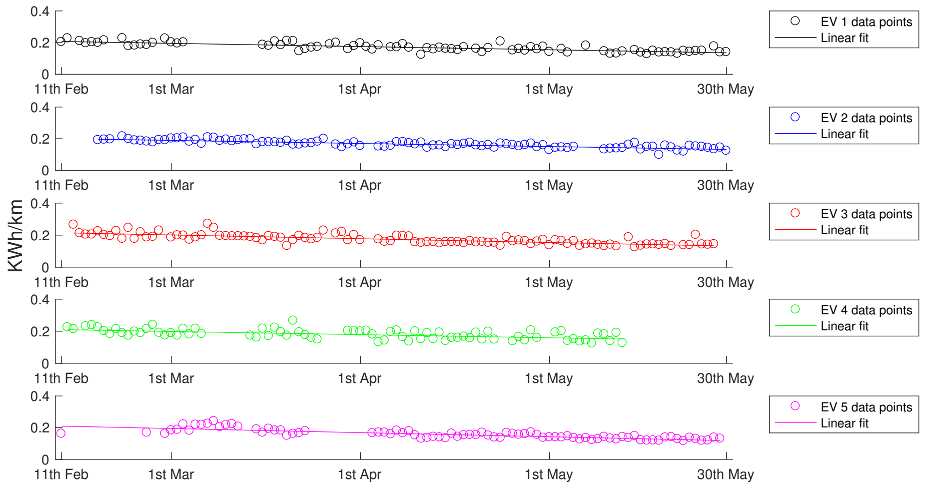


Figure 3.12: *Total energy ccnsumption from the battery in kWh for each EV over the entire time periods. Both kWh and SoC% axes are included in the diagrams, these are linearly converted where 100 % is equal to 24.2 kWh.*

There is quite a strong correlation between distance driven and consumed energy since the EVs (EV 2, EV 3, EV 8 and EV 14) that have been driven the most also have the highest consumption. Moreover, this is true for the rest of the EVs too, although with some deviations. For instance EV 7 still has the lowest number, but in more competition now. Looking at the total distance driven and consumed energy EV 4 and EV 5 consume differently but drive equally long. Here EV 4 consumes quite a bit more than EV5 but, as mentioned, has been driven almost the same distance. By this it can be clearly seen that the driving behaviour has a substantial influence on the energy consumption of the EV. As a side note we can address the fact that mean and median values differ in not only figure 3.11 but also 3.1 and 3.3, suggesting that the values not are evenly distributed between the maximum and minimum ones.

As already stated in the comparison between distance driven and energy consumed there are variations in how much energy the different EVs consume. Therefore further analysis on how energy consumption changes over the time periods have been included, see figures 3.13 and 3.14. More specifically the data points for each EV have been plotted together with a linear fit to be able to distinguish trends of consumption. Looking at all these figures there are quite strong tendencies towards higher energy consumption when reaching winter. There are also differences between the test drivers as they consume differently during the same time period. However, as the energy consumption changes over the time period we can see that some drivers consume more evenly than others. Therefore a test driver can be a high consumer in the summer or autumn but low consumer in winter. Basically, the increase in energy consumption for individual drivers span from 25 to over 100 %. Since temperatures fluctuations could occur during seasons yielding the same temperature in, for instance autumn and winter we also have considered energy consumption variance relative to daily mean outdoor temperature, see figures A.2 and A.3 in appendix A.2. Here we saw almost the same behaviour with around twice the energy consumption at the coldest temperatures compared to the warmer ones.



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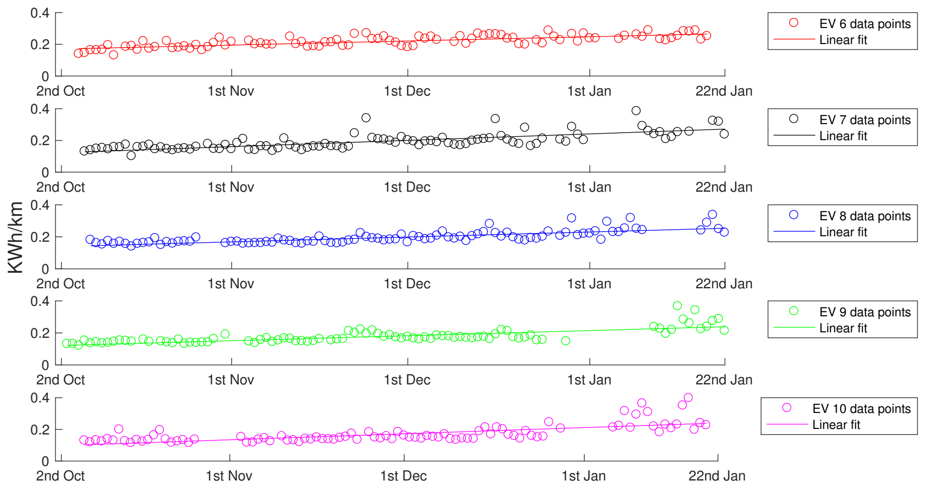

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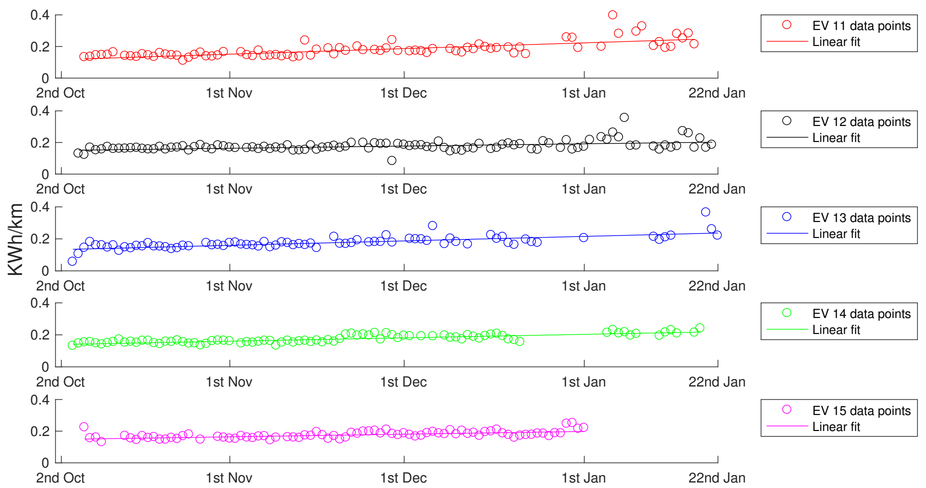
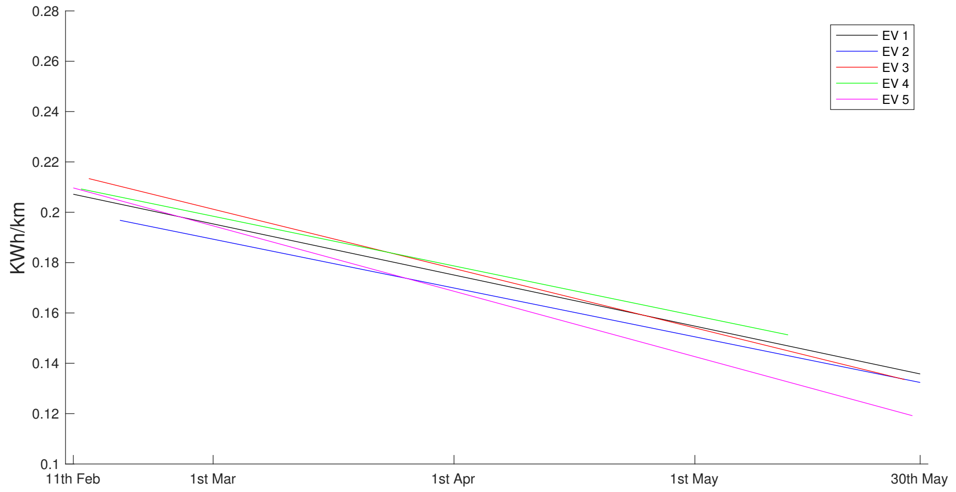
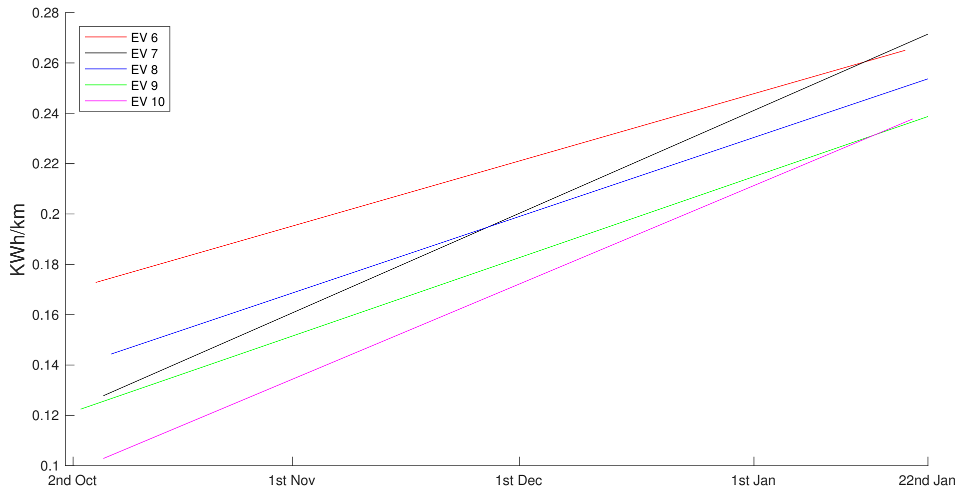


