Bachelor of Science Thesis in Electrical Engineering
Department of Electrical Engineering, Linköping University, 2020

Analysis and Modelling of Charging Profile on a Plug-in Hybrid Electric Vehicle

Marcus Törngren

Bachelor of Science Thesis in Electrical Engineering

Analysis and Modelling of Charging Profile on a Plug-in Hybrid Electric Vehicle:

Marcus Törngren

LiTH-ISY-EX-ET--20/0493--SE

Supervisor: **Max Johansson**
ISY, Linköpings universitet

Examiner: **Daniel Jung**
ISY, Linköpings universitet

Vehicular Systems
Department of Electrical Engineering
Linköping University
SE-581 83 Linköping, Sweden

Abstract

As the interest for electrified vehicles increases due to a conversion from a fleet of vehicles powered by fossil fuels to more environment friendly and climate neutral options it is important to investigate the different alternatives closely. This thesis analyzes one of the options on a micro level. Data have been collected from a Mitsubishi Outlander plug-in hybrid, including travelled distance, battery state of charge and outdoor temperature. The objective is to develop a model describing how these different factors affect the charging profile. Two models have been developed: one focusing on the total charging time and one for the total electrical charge transferred from the charging station. The analysis show for instance that at higher outside temperatures the charging time decreases but the total charge transferred increases. The final multidimensional models are created by separately looking at one variable at a time to see how it affects the total outcome.

Sammanfattning

Eftersom intresset för elektrifierade fordon ökar på grund av omställningen från en fordonsflotta som drivs av fossila bränslen till mer miljövänliga och klimatneutrala alternativ är det viktigt att undersöka de olika alternativen. Den här avhandlingen analyserar ett av alternativen på mikronivå. Data har samlats in från en Mitsubishi Outlander plug-in hybrid, innehållande körd sträcka, batteriets laddningsnivå och utetemperatur. Målet var att skapa en modell som beskriver hur dessa faktorer påverkar laddningsprofilen. Två modeller har tagits fram: en modell med fokus på den totala laddningstiden och en för den totala elektriska laddningen som överförts från laddningsstationen. Analysen visar bland annat att högre utomhustemperatur bidrar till att laddningstiden förkortas men att den överförda laddningen ökar. De slutgiltiga flerdimensionella modellerna är framtagna genom att separat undersöka en variabel åt gången för att se hur de påverkar resultatet.

Acknowledgments

The work for this thesis started around the same time as the university closed to prevent the spreading of COVID-19 in Sweden. A large readjustment of the normal work routine and it would not have gone so smooth without the help from all involved. I would like to thank Christofer Sundström, my supervisor Max Johansson and my examiner Daniel Jung for all their support during these ten weeks.

I would also like to thank my friends and family, especially my partner who was forced to make some sacrifices for my education and my father for always believing in me.

Linköping, June 2020
Marcus Törngren

Contents

Notation

Abbreviation	Meaning
AC	Alternating current
DC	Direct current
EV	Electric vehicle
ICE	Internal combustion engine
MSE	Mean squared error
PHEV	Plug-in hybrid electric vehicle
RCD	Residual current device
SoC	State of charge
SoH	State of health
SSE	Error sum of squares

1

Introduction

The time in which we currently find ourselves in gives us many options to what kind of energy our fleet of vehicles should be powered by. During the last decades there have been a number of supplements for the normal motorist to choose from beyond petrol and diesel. These are, for instance E85, HVO100, gas and needless to say, electricity. The choice for a motorist is not straightforward and many factors must be taken into consideration, not only personal preferences but also the economical and environmental impact of the different types of energy sources. The future of the environmental friendly alternatives vary depending on where in the world they are produced, however, all the alternatives should be considered to get the best possible outcome.

This bachelor's thesis will analyse one of the options above closer. More specific, the behavior of a plug-in hybrid electric vehicle (PHEV) during charging.

1.1 Motivation

Electric vehicles (EV's) in all of its forms is one path to more environment friendly transportation. Many car manufacturers already have some type of electrified vehicle available for purchase and more are under development. Volvo Cars for example, have a vision that by the year of 2025, 50% of all their sold cars will be pure EV's and the other 50% will be hybrids [1].

With a growing demand for electrified vehicles and manufacturers meeting that demand, it is important for the ordinary motorist to have an understanding of the practical aspects of electrified vehicles. Especially the part that all motorist have to deal with, charging their vehicle. As the number of electrified vehicles increase the stress and stability of the electrical grid will be affected [2]. A correct model of a charging session would give a more realistic analysis of the impact EV's and PHEV's have on the grid.

1.2 Purpose

For a motorist that is familiar with owning and driving a car with an internal combustion engine (ICE) it requires some readjustments to be able to live with an electrified vehicle. One large difference is refueling versus recharging. The old habits of being able to stop for a few minutes to refuel will no longer be an option when it comes to recharging a battery. It requires more planning of when the vehicle is going to be used and the distance of the trip. One option is to recharge at a station that offers fast charging, given that the vehicle supports it. However, the received range per time unit is still not as high as refueling with petrol or diesel.

The range anxiety some PHEV owners feel is not as big as for those who own an EV. With a PHEV, the ability to drive via the ICE is still there when the battery is completely discharged. The majority of electrified vehicles available will regenerate some energy when breaking which helps increasing the total range.

1.3 Problem statements

The main goal with this thesis is to analyze and model the charging profile of a specific PHEV based on the collected data: battery state of charge, distance travelled and outdoor temperature. A specific list of problem statements follows below.

- How does the external factors affect the charging profile?
- Can a reliable model of the charging profile be produced?

1.4 Delimitations

This analysis is performed on one specific vehicle, charging at one specific charging station. The data collected was gathered starting from the end of 2015 until the beginning of 2017. Thus there is no way to acquire additional information from the vehicle nor the charging station.

2
Background

The vehicle analyzed in this thesis is owned and driven by a private citizen and the collected data from the car is recorded by the same individual. All information gathered from the car is not extracted with any special tools or programs, only data that is available to the end customer has been used. A compilation of the used data is included as Appendix A.

The data recorded from the charging station was made possible by Marcus Knutfelt as a part of his master's thesis *Charging Cost Optimization of Plug-in Hybrid Electric Vehicles*[3]. Information about the charging session is saved as two arrays with data about the charging current at a specific time.

2.1 The vehicle

The car that this data was collected from is a Mitsubishi Outlander PHEV model year 2015.

Relevant data selected from the specification sheet [4]:

- Drivetrain: PHEV
- Combustion engine: 2.0, four cylinder petrol (121 hp, 190 Nm)
- Electric motor, front axle:
  - Rated power: 25 kW (34 hp)
  - Maximum power: 60 kW (82 hp)
  - Maximum torque: 137 Nm

- Electric motor, rear axle:
  - Rated power: 25 kW (34 hp)
  - Maximum power: 60 kW (82 hp)
  - Maximum torque: 195 Nm
- Battery:
  - Type: Lithium ion
  - Voltage: 300 V
  - Number of cells: 80
  - Capacity: 12 kWh
- Charging:
  - Normal 10 A: 5 h
  - Fast charging: 0.5 h

2.2 The charging station

The charging station used for charging the vehicle was CSR100 from Chargestorm, currently known as CTEK E-mobility.

Relevant data selected from the specification sheet [5]:

- Electrical:
  - Charging capacity: 6-32 A, 230/400 V, 1.4-22 kW
  - Safety: Fuse and RCD. Type B or Type A + DC leakage detector

3 Theory

This chapter contains the theoretical foundation for the thesis.

3.1 Battery

Two terms are commonly used when discussing batteries, SoC (state of charge) and SoH (state of health). SoC is given as a percentage of the battery capacity available, $Q_{available}$. SoC is defined in equation 3.1 as

$$SoC = \frac{Q_t}{Q_{available}} \cdot 100\% \tag{3.1}$$

where Q_t is the energy stored in the battery at a certain time [6]. SoH is a measurement of wear of the battery, which is given as a percentage of the rated charge the battery can store, Q_{rated}. SoH is defined in as

$$SoH = \frac{Q_{max}}{Q_{rated}} \cdot 100\% \tag{3.2}$$

where Q_{max} is the maximum charge the battery can store [6]. To maintain the SoH and extend the lifespan of the battery manufacturers does not give access to the whole battery capacity right away. It is often limited to not charge or discharge over and under a certain percentage. The battery capacity available may vary. For example in [3] Knutfelt assumes 80% as the available capacity. Manufacturers do this to account for the battery cell degradation [7].