(c)

Figure 3.13: *Data points and linearly fitted lines of driving consumption of energy relative to time of year for each EV.*



(a)



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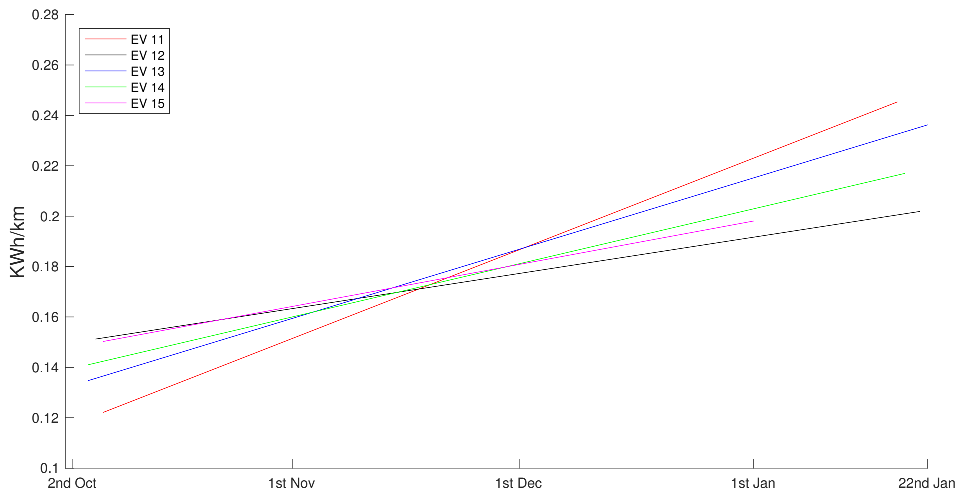

(c)

Figure 3.14: *Comparison of the linearly fitted lines illustrating driving consumption of energy relative to time of year for each EV.*

3.4 Cost savings due to shifted charging time

The first step in this analysis has been to compare plug in and charging time to get to know the time when the car is actively charged vs. the time the car is plugged in (nowadays the charging starts as soon as the car gets plugged in). Dead time is defined as the hours where the electric vehicle is plugged in, but not charged. This is due to the fact that the EV car battery has already been completely charged. Long dead time results in a big potential cost saving for the EV driver. As the EV charging time is bigger than the plug-in time this means that the car could have been charged during a shorter time period, e.g. during the night where the electricity price is on average lower, instead of during the afternoon, which is the status-quo in this analysis.

3.4.1 Electricity curve and prices in SE3

The region of Västra Götaland, where the EV test data has been collected, is located in SE3 of the Nordpool electricity price region. In the figure 3.15, which is shown below, the electricity price per €/MWh can be seen for the EV test periods from October 2015 to May 2016. The electricity curve of Sweden is also dependent on the electricity production and usage of its neighbour regions like SE2 (north of Stockholm) and SE4 (south of Gothenburg). Furthermore the electricity system of Sweden is nowadays interconnected due to electricity trade with e.g. Denmark, Norway and Finland. This makes it possible for the whole Nordpool region to use e.g. cheap overproduction wind energy from Denmark.

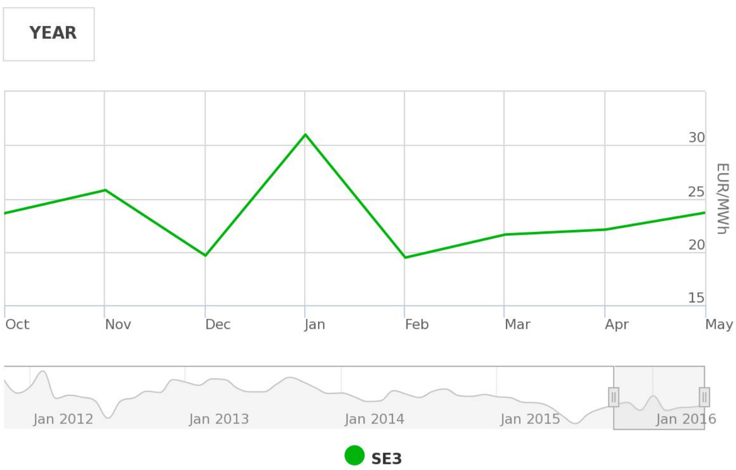

Figure 3.15: *Average Nordpool electricity price for SE3 in the test periods autumn 2015 and spring 2016*

In addition to the monthly average electricity price in figure 3.15, the average electricity prices for each hour of the day can be seen in table 3.1. The values have been calculated separately for both test periods autumn 2015 and spring 2016, by using historic market data extracted from Nordpool.

Table 3.1: *Average electricity price per hour for both test periods (autumn 2015 and spring 2016) in €/MWh*

	Autumn 2015 1.10.2015 - 22.02.2016	**Spring 2016 11.01.2016 - 30.05.2016**
0-1 h	19.3044	20.1131
1-2 h	19.0474	19.3806
2-3 h	18.3591	18.8379
3-4 h	17.9626	18.8111
4-5 h	18.0285	19.1599
5-6 h	18.6360	20.1073
6-7 h	19.6540	21.3413
7-8 h	21.8300	27.0406
8-9 h	28.6212	30.0111
9-10 h	31.5350	28.8374
10-11 h	29.7975	26.2370
11-12 h	27.7975	24.9305
12-13 h	26.0919	24.1423
13-14 h	25.4218	23.7380
14-15 h	24.9600	23.2124
15-16 h	24.8049	23.5721
16-17 h	26.0379	26.5936
17-18 h	30.8616	29.3149
18-19 h	34.6631	27.6575
19-20 h	30.3540	24.4282
20-21 h	25.0328	22.9396
21-22 h	22.6361	22.1621
22-23 h	21.3882	21.4595
23-24 h	20.3474	20.4826

Having a closer look at the electricity price values in the autumn test period it can be seen that the lowest electricity price is on average 17.96 [€/MWh], while the highest electricity price is on average 34.66 [€/MWh] throughout the day in test period autumn 2015. The highest hourly value is nearly double as high as the lowest hourly value in autumn 2015.

The gap between minimum average, 18.81 [€/MWh], and maximum average, 30.01 [€/MWh], electricity price per hour in spring 2016 is lower compared to autumn 2015. While the lowest electricity price is in both cases between 3-4 h in the night, the highest can be found between 8-9 h in the morning during spring 2016. In contrast to this the highest hourly electricity price in autumn 2015 can be found between 18-19 h in the evening.

Looking at the electricity price per hour in spring (figure 3.19) it can be seen that only seven days of the test period have an electricity price of over 50 [€/MWh] during one time of the day. In comparison to this it can be said that in test period autumn, throughout the day, (figure 3.17) about double as many days had an electricity price of over 50 [€/MWh] during one time of the day. This could be explained by the ambient temperature differences between the test periods and the resulting higher electricity demand, as the higher demand with constant supply results in higher prices.

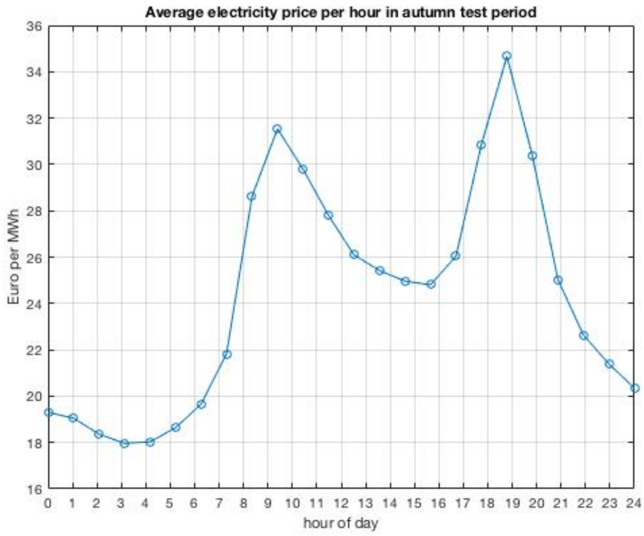

Figure 3.16: *Average electricity price [€/MWh] per hour in autumn test period*

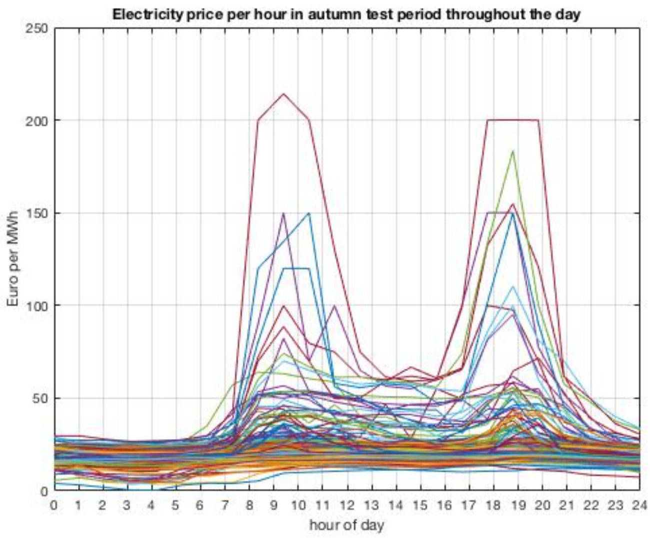

Figure 3.17: *Electricity price [€/MWh] per hour in autumn test period throughout the day*

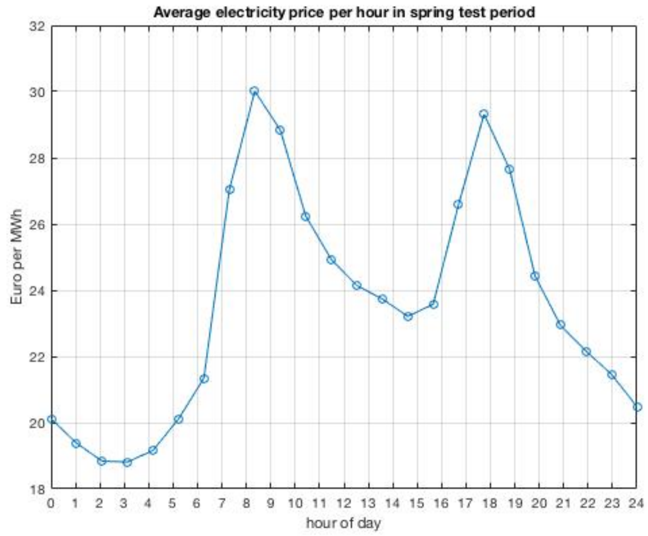

Figure 3.18: *Average electricity price [€/MWh] per hour in spring test period*

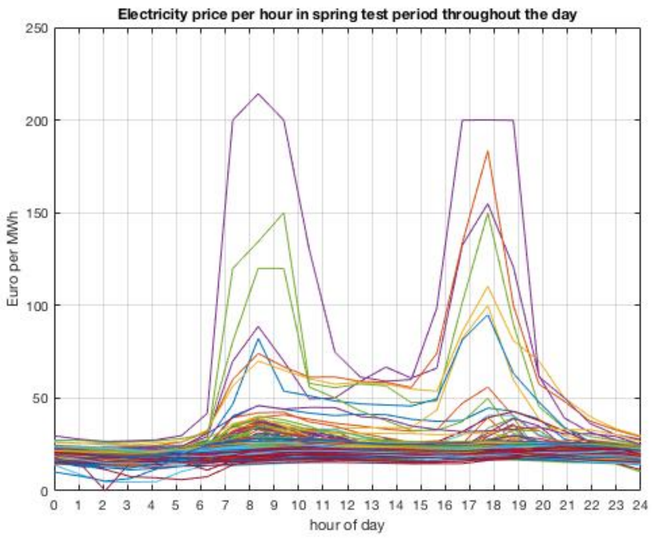

Figure 3.19: *Electricity price [€/MWh] per hour in spring test period throughout the day*