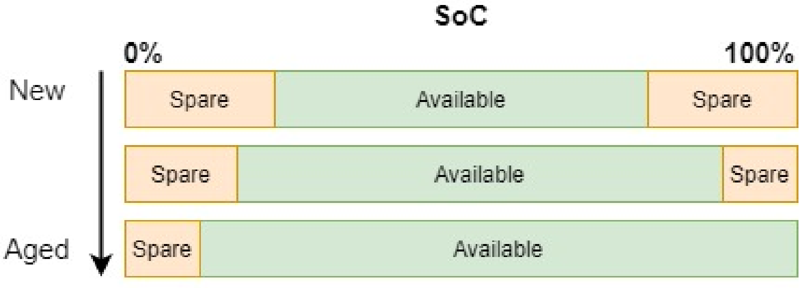


Figure 3.1: *Illustration of battery cell degradation.*

As shown in figure 3.1 the available part of the battery increases with age, but the available range to the driver remain somewhat the same.

To get information about how much electrical charge transferred to the battery during a charging session one can integrate the current over time according to

$$Q_{transferred} = \int_{t_{start}}^{t_{stop}} i(t)dt \text{ [Ah]} \tag{3.3}$$

where t_{start} represent the start time and t_{stop} the stop time.

3.2 Analysis and modelling

Creating a model from a set of collected data is done by analyzing the correlation between the different variables gathered. Often performed via a scatter plot that plots the observed data points at their respective y and x values (two dimensional).

3.2.1 Simple linear regression model

The most trivial mathematical relationship between two variables y and x is a simple linear expression $y = \beta_0 + \beta_1 x$, a straight line [8]. The goal with the model is to approximate β_0 and β_1 to best fit the observed data.

The simple linear regression model is defined as

$$y = \beta_0 + \beta_1 x + \epsilon \tag{3.4}$$

where ϵ is a random variable that is assumed to be normally distributed with expected value equal to 0 and variance equal to σ^2 [8].

3.2.2 Polynomial regression model

The goal here is the same as for the simple linear regression model, to estimate unknown variables β_i. However, with a polynomial of higher degree the estimations are rarely done by hand due to more complex calculations.

The model equation for a kth degree polynomial is written as

$$y = \beta_0 + \beta_1 x + \beta_2 x^2 + \cdots + \beta_k x^k + \epsilon \tag{3.5}$$

where ϵ is a normally distributed random variable with mean value equal to 0 and variance equal to σ^2 [8].

3.2.3 Principle of least squares

To estimate the model parameters one can make use of the principle of least squares. The point estimates of β_i, denoted $\hat{\beta}_i$ are called the least square estimates. The estimates are the values of b_i that minimize

$$\min_{\beta_0,\beta_1,\ldots,\beta_k} f(\beta_0,\beta_1,\ldots,\beta_k) = \sum_{i=1}^{n}[y_i - (\beta_0 + \beta_1 x_i + \beta_2 x_i^2 + \cdots + \beta_k x_i^k)]^2 \tag{3.6}$$

where x_i denotes sample i. There will always theoretically exist a polynomial of degree $n-1$ that fits the observed data perfectly, however, it is not used due to overfitting, since unnecessarily high order polynomials perform poorly on data that is not used in the fitting process [8].

3.2.4 Evaluating the model fit

To evaluate the model after parameter estimation, one can make use the goodness of fit available in MATLAB via the curve fitting toolbox [9]. That gives certain values of variables to determine how good the model fits to the measured data. The information received from the goodness of fit is explained below.

Error sum of squares

The SSE (error sum of squares) is the residual sum of squares from the model [8].

$$SSE = \sum (y_i - \hat{y}_i)^2 \tag{3.7}$$

where $\hat{y}_i = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + \ldots + \beta_k x_i^k$. A SSE value closer to 0 tells that the model will be more useful for predictions.

Coefficient of multiple determination

The R^2 value or coefficient of multiple determination is a measurement of how good the model curve fits to the observed data. A higher degree model will result in a larger R^2 value where $R^2 = 1$ is a perfect fit [9]. Note that a higher degree polynomial will cause the model to be less accurate for data outside the range of the training data. The equation for R^2 is given by

$$R^2 = 1 - \frac{SSE}{SST} \tag{3.8}$$

where $SST = \sum(y_i - \bar{y})^2$ and $\bar{y}$ is the mean [8].

Adjusted coefficient of multiple determination

The $adjusted\ R^2$ value takes the fitment gain in consideration when going from a kth degree polynomial to a $k+1$th degree polynomial. Although a higher k value results in a better fit it is not always practical to end up with a high degree polynomial. The equation for $adjusted\ R^2$ written as [8]

$$adjusted\ R^2 = 1 - \frac{SSE(n-1)}{SST(n-(k+1))} \tag{3.9}$$

Mean squared error

The MSE (mean squared error) value is measured in a similar way to the SSE, a value close to 0 indicates that the model is more useful for predictions [9]. The MSE is calculated as

$$MSE = \frac{SSE}{n-(k+1)} \tag{3.10}$$

4 Method

This chapter describes how the work of the project was executed.

4.1 Data sorting

The data collected by the driver was written down by hand and the data from the charging station was saved as a .mat file. The handwritten data was transferred to an Excel document to easily be imported into MATLAB. The data included information about the battery's state of charge, distance travelled and outdoor temperatures when the car was connected to the charger. The .mat files were named with the date the log was downloaded from the charging station, not the actual date the data recording was performed. To pair the notes with their corresponding .mat file a shift of the dates was required.

Since there were no notes regarding the SoC, right after disconnecting the vehicle from the charger, some necessary assumptions had to be made. To be able to sort out occasions when the charging session was not completed, all of the logs were inspected visually. As figure 4.1 shows, the current ramps down to approximately 2 A before cutting off completely. That behavior is recurrent for what is assumed to be a complete charging session. If figure 4.1 is compared to figure 4.2 or 4.3 the differences at the end of the session are clear. In figure 4.2 the current ramps down to somewhere between 11 A and 12 A before the charging is aborted. In figure 4.3 the difference is not as distinct but the current cuts off right below 4 A.