Autumn 2015 probability distribution

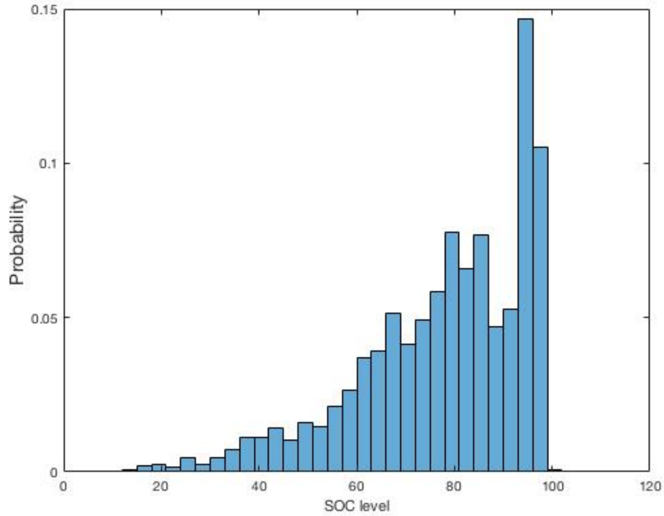

Figure 3.20: *Probability of SOC level when starting to charge in autumn 2015*

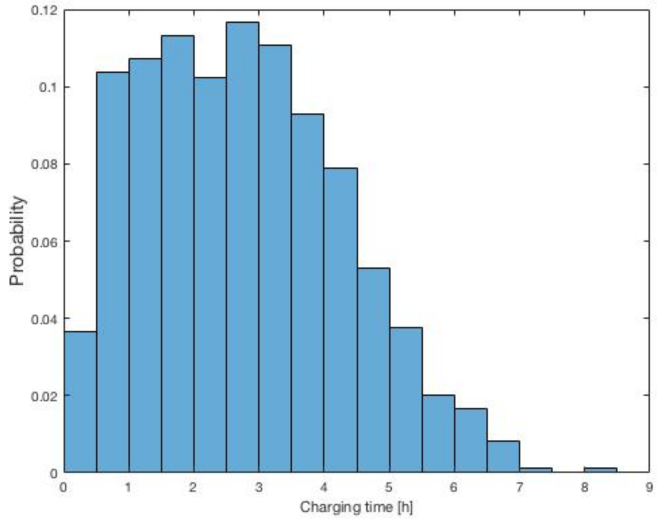

Figure 3.21: *Probability of charging time in autumn 2015*

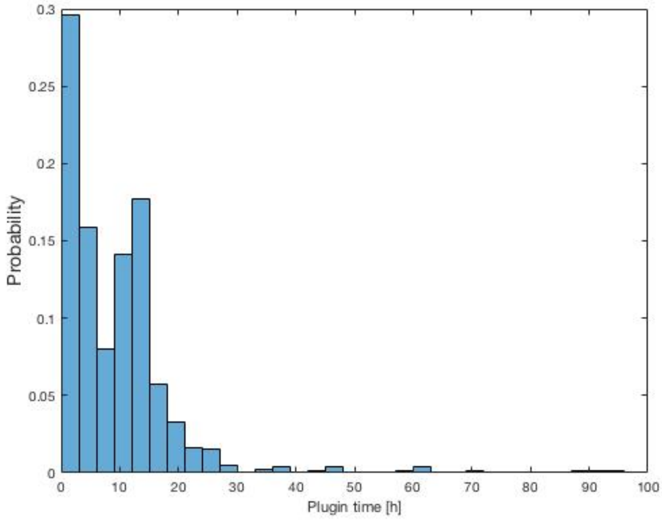

Figure 3.22: *Probability of plugin time in autumn 2015*

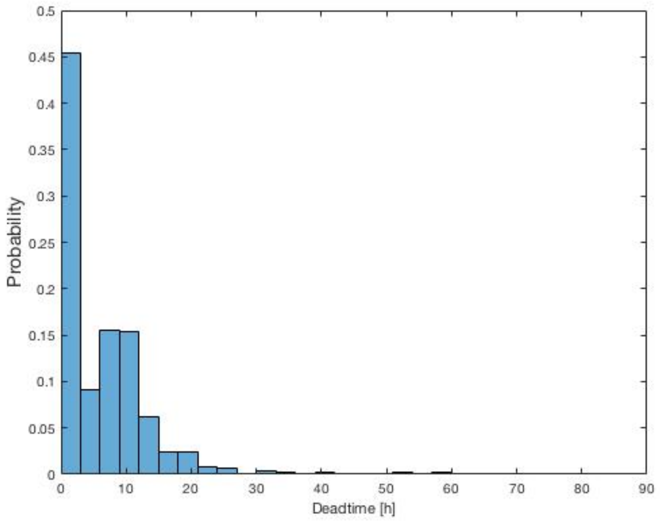

Figure 3.23: *Probability of dead time in autumn 2015*

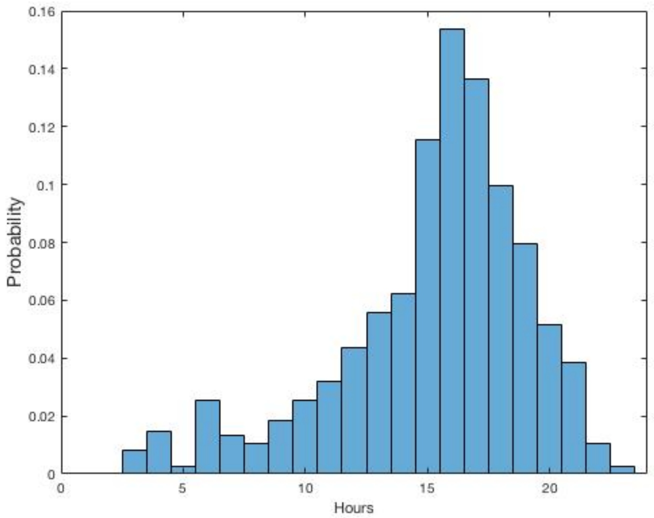

Figure 3.24: *Probability of start charging time in autumn 2015*

Spring 2016 probability distribution

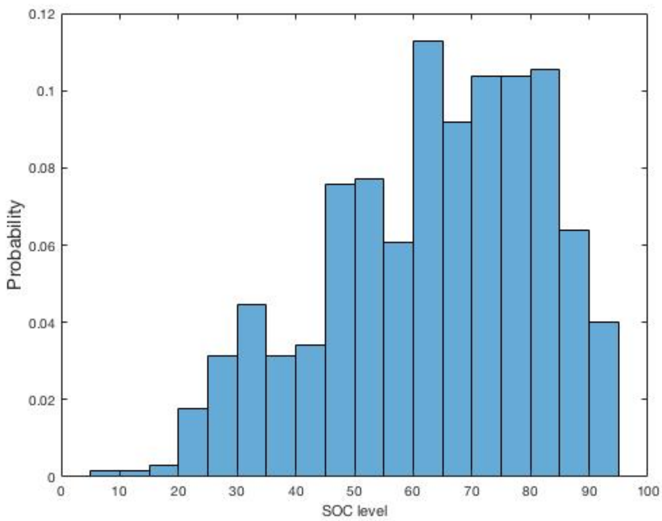

Figure 3.25: *Probability of SOC level when starting to charge in spring 2016*

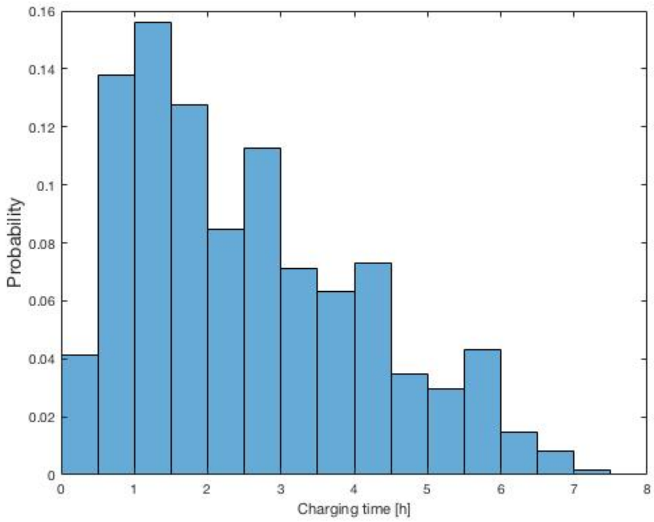

Figure 3.26: *Probability of charging time in spring 2016*

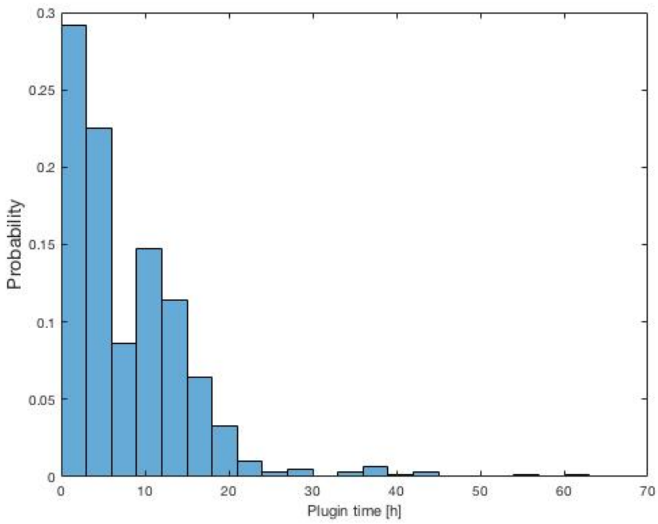

Figure 3.27: *Probability of plugin time in spring 2016*

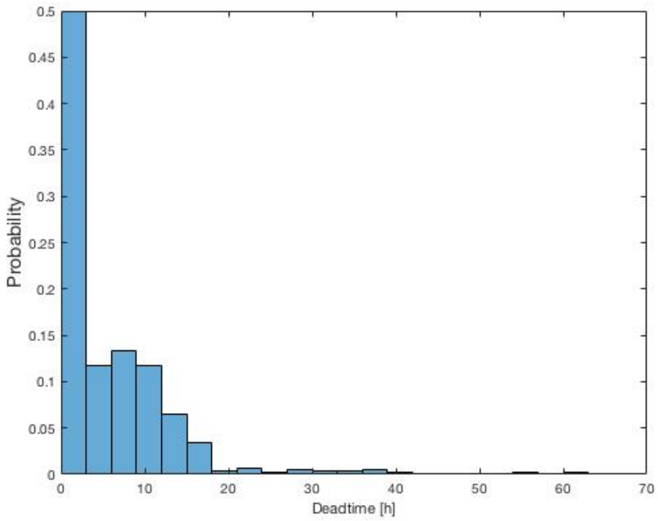

Figure 3.28: *Probability of dead time in spring 2016*

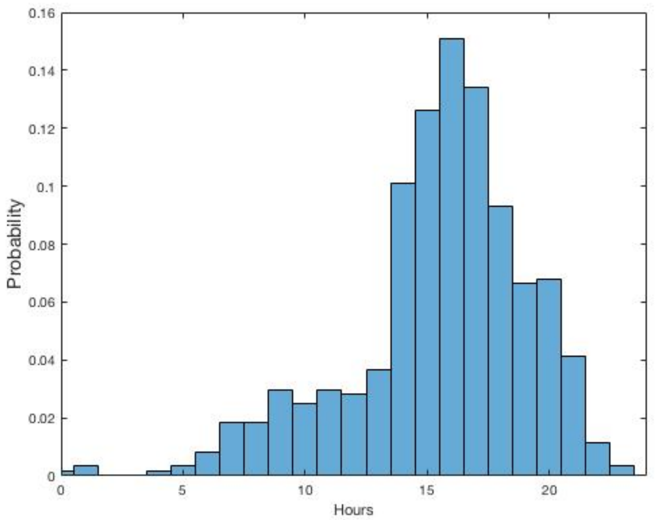

Figure 3.29: *Probability of start charging time in spring 2016*

In the test period autumn 2015 more than 84.4 % of the SOC level when starting charging was higher than 60 % (figure 3.20), which relates to an average value of 77.55 %. Compared to this the average value for the test period in spring 2016 is 63.32 % (figure 3.25). Whereas the starting times for charging the EV are very similar, 15:59 h for spring 2016 and 15:45 h for autumn 2015. This shows a similar behaviour of starting the charging when coming home after work in the afternoon. In 60 % of the cases the charging started between 15-19 h in autumn 2015 (figure 3.24) and 44 % of home charging started between 14-18 h in spring 2016 (figure 3.29). The probability of dead time below 5 h is in both cases around 60 % , which fits to the average values. The average dead time is 5 h 33 min for spring 2016 and 6 h 31 min for autumn 2015 (figure 3.23 and 3.28).

Regarding plug-in time it can be calculated that this value has been more than one hour higher for autumn 2015, 9 h 17 min, than for spring 2016, 8h 6 min. This could be explained by people leaving home later in the morning during winter compared to summer (figure 3.27 and 3.21). The values for charging time are nearly similar, 2 h 46 min for autumn 2015 and 2 h 33 min for spring 2016.

3.4.2 Charging Strategies

Three different strategies have been evaluated in this analysis to calculate cost savings by shifting EV charging using historic electricity price data from Nordpool.

- **Status-quo** is defined by the average start charging time and average charging time calculated for both test periods.
- **Strategy A** is defined as shifting the average charging time for both test periods to a start charging time of 12 p.m.
- **Strategy B** is an extension to Strategy A, which adds the de-charging of the EV before charging it during the night (11 p.m. to 6 a.m.).
- **Strategy C** including ex-post and ex-ante uses historic Nordpool data to calculate the cheapest possible charging price (ex-post), as well as the cheapest charging price by using a cap, which starts charging as soon as the electricity price drops below a set level (ex-ante).

Strategy A

Different strategies have been evaluated to look into possible cost saving effects of shifted charging for electric vehicles. Strategy A is evaluating the usage of the cars electronic to schedule the charging of the electric vehicle from 12 p.m. in the night to 6 a.m. in the morning. This time has been set as the last time to be finished with charging to make sure that people can go to work with a charged EV. This strategy aims to use the on average lower electricity prices during night to save costs.

Firstly it can be said that only 2.71 % in the autumn 2015 test period and 2.49 % in the spring 2016 test period of all home charging events are longer than six hours and can therefore not be fit in the proposed charging period of strategy A. This results in the fact that over 97 % of the home charging events could be conducted in the time window from 12 p.m. to 6 a.m. without compromising full charging of the battery.

To calculate the cost savings on a daily level the actual charging habits of the test drivers (status-quo) need to be compared with strategy A. On average the electric vehicles, in the test period of spring 2016, have a start SOC level of 63.32 % and start charging at 15:59 h. While the average charging start time was 15:45 h and a start SOC level of 77.55 % in autumn 2015.

Table 3.2: *Average start time for home charging and the average SOC value when starting home charging in the test periods autumn 2015 and spring 2016*

	Autumn 2015 1.10.2015 - 22.02.2016	**Spring 2016 11.01.2016 - 30.05.2016**
start_charg_SOC	77.55 %	63.32 %
start_charg_time	15:45 h	15:59 h

Strategy B

An extension to strategy A would be the discharging of the electric vehicle during the peak period of 16h to 23h in the evening, when coming home, and then charging during the off-peak period between 23h to 6h in the night, as 7 h are needed to fully charge the EV. Discharging the car first in the afternoon, would create a cost saving for the household as it is basically purchasing electricity for the off-peak price while there is actually a peak price in that moment. This can be explained by the fact that the electric vehicle is charged during off-peak in the night, where electricity is cheaper, while using the electricity actually during the evening between 4 p.m. and 10 p.m. when electricity is more expensive. In addition to this, the charging itself also saves electricity costs as it is, generally speaking, cheaper to purchase electricity during night than during the afternoon.

Every day there is, due to different driving behavior (weekend/weekday, weather, outer temperature, light hours etc), a different re-charging possibility. As displayed in table 3.3, on average the electric vehicle got home with a SOC of 63.32 % in the test period of spring 2016. In this period 86.80 % of the cars had a SOC value >40 %. More than half of the electric vehicles (61.28 %) had a SOC value >60 % when starting home charging, and 20.18 % even had a SOC value >80 %. The average SOC level of the EVs in the autumn 2015 test period where 77.55 %, which implies a definite possibility to use the battery for cost saving de-charging in the evenings peak-period.

Table 3.3: *Probability for EV battery SOC levels when starting the home charging in the test periods autumn 2015 and spring 2016*

	Autumn 2015 **1.10.2015 - 22.02.2016**	**Spring 2016** **11.01.2016 - 30.05.2016**
start_charg_SOC >40%	95.74 %	86.80 %
start_charg_SOC >60%	84.62 %	61.28 %
start_charg_SOC >80%	51.60 %	20.18 %

By using the average electricity prices per hour, which have been shown for both test periods in table 3.1, as well as the average SOC value and time when starting the charging from table 3.2, the cost savings using this strategy can be calculated for both test periods individually.

According to Energiföretagen [29] on average a Swedish citizen uses 32.9 kWh per day in the household. This means that 31.86% in spring 2016 and 42.33% in autumn 2015 could be provided by using the battery of the electric vehicle.

Strategy C

The third strategy uses ex-post pricing based on Nord Pool spot prices to calculate financial gains by shifting the charging period from the afternoon to the night. Elspot pricing from the Nordpool database for 2015 and 2016 in €/MWh has been used for the calculations [28].
The cheapest electricity prices for charging the car 2:33 h in spring 2016 and 2:46 h in autumn 2015, which are the average charging times for these periods, in the time window of 4 p.m. to 6 a.m. have been collected for the first week of each test period and are displayed in table 3.4 and table 3.5. By using these, the absolutely lowest charging price

can be calculated for this week. Comparing these ex-post calculated charging prices to the average price for charging after coming home in the afternoon (15:45 h in autumn 2015 and 15:59 h in spring 2016) the cost savings for each strategy related to the status-quo can be extracted.

Table 3.4: *The cheapest average price for 2:33 hours charging in week 2 during test period spring 2016 [€/MWh]*

11 Jan	**12 Jan**	**13 Jan**	**14 Jan**	**15 Jan**	**16 Jan**	**17 Jan**
19.58	18.79	18.82	22.21	22.99	24.30	20.61

Table 3.5: *The cheapest average price for 2:46 hours charging in week 2 during test period autumn 2017 [€/MWh]*

01 Oct	**02 Oct**	**03 Oct**	**04 Oct**	**05 Oct**	**06 Oct**	**07 Oct**
10.29	7.07	11.03	12.39	12.81	11.27	11.16

The cheapest electricity prices in both test periods are usually between 2 a.m and 5 a.m. As the range for the average electricity prices varies between 18.82 [€/MWh] and 24.30 [€/MWh] for the first week of spring 2016, and 7.07 [€/MWh] and 12.81 [€/MWh] for the first week of autumn 2015 it is hard to give an average cost saving for this charging strategy. When comparing table 3.4 and 3.5 it can be seen that the lowest electricity price in the first week of the test period in spring 2016 is nearly equal to the highest electricity price in the first week of the test period in autumn 2015. When comparing the absolute highest and lowest average electricity price for the night charge period a difference between 17.23 [€/MWh] can be seen (24.30 [€/MWh] to 7.07 [€/MWh]).