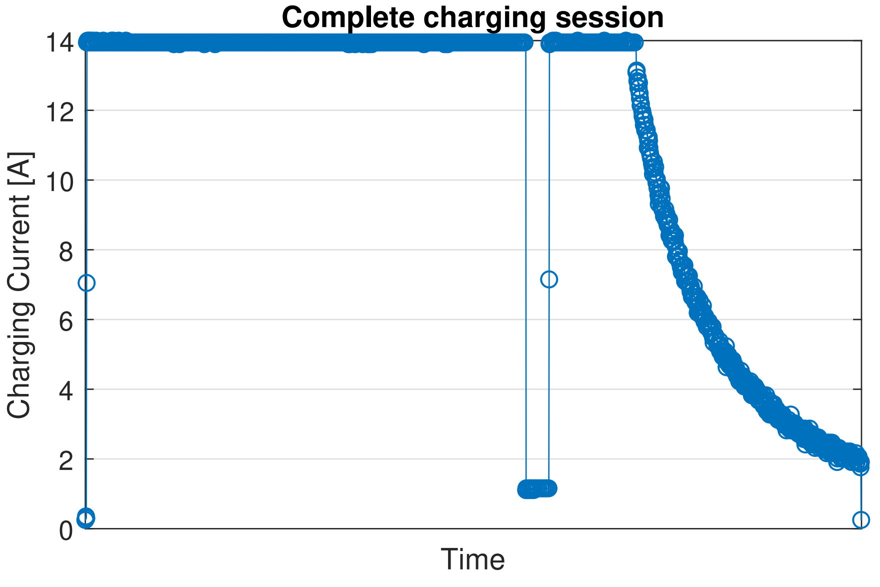


__Figure 4.1:__ Complete charging session, vehicle charges from 0% to 100%.

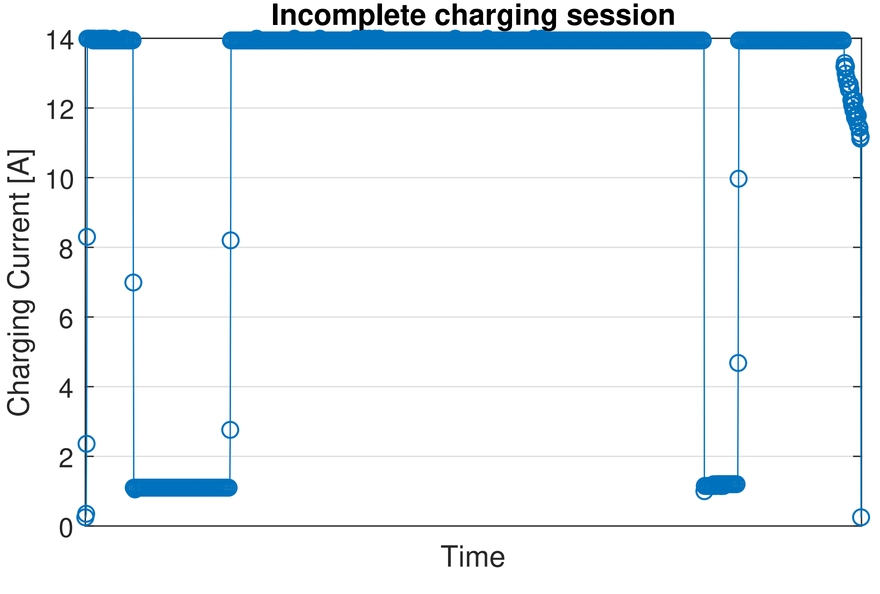


__Figure 4.2:__ Example of an incomplete charging session.

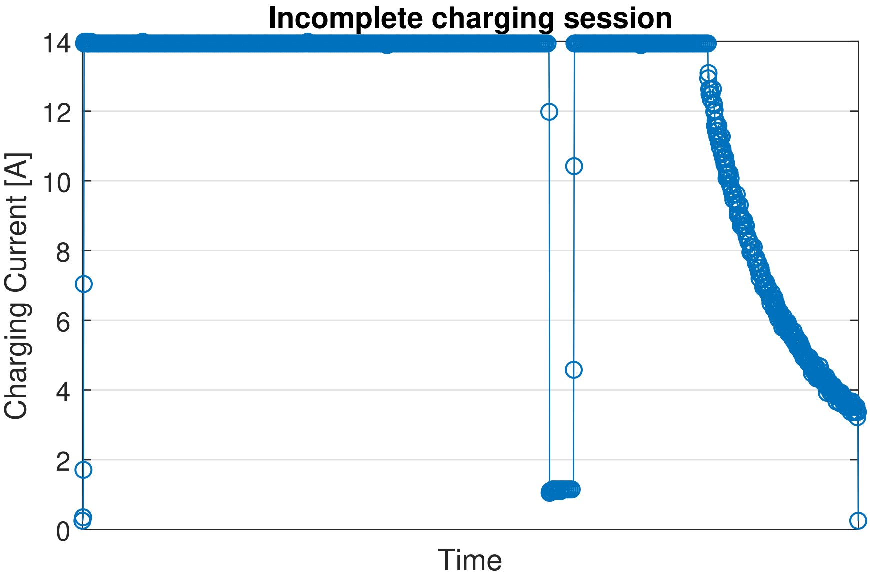


Figure 4.3: *Example of an incomplete charging session.*

4.2 Battery capacity

Since the data logs from the charging station do not provide any information about the voltage during charging and the voltage varies during a charging session, nothing can be said about the energy with enough precision. The manufacturer specifies according to [4] the battery capacity to be 12 kWh and for the charging to take 5 h at normal charging (10 A). Instead the capacity expressed in electrical charge can be written as

$$Q = It = 10 \cdot 5 = 50\,[\mathrm{Ah}] \tag{4.1}$$

Note that the capacity is what the manufacturer specifies, this says nothing about the actual available capacity.

4.3 Impact of the variables

With somewhat limited data available we choose to model the total charging time and transferred electric charge. To be able to tell how the different variables affects the charging time and electrical charge, it is important to look at the correlations. To easier see the impact of the different variables two cases were considered. One case where the PHEV's battery was completely discharged and the other when the battery was partially discharged. That is because the SoC is assumed to have the largest impact.

4.4 Modelling

When the most significant variables are found the modelling part can begin. The final multidimensional model is first separated to closer analyze one axis at a time. For each axis several models with different degrees of polynomial are produced with the mathematical theory from section 3.2. Further analysis decides what degree of polynomial that fits the data best according to the different parameters mentioned in section 3.2. This is done to easier visually analyze the goodness of fit for the model with respect to the observed data points.

4.4.1 Model validation

For validation many models were created by using bootstrapping [10]. Bootstrapping generates new datasets from an existing dataset by randomly selecting observed data point with replacement until the sample sizes were equal. The randomly selected data points were used to create a new model, the process was executed repeatedly. Coefficients for all the new models were produced in the same way as for the real model and then plotted as a histogram. The distribution of the coefficients were analyzed via parameters such as mean, variance and standard deviation to measure the real models certainty.

For each iteration the model is tested against the observed data not included as training data for the bootstrap model. The validation data is used to calculate residuals against the true observed data.

5

Results

The results and some small comments are presented in this chapter. A more thorough discussion of the results are made in chapter 6.

5.1 Completely discharged battery

For the case when the battery is completely discharged there are two variables left to look at, outside temperature and distance driven. Both of them are measured once, just before the vehicle connects to the charger. Since the majority of the charging sessions are performed when the driver has arrived at work in the mornings, the distance driven is the same in most cases. The variable distance driven before charging is therefore excluded in the analysis due to insignificant variations. As figures 5.1 and 5.2 show, the majority of the charging sessions are executed after driving 40 km. That results in a correlation coefficient between charging time and distance driven equal to 0.186 and 0.223 between charge and distance driven. When ignoring the the distance driven the outside temperature becomes the most significant variable for the case when the battery is completely discharged.

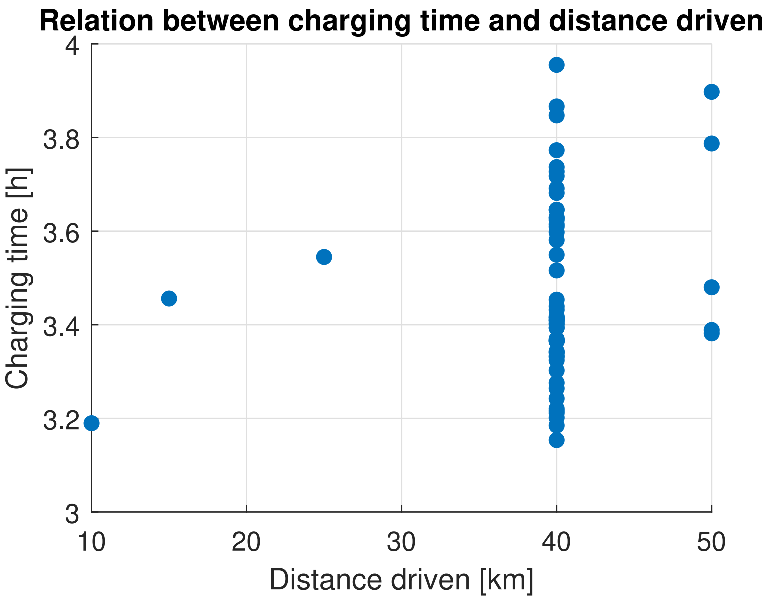


Figure 5.1: Scatter plot of the relation between charging time and distance driven right before charging.

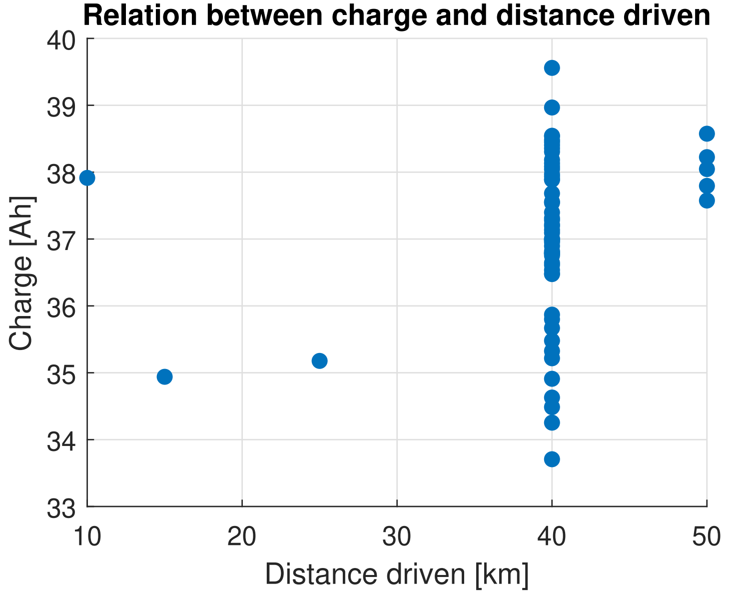


Figure 5.2: Scatter plot of the relation between charge current and distance driven right before charging.

5.1.1 Charging time

The total charging time is easily calculated according to equation

$$t_{total} = t_{stop} - t_{start} \tag{5.1}$$

for every charging session. Where t_{stop} and t_{start} is given in datenum format in MATLAB.

Figure 5.3 shows the relation between charging time and outside temperature, the correlation coefficient is -0.576. The fitted curve is shown in figure 5.4 and is modeled as

$$t(T) = \beta_1 T + \beta_2 = -0.01722T + 3.586 \tag{5.2}$$

where t is the charging time in hours and T is the outside temperature.

SSE	1.56
R^2	0.33
Adjusted R^2	0.32

Table 5.1: *Values taken from the goodness of fit for equation 5.2*

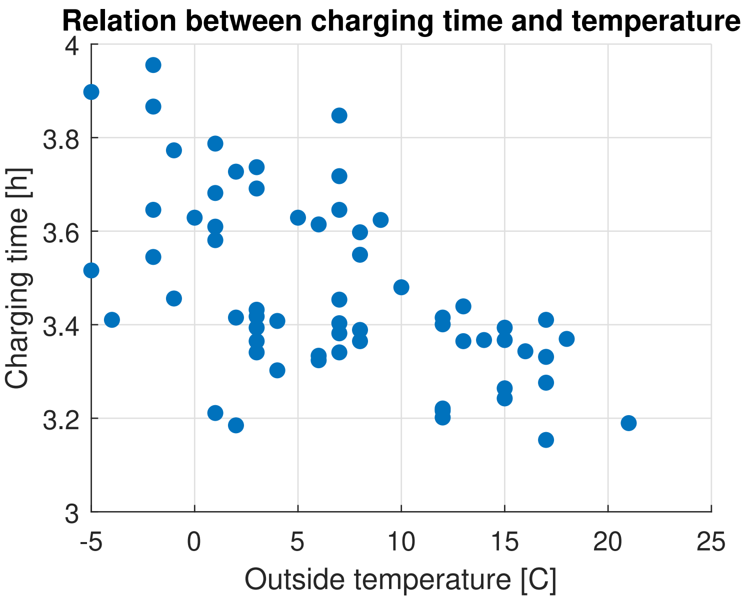


Figure 5.3: *Scatter plot of the relation between charging time and outside temperature.*

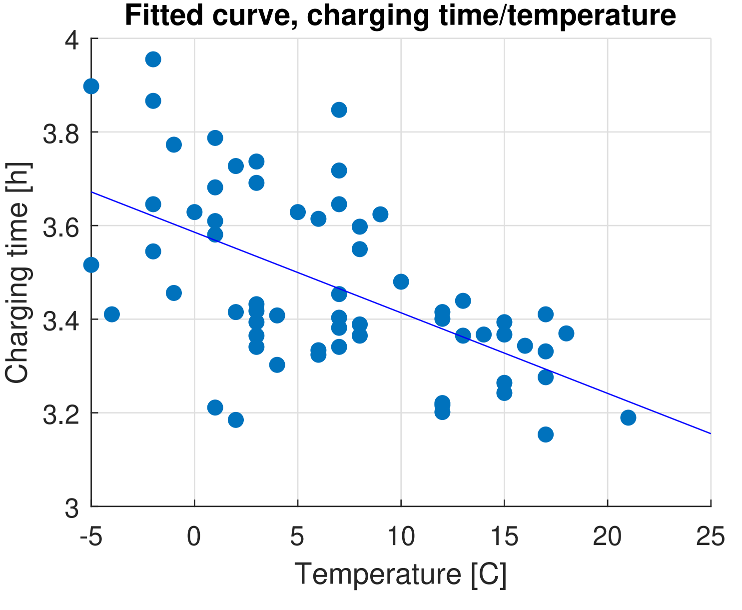


Figure 5.4: *Fitted charging time curve.*

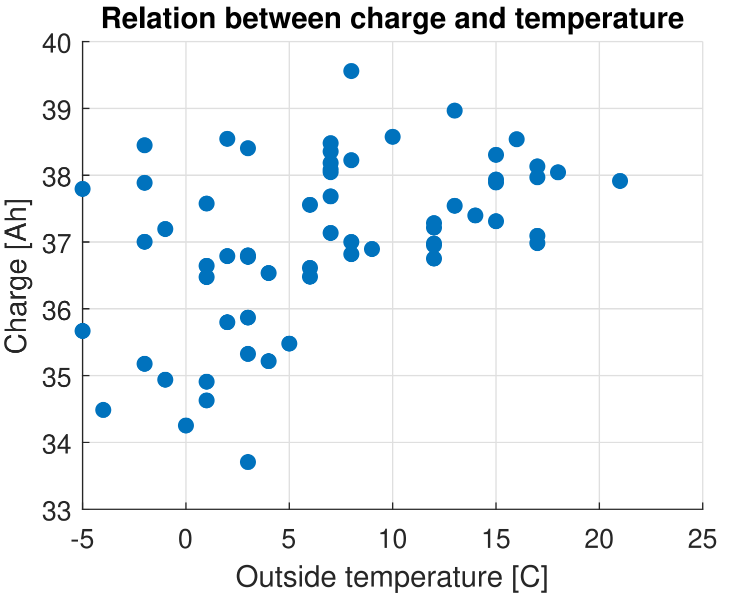


Figure 5.5: *Scatter plot of the relation between charge and outside temperature.*

5.1.2 Electrical charge

The total electrical charge from the charging station is calculated by the integral in equation 3.3. Figure 5.5 shows the relation between charge and temperature. The correlation coefficient in this case is 0.471. In figure 5.6 the fitted curve is shown above the scatter plot, with associated equation 5.3 where Q represent the charge and T is the outside temperature.

$$Q(T) = \beta_1 T + \beta_2 = 0.09114T + 36.44 \tag{5.3}$$

SSE	76.22
R^2	0.22
Adjusted R^2	0.21

Table 5.2: *Values taken from the goodness of fit for equation 5.3*

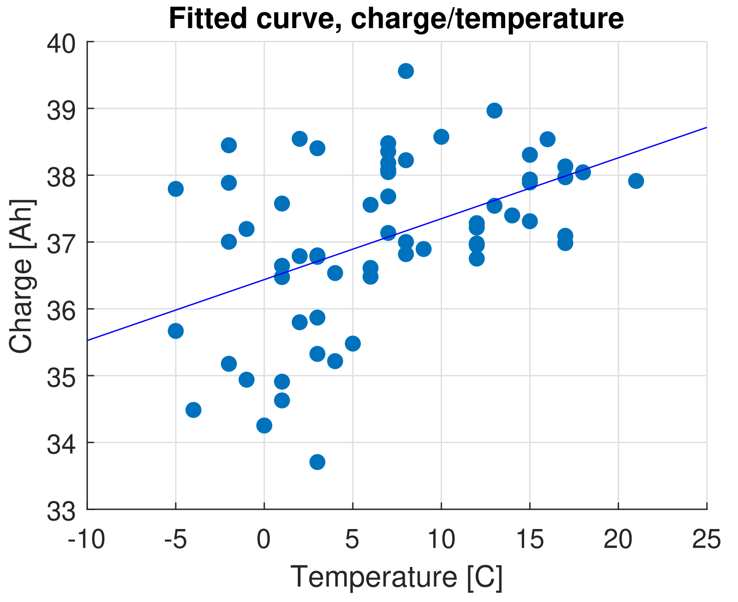


Figure 5.6: Fitted charge curve.