The ex-ante cost savings are harder to approach, one possibility would be to set a cap for the electricity price, with checking the price every hour. The car would then start charging as soon as the price is lower than this cap. Assuming a cap of 20 [€/MWh] for spring 2016 and 12 [€/MWh] for charging from 4 p.m. to 6.00 a.m. a cost saving from 24 to 62 % can be calculated. If the electricity price drops under the set cap the car starts charging. The charging is done without any breaks, even if electricity price is no longer underneath the cap in the following hour. If the price does not drop under the cap the EV starts charging automatically so it is fully charged at 6 a.m. in the morning.

By comparing these two solutions it can be seen that the cost saving effects of the two different approaches (ex-post and ex-ante) are delivering similar cost saving results. The calculation has been performed for the average charging time of 2:33 hours in the Second week of the spring test period and for 2:46 hours in the Second week of the autumn test period.

Comparing the different strategies

When comparing all three examined strategies the cost savings per test period related to the status-quo can be given.

Table 3.6: *Charging costs per strategy and cost savings compared to the status-quo in autumn 2015*

Autumn 2015 01.10.2015 - 07.10.2015				
status-quo	*strategy A*	*strategy B*	*ex-post*	*ex-ante*
0.27021 €	0.16976 €	0.0280 €	0.101881 €	0.102323 €
	- 37.17 %	- 89.64 %	- 62.29 %	- 62.13 %

Table 3.7: *Charging costs per strategy and cost savings compared to the status-quo in spring 2016*

Spring 2016 11.01.2016 - 17.01.2016				
status-quo	*strategy A*	*strategy B*	*ex-post*	*ex-ante*
0.2421 €	0.16404 €	0.17438 €	0.182664 €	0.183749 €
	- 32.24 %	- 27.97 %	- 24.55 %	- 24.10 %

All in all, the charging costs per strategy and cost savings compared to the status-quo, are displayed in table 3.6 for autumn 2015 and in table 3.7 for spring 2016. Shifting the charging time results in cost savings of 37.17 to 89.64 % in autumn 2015 and 24.10 to 32.24 % in the test period in spring 2016.

Strategy A, which is the easiest to implement by the test drivers themselves has an average cost saving of 32.24 to 37.17 % per day. The highest savings could be seen for strategy B in autumn 2015 as a lot of electricity has been used from the battery for a very low price compared to the actual grid price. Strategies to shift charging periods, using off-peak electricity, as well as using the battery of the EV during peak are worth investigating further.

4
Discussion

In this thesis we have analyzed data of 15 EVs placed at different test drivers situated in the Gothenburg region. The data consists of parameters related to driving and charging split up in four data sets, two for each time period. In the analysis we have found driving and charging behaviours including energy consumption, and in the process some assumptions have been made. One assumption was that of a constant charge rate over the entire span of battery capacity, which is true for lower charging powers like 3.4 kW used during home charging. However, in some, very few away charging events higher charging power has been used, and then assuming a constant charge rate is far from accurate. Still, this assumption was considered valid due to the low number of such events. We also assumed that SoC% is linearly convertible to kWh through a conversion factor which was calculated through calibration when comparing home charging events in charging and trip data. As we illustrated in the results this calibration was fairly good but not 100 %, which could have something to do with uncertainty of SoC% values taken from the OBD system, as well as the fact that we were not able to match all of the home charging events. In the paper "Charging behaviour of Dutch EV drivers" published by Spoelstra from Utrecht University in the Netherlands [18] it was stated that behavioural training and knowledge about TOU-pricing is essential to stabilize the energy system and keep prices low for the consumer. In our results it can be clearly seen that the a few EV test drivers have a different driving behaviour than the majority. For instance, some test drivers consumed more than others during the same time of the year. This could, however switch depending on season were some of the drivers that consumed little in summer now had problems maintaining that during winter. Generally, the consumption of energy increased when reaching colder time periods. This can partly be explained due to that it is harder to draw energy from cold batteries, which is a problem especially when the driving range is short. Furthermore, a higher energy is needed to heat the car and its' inside climate at colder temperatures compared to moderate temperatures [20]. In conclusion from the driving behaviour there are cases in which energy savings, as well as lower stress on the electricity system potentially are possible. Therefore, education such as presented in the Dutch report could be a solution in order to lower energy consumption, as well as even it out among EV consumers. In the best case scenario this should possibly be realized already before the purchase of an EV.

The charging behaviour of the test drivers indicated that most them charged at home, with the exception of one EV (EV 10) that had been charged at the workplace in 89 % of the cases. There were other EVs that also had been charged at the workplace, and this is interesting since it will demand electricity during working hours (08:00-17:00) instead at times during homecoming in the late afternoon. Thereby, the possibility of shifting the peak demand of electricity probably increases with the possibility to charge at the workplace. We also saw that most test drivers charged their EVs mostly when the batteries had a SoC% level in the range of 20-80 %. The SoC% values when charging was ended were in the range of 80-100 % in almost all of the cases. Both these latter results indicate that most test drivers prefer not to wear out the battery too much, as well as not to gamble on the battery level risking a stop without the possibility to charge. From the average load curve in the charging behaviour section one can see that charging tend to occur mostly during the afternoon with a smaller peak in the morning. There is a risk that this will coincide with behaviour of electricity usage by households resulting in a very contra productive situation, when planning to use the EVs to stabilize the electricity system and ease out peaks. In order to make it work in a V2G system it would be necessary to develop ”smart grid” technologies. Another, more near future solution to ease out charging peaks during afternoons could for instance be to make use of incentives for charging during off-peak hours. Furthermore, the possibility for charging at work or other places outside home, might perhaps be larger in the future, which would shift the majority of the EV charging events away from the peak-hours and stretch it out over the day. The energy consumed through charging during a day varied depending on if it was an average day of charging or maximum. Here we had to separate EVs 1-5 and 6-15 since their data was conducted during two different time periods, and therefore we did not know if they could be charging at the same time. What we do know is that four out of EVs 1-5 were charging simultaneously during their day of maximum energy, whereas this were only true for six out of EVs 6-15 during the day of maxmimum power. Though, there was one day were all of EVs 1-5 and seven of EVs 6-15 were charging but here the charging energy demand was substantially lower during those two days. In conclusion it seems that not all EVs in a system will be charged at the same time. Though, since we had a small data set of only 15 EVs one should be careful drawing too big conclusions. For the actual consumption when charging all EVs demanded 120 kWh during an average day, whereas during the day of maximum energy EVs 1-5 and 6-15 demanded 122 and 153 kWh, respectively. Note that Evs 1-5 and EVs 6-15 consumed less energy during the day of maximum power: only 86 and 124 kWh, respectively.

We have contributed with charging and driving behaviour including energy consumption, which can be suitable to include in another context such as energy system modeling including a V2G system. Another angle for continued work could be to use these analyzes in the work of education charging behaviour, maybe as a before case. It has been shown from one of the reports in the literature study that different stress is put on the energy system in the week and on weekends by EVs. EVs are mostly driven during the week for going to work, doing grocery shopping, picking up the kids etc., and less at the weekends. In contrast to that energy usage by household are higher for the weekend than weekdays, as people spend more time at home during the weekend, doing the laundry, watching TV etc. By introducing more EVs into the energy system these two contrary effects could ease out each other, creating a more even energy use during the week, which will be easier to be provided by the usual energy production. Separating energy consumption in weekdays and weekends is, however not something that we have covered but could definitely be included in future research within this field.