5.2 Partially discharged battery

The measurements for this case are taken in the same way as for the completely discharged battery case. The most dependent variable when the battery is partially discharged is the SoC at the instance when charging begins, both for the charging time and electrical charge model. The calculations of charging time and electrical charge are performed in the same way as in section 5.1.

5.2.1 Charging time

Figure 5.7 shows the relation between charging time and SoC, the correlation coefficient is equal to -0.911. The fitted curve is shown in figure 5.8 and the model equation is presented in equation 5.4, t represents the charging time and c the SoC.

$$t(c) = \beta_1 c^3 + \beta_2 c^2 + \beta_3 c + \beta_4 = -7.79c + 9.494c - 4.982c + 3.464 \tag{5.4}$$

SSE	1.86
R^2	0.90
Adjusted R^2	0.88

Table 5.3: Values taken from the goodness of fit for equation 5.4

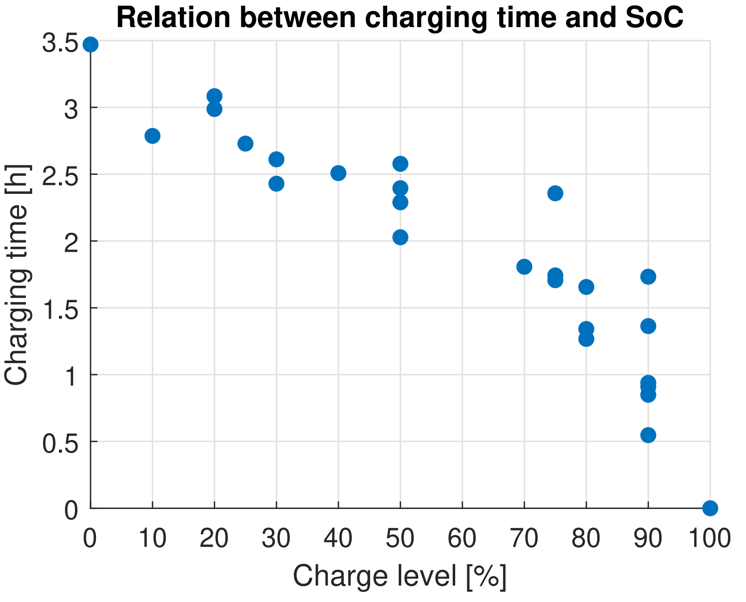


Figure 5.7: *Relation between charging time and SoC.*

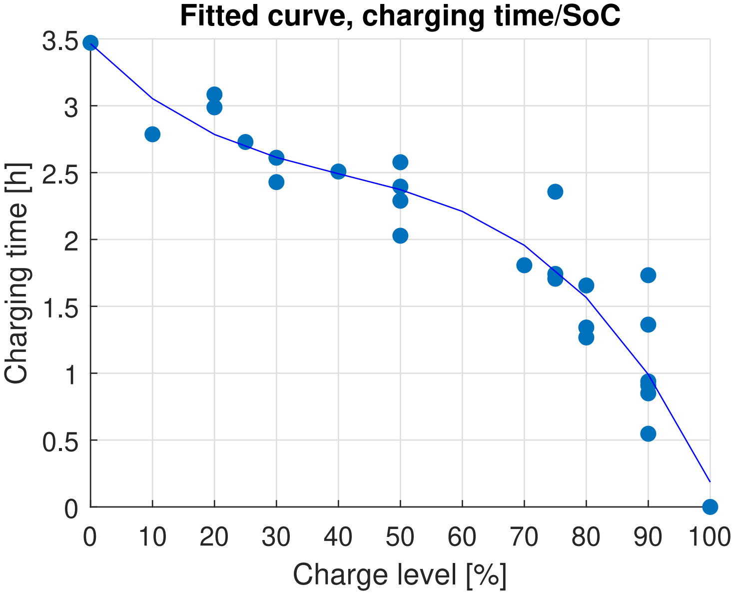


Figure 5.8: *Fitted charging time curve.*

5.2.2 Electrical charge

Figure 5.9 presents the relation between the electrical charge transferred from the charging station to the battery and the starting SoC. The correlation coefficient is equal to -0.931. The fitted curve model is presented in figure 5.10 and is given by

$$Q(c) = \beta_1 c^4 + \beta_2 c^3 + \beta_3 c^2 + \beta_4 c + \beta_5 = -124.8c^4 + 156.6c^3 - 21.22c^2 - 48.81c + 37.26 \tag{5.5}$$

SSE	164.78
R^2	0.92
Adjusted R^2	0.90

Table 5.4: *Values taken from the goodness of fit for equation 5.5*

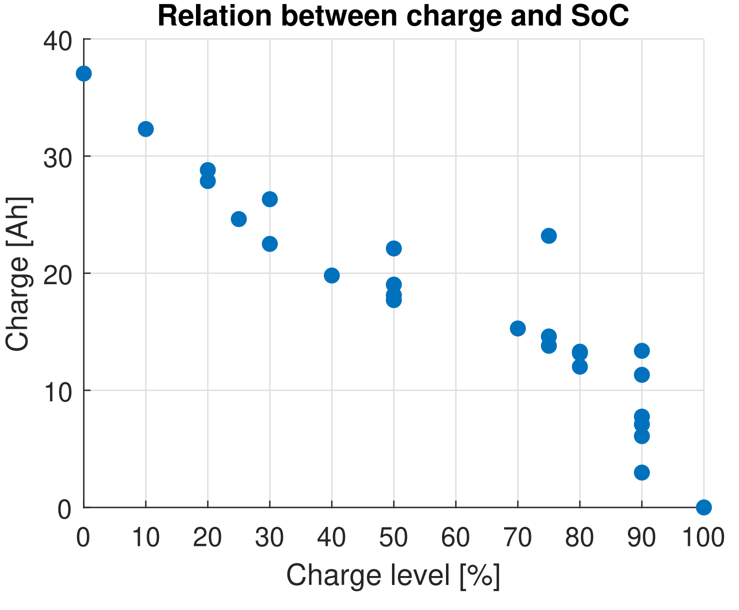


Figure 5.9: *Relation between charge and initial SoC.*

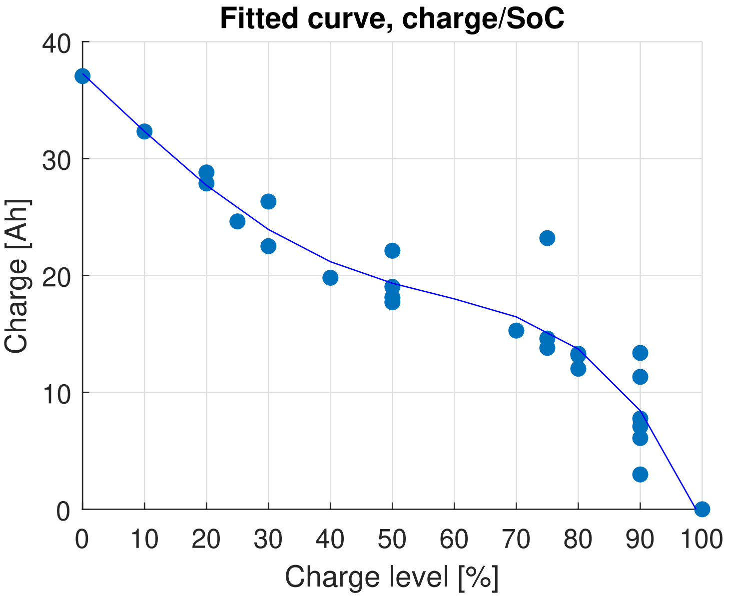


Figure 5.10: Fitted charge curve.

5.3 Three dimension model

The three dimension model is built upon the results from section 5.1 and 5.2, the same order of polynomials are used for the respective axis. Since a scatter plot in three dimensions is hard to interpret when stationary the multidimensional plot of the model will be presented immediately.

5.3.1 Charging time

The plot is shown in figure 5.11. The model has the structure

$$t(c,T) = p_{00} + p_{10}c + p_{01}T + p_{20}c^2 + p_{11}cT + p_{30}c^3 + p_{21}c^2T \tag{5.6}$$

and the optimized parameters are given by

$$t(c,T) = 3.592 - 6.46c - 0.01767T + 13.31c^2 + 0.003206cT - 10.42c^3 + 0.01316c^2T \tag{5.7}$$

SSE	3.26
R^2	0.99
Adjusted R^2	0.99

Table 5.5: Values taken from the goodness of fit for equation 5.7

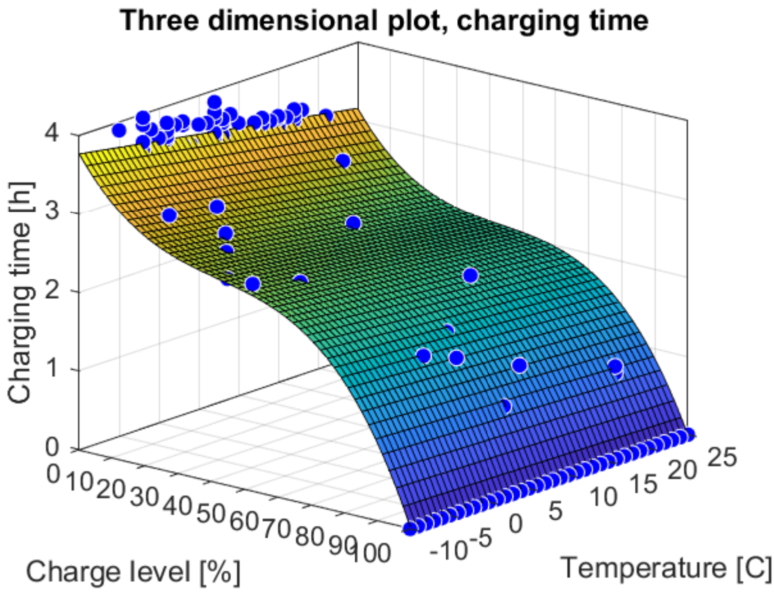


Figure 5.11: *Three dimensional plot for charging time.*

5.3.2 Electric charge

Figure 5.12 represent the three dimensional model of electric charge. The model of the electric charge is given by

$$Q(c, T) = p_{00} + p_{10}c + p_{01}T + p_{20}c^2 + p_{11}cT + p_{30}c^3 + p_{21}c^2T + p_{40}c^4 + p_{31}c^3T \quad (5.8)$$

and the coefficients are presented in table 5.6.

p_{00}	36.48
p_{10}	-46.37
p_{01}	0.08392
p_{20}	-18.7
p_{11}	0.4945
p_{30}	146.2
p_{21}	-1.871
p_{40}	-117.6
p_{31}	1.285

Table 5.6: *Coefficients for electric charge model*

SSE	236.44
R^2	0.99
Adjusted R^2	0.99

Table 5.7: *Values taken from the goodness of fit for equation 5.8*

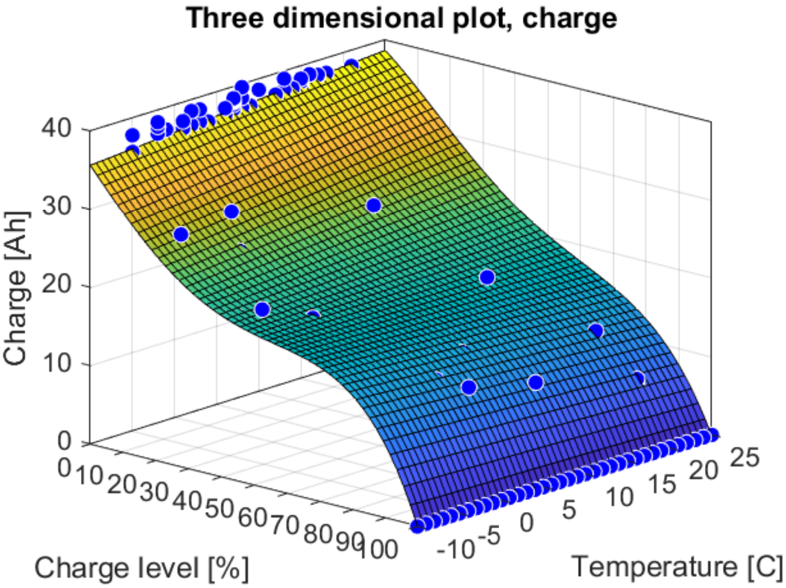


Figure 5.12: *Three dimensional plot for electric charge.*

5.4 Model verification

The two multidimensional models were verified by bootstrapping (1000 times), to investigate the variations of the coefficients. A histogram for the coefficients are included as Appendix B for the charging time model and Appendix C for the electrical charge model. Below there are two tables where the differences between the models coefficients and the mean of the bootstrapped coefficients are presented along with standard deviation. Table 5.8 belongs to the charging time model and table 5.9 belongs to the electrical charge model. Calculations were performed in MATLAB with more decimals than reported earlier for a higher accuracy.

Coefficient	Difference [%]	Standard deviation [%]
p_{00}	0.01	0.93
p_{10}	0.79	12.69
p_{01}	0.09	15.57
p_{20}	1.07	17.93
p_{11}	21.42	933.54
p_{30}	0.88	15.36
p_{21}	5.05	282.67

Table 5.8: *Table for charging time model*

Coefficient	Difference [%]	Standard deviation [%]
p_{00}	0.03	0.66
p_{10}	1.70	46.76
p_{01}	3.45	24.41
p_{20}	27.38	897.92
p_{11}	14.24	262.45
p_{30}	6.02	146.35
p_{21}	7.13	171.92
p_{40}	3.79	89.54
p_{31}	4.77	153.42

Table 5.9: *Table for electrical charge model*

For every bootstrap iteration the data points not included to create the model were used to calculate the residuals. Figure 5.13 shows the result for the charging time model and in figure 5.14 the result for the electric charge model is shown. The standard deviation is 0.0353 h or 2 min and 7 s, the largest residual value is approximately +7 min and the smallest -9 min for the charging time. For the electric charge model the standard deviation is approximately 0.393 Ah, the largest residual is +1.62 Ah and the smallest -3.55 Ah.