5

Conclusion

- The driving behaviour differed between the test drivers, some more than others, and therefore also the energy consumption as seen in values regarding: kWh/day (figure 3.11); total kWh (figure 3.12); and kWh/km/day (figure 3.13). Note that the driving behaviour correlated to the energy consumption for the respective driver.

- The charging behaviour of the test drivers showed that most of them charged at home, with some exceptions. One of the EVs (EV 10) had been charged at the workplace in 89 % of all the cases, whereas the second biggest, EV 1, only 50 %. Logically, the charging load curves in figure 3.10 showed a large tendency towards charging directly at upon homecoming to the evening (17:00-21:00), although with a smaller peak in the morning (07:00-09:00).

- With input from previous studies we concluded that educational and economical (TOU pricing) measures could be useful for new and old EV drivers, in order to lower energy consumption and change time upon charging.

- The analysis of possible shifting of charging showed a big potential for cost savings of about 30 to 50 % during both test periods.

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A

Appendix A

A.1 Calibration and validation

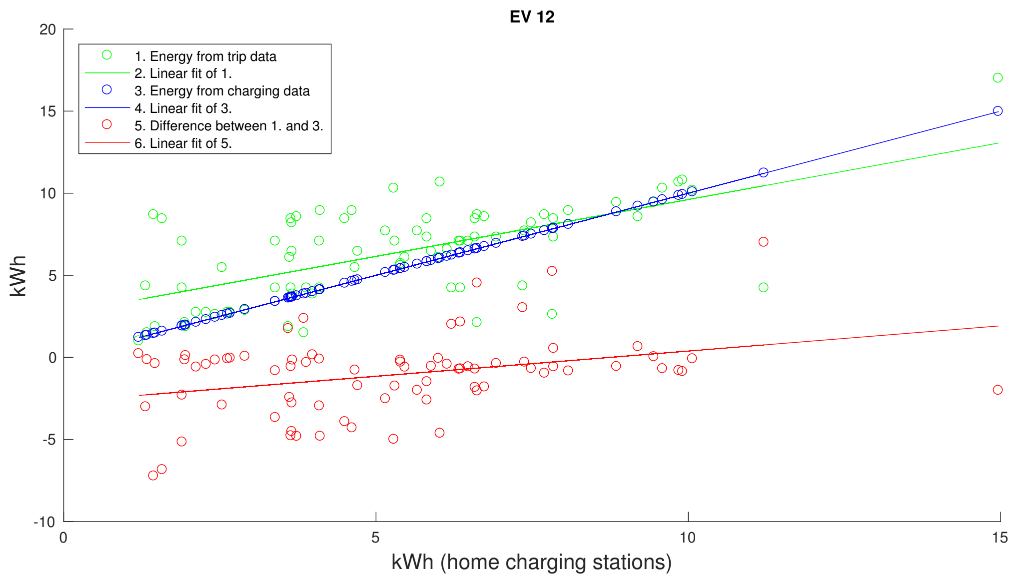
The calibration process included a comparison of energy values in home charging data and SoC% values in trip data for each EV. In figure A.1 the worst (EV 12) and best (EV 8) match are illustrated. Basically, we matched the time points where charging occurred in home charging and trip data, and from there we found linearity between the two with a nearly constant difference of zero.

A calibration value of 31 kWh has been used converting SoC% difference to kWh when charging, since that matched best considering all vehicles. In theory this indicates that if charging the battery fully from 0 to 100 SoC% (24.2 kWh) there will be charging losses of 6.8 kWh in the process. On average we were able to match the charging time intervals between the two data sets in about 65 % of all the home charging events. For the best match, figure A.1b as many as 90 % of the events were practically identical. The time points of the remaining charging events differed irregularly between the data sets inhibiting a time synchronization and further matching of events.

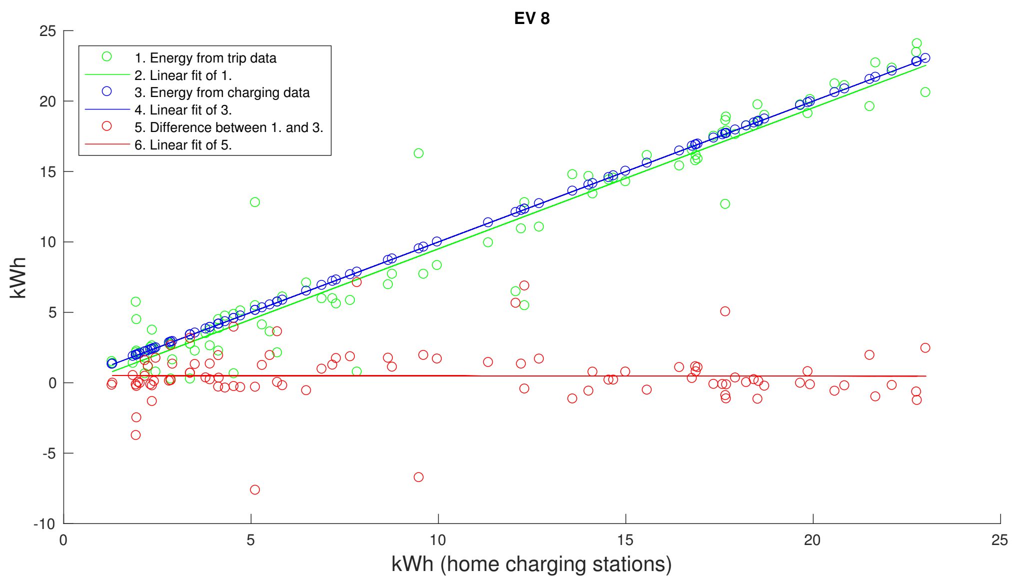
The discrepancies between data points for home charging events in the data sets can be partially explained due to that some test drivers were using the car heater simultaneously as the vehicle were charged, thus using more energy from the charging box than stored in the battery. In addition, data errors probably are another reason, however this is not validated.

In order to validate the assumption of a constant charge rate we found the home charging events in the trip data where the plug-in duration matched actual charging duration. A reorganized version of equation 2.1 in section 2 were used to calculate P_{charg} in order to find the events with a charging power of 3.4 kW, without adjusting for the end charge time points ($t_{charg,end}$). At these events the SoC% levels have been analyzed whereupon a charging rate ($\dot{C}$) has been calculated as SoC% difference per hour, equation (A.1).

$$\dot{C} = \frac{\Delta SoC\%}{\Delta T_{plug-in}} \tag{A.1}$$



(a)



(b)

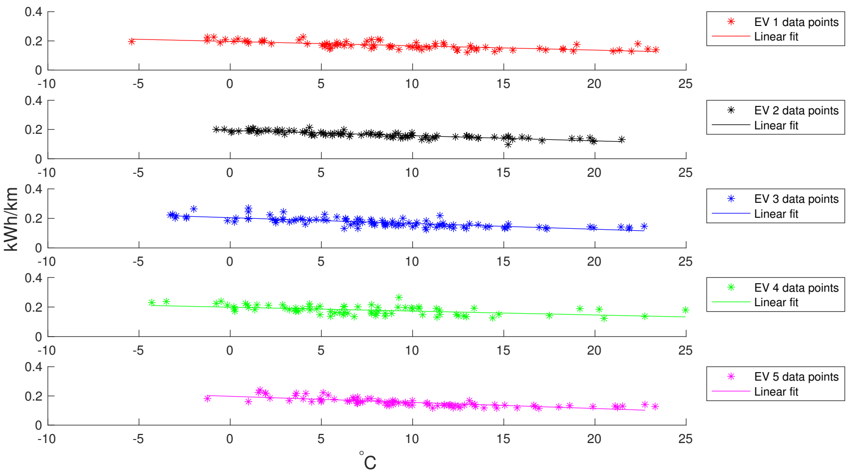
Figure A.1: *The energy and converted SoC% values for matched charging events plotted against energy values from home charging data, where (a) illustrates the worst match and (b) the best. The energy values from the charging data are indicated by blue, converted values from trip data by green and the difference between the two by red.*

In table A.1 home charging events with charging power of around 3.4 kW are summarized for analysis of the charging rate at different SoC% levels. The charging rate were close to constant between all of the charging events, which confirmed the assumption of constant charging rate used in SoC% difference to kWh calculations.