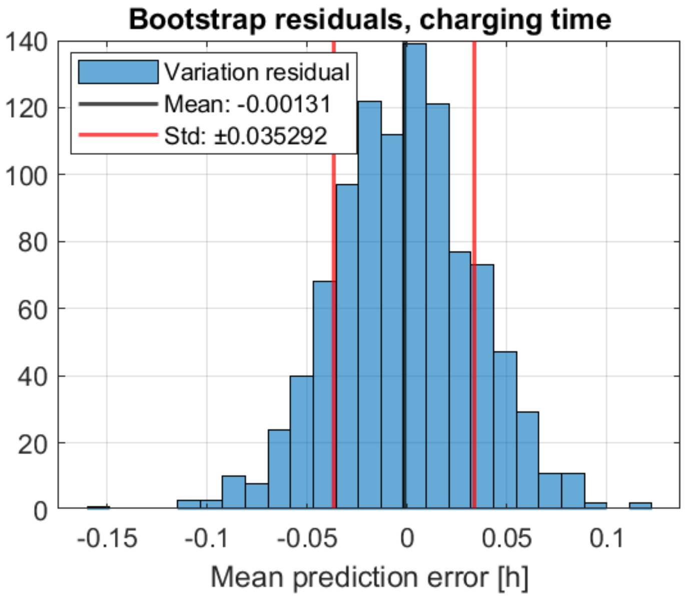


Figure 5.13: *Residuals from bootstrapping for the charging time model.*

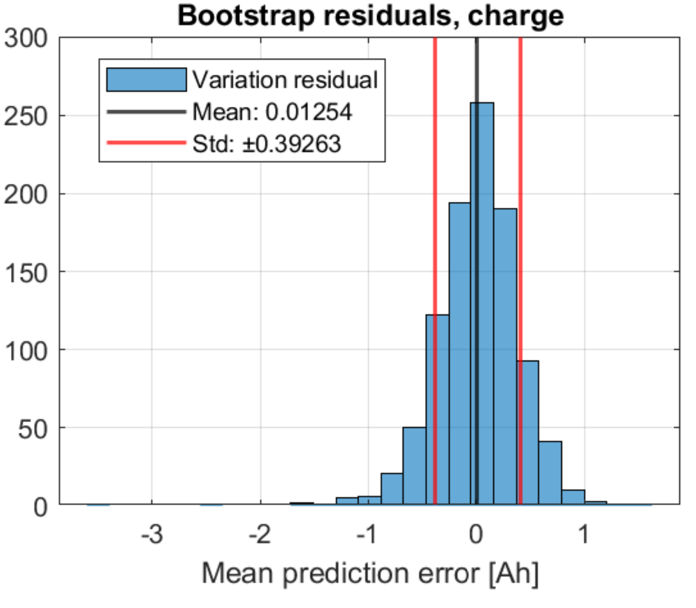


Figure 5.14: *Residuals from bootstrapping for the electric charge model.*

6 Discussion

This chapter covers the thoughts and reflections made during the project.

6.1 Results

As mentioned in section 3.1, the driver does not have access to the full battery capacity. According to [11] the available capacity of the battery in a PHEV is around 60 %, the Mitsubishi Outlander PHEV battery is specified at 12 kWh or 50 Ah which in that case gives 7.2 kWh or 30 Ah available to the driver. For all the charging sessions with a completely discharged battery to begin with, the minimum charge transferred from the charging station was 33.7 Ah, the maximum 39.6 Ah and the mean 37.0 Ah. Which is 67.5 - 79.2 % with a mean of 74 %. That is quite reasonable if charging losses and heating or cooling is taken in consideration.

This analysis shows that a higher outside temperature contributes to a faster charging time. One conclusion is that the higher temperature has a positive contribution and makes it easier for the battery pack to be within optimal temperature range for charging. According to [12] that range is between 0°C and 40°C. Similar argument can be made for the electric charge model, at higher outside temperatures more charge is transferred and even though there is no information about the voltage we can assume a higher overall energy transfer which makes the vehicle charge quicker.

6.1.1 Charging time

The reason for going with a polynomial of degree three for the SoC and a straight line for the outside temperature is the goodness of fit values. Table 6.1 shows how the values change when going from a linear to a quadratic model for the temperature.

Polynomial degree	1	2
SSE	1.56	1.56
R^2	0.33	0.33
$adjusted\ R^2$	0.32	0.31

Table 6.1: *Comparison between different degrees of polynomial for charging time and temperature*

As seen in Table 6.1, going from linear to quadratic does not affect the SSE and R^2 but has a negative impact on $adjusted\ R^2$. Which is to be expected when going to a more complicated model with no gains in accuracy.

The same comparison is made with the model for SoC and can be seen in Table 6.2. Where a small improvement is made considering the SSE but the $adjusted\ R^2$ remains the same. Thus there is no clear benefits of going from a third to a fourth degree polynomial.

Polynomial degree	2	3	4
SSE	2.49	1.86	1.81
R^2	0.86	0.90	0.90
$adjusted\ R^2$	0.85	0.88	0.88

Table 6.2: *Comparison between different degrees of polynomial for charging time and SoC*

6.1.2 Electric charge

For the electric charge model the same arguments for the polynomial degrees can be made as for the charging time model. The best fitting curve for the SoC was of degree four, and the outside temperature a straight line. In Table 6.3 is the comparison for the temperature, a small improvement in SSE but no practical gains according to the $adjusted\ R^2$.

Polynomial degree	1	2
SSE	76.22	75.92
R^2	0.22	0.22
$adjusted\ R^2$	0.21	0.20

Table 6.3: *Comparison between different degrees of polynomial for electrical charge and temperature*

Table 6.4 shows that there is no evidence of practical improvement of going from degree four to five for the modelling of electrical charge with SoC as a variable.

Polynomial degree	3	4	5
SSE	176.78	164.78	161.38
R^2	0.91	0.92	0.92
$adjusted\ R^2$	0.90	0.90	0.90

Table 6.4: *Comparison between different degrees of polynomial for electrical charge and SoC*

6.1.3 Bootstrap

The bootstrap results presented in section 5.4 indicate that the charging time model is more robust. The difference between the model and the bootstrap result is not that large. The coefficient that stands out is p_{11} with a difference of 21.42% and a standard deviation of 933.654%. p_{21} should also be mentioned with a standard deviation of 282.67%. This will most likely not affect the model so much due to the values (0.003206 and 0.01316), which are the two smallest value coefficients in the model.

The electric charge bootstrap shows a large difference compared to the real model. Furthermore, the standard deviation is extremely high, one explanation for that is the higher degree of polynomial used for that model. Depending on which data points being picked, the curve will adjust the fit to just those points and will fit worse to points not included in the bootstrap test.

When analyzing the bootstrapped residuals for both models it shows that the deviation from the actual model is not very large. Which concludes that even though some coefficients tends to drift when testing the model with bootstrapping, the data not used as training data fits the model with acceptable accuracy.

6.2 Method

The approach for analyzing and modelling the charging profile was pretty clear after various researches. To be able to do a good model a close analysis of the depending variables had to be done. A different approach that was considered was to take a closer look at the SoC. However with the lack of data about the SoC when the vehicle was disconnected from the charging station there was to much uncertainty. The calculated SoC at the start of charging differs between 1 to 38 percentage points from the noted SoC, with a mean difference of 10 percentage points. Therefore an approximation of a partially complete charging session would not bring enough accuracy.

6.3 Ethical and societal aspects

There is not so much discussion to be had regarding ethical or societal aspects of the work in this thesis, but a discussion can be had about the electrification of vehicles in a larger perspective. Owning an electrified vehicle comes with advantages and disadvantages as mentioned briefly in Chapter 1. However it is not only on an individual level that readjustments have to be made, the society on a larger level will have to make changes as well.

One aspect that can be seen as a problem is the cost of electrifying our fleet of vehicles. Who is going to be responsible for building and maintaining the infrastructure needed with a increasing number of EV's and PHEV's? How will that eventually affect the end customer, for example what form of taxes will be introduced to compensate for the taxes on fossil fuels. My opinion is that all parties involved have to work closely together and make changes gradually.

7 Conclusion

This thesis shows that a model can be produced from the available data. The statistical analysis showed that the outdoor temperature and initial battery state of charge have a clear correlation with the total charging time and the charge transferred. The models are not a perfect fit, but they approximate the charging time and electrical charge well enough to be used for similar data inside the same range as the training data. If the data collected would have included additional variables with more variation, the foundation to create a more precise model had been better.

7.1 Future work

There are plenty of publications regarding the charging of EV's and PHEV's but most of them are on a macro level. This thesis covers only a tiny bit of what there is to analyze on a micro level. Below follows a few ideas regarding possible research about electrified vehicles. Most of them include a close cooperation with vehicle manufacturers for more data from the car.

Similar analysis

To get a more precise model, a similar analysis could be done with additional gathered information. A cooperation with the vehicle manufacturer to get access to more vehicle data, not only the information shown on the car's display, would be a good starting point for a deeper analysis.