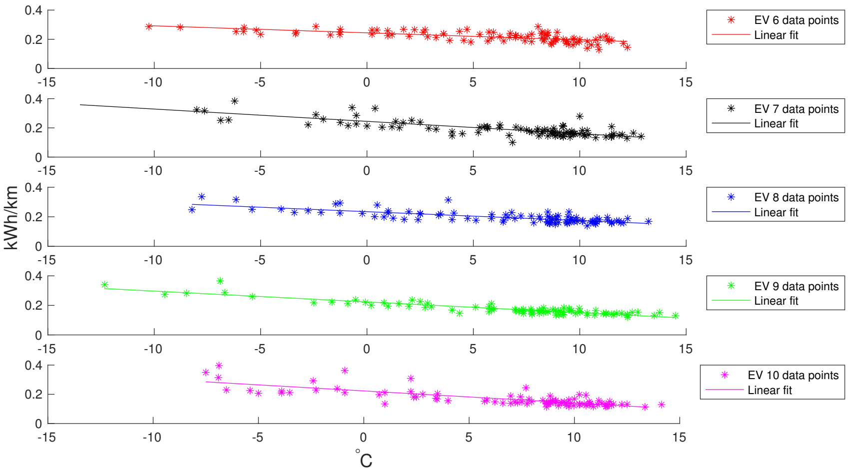
Table A.1: *Charge rate for home charging events (3.4 kW) at different SoC% levels where charging and plug-in duration are equal.*

EV id	index	ch. duration [h]	ch. interval [SoC%]	ch. rate [SoC%/h]
2	120	1.6	30.8 - 49.6	11.4
2	302	1.5	61.2 - 77.2	10.7
2	336	3.5	50.8 - 88.8	11.2
2	364	4.9	33.2 - 84.8	10.6
3	59	2.0	42.8 - 63.6	10.5
3	136	3.8	32.8 - 72.0	10.4
3	181	6.3	25.6 - 91.2	10.4
3	187	4.5	24.8 - 74.4	10.9
3	249	2.0	36.8 - 57.6	10.4
3	368	3.1	49.6 - 82.4	10.7
4	70	3.5	54.0 - 92.0	10.8
5	25	1.4	39.2 - 54.8	10.9
5	249	1.7	43.6 - 62.4	11.0
5	287	3.4	60.8 - 97.2	10.7

A.2 Temperature dependent energy use



(a)



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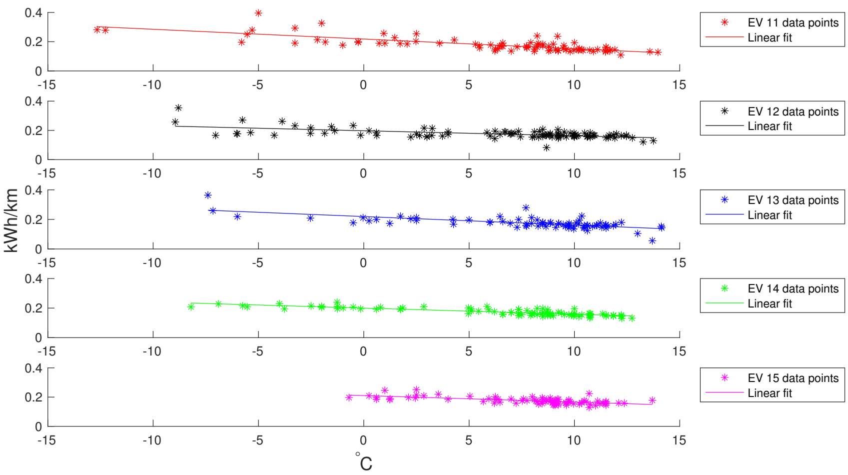
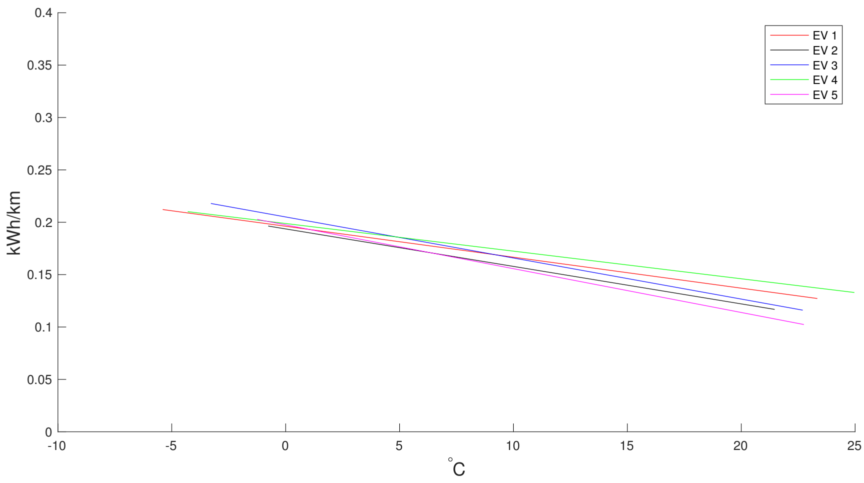
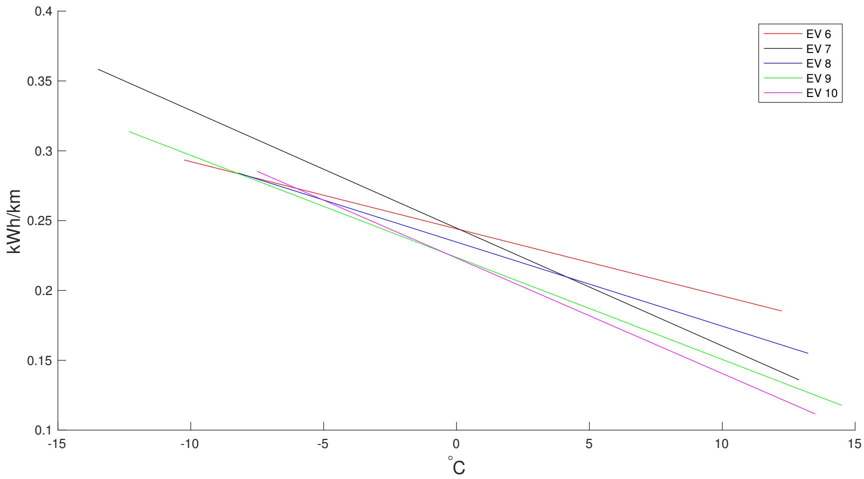


(c)

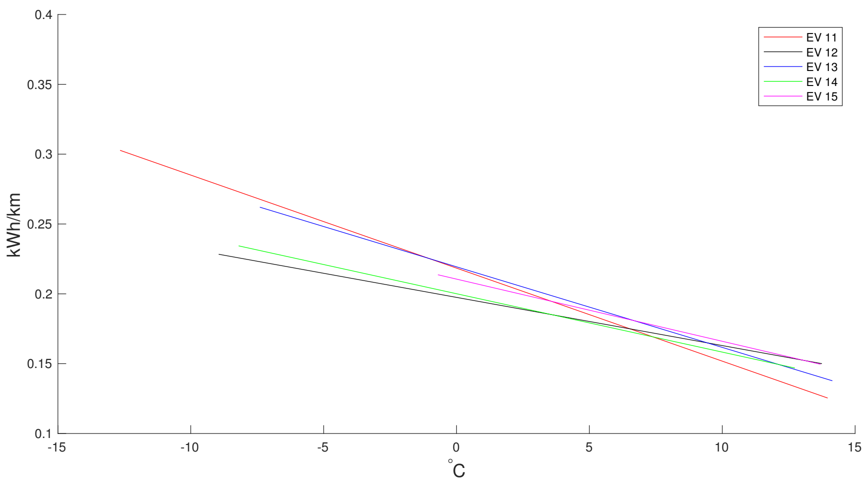
Figure A.2: *Data points and linearly fitted lines of driving consumption of energy relative to temperature for each EV.*



(a)



(b)



(c)

Figure A.3: *Comparison of the linearly fitted lines illustrating driving consumption of energy relative to temperature for each EV.*