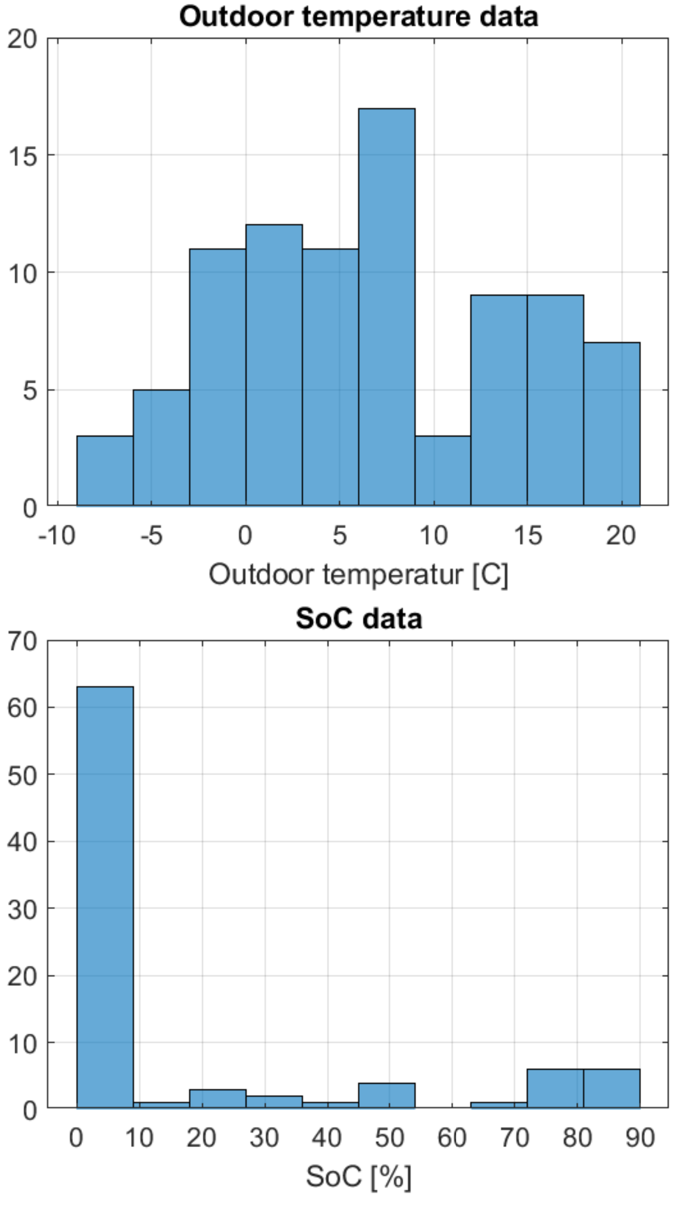
Long term data logging

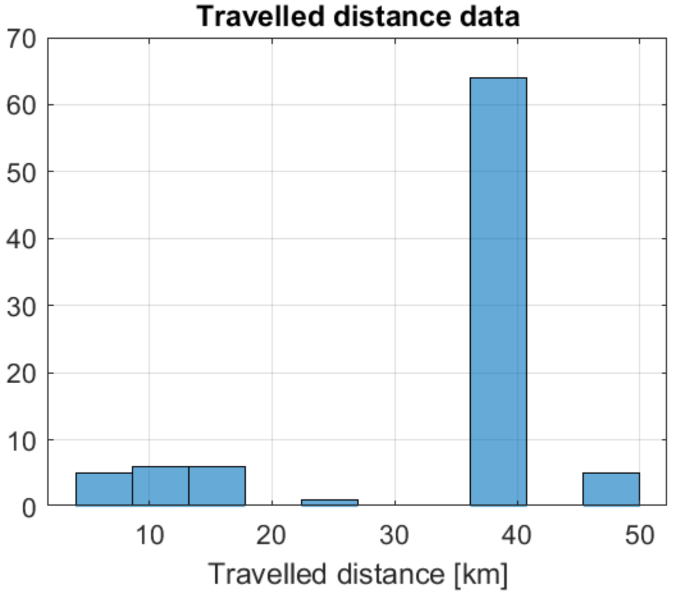
Both EV's and PHEV's are starting to become very popular, they have been on the market for a longer time but the conversion to more environmental friendly vehicles fleet is growing rapidly. One interesting aspect is to analyze long term data collected from the vehicle and take a look at how battery degradation affects the charging profile.

Appendix

A

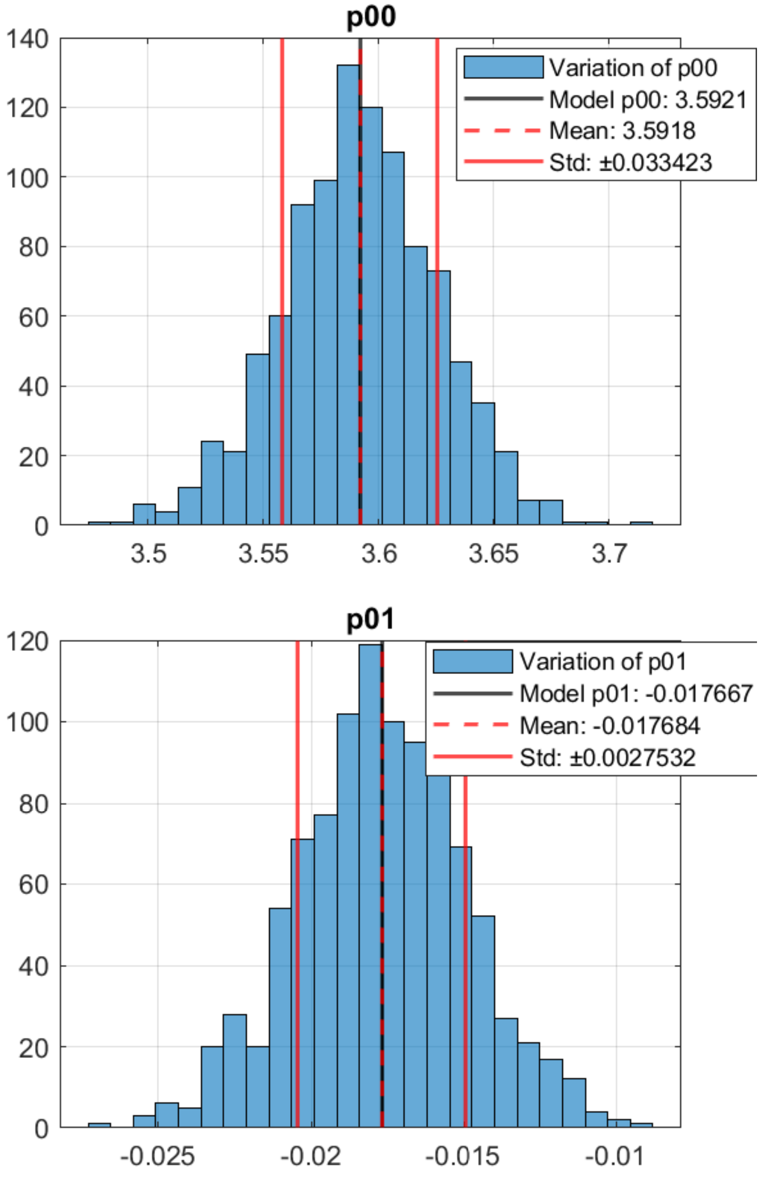
Notes by the driver of the car

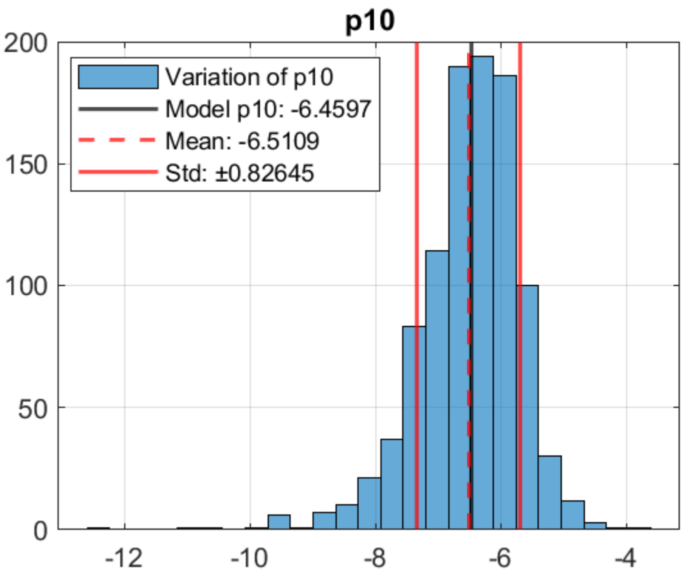

Outdoor temperature data
20
15
10
5
0
-10
-5
0
5
10
15
20
Outdoor temperatur [C]
SoC data
70
60
50
40
30
20
10
0
0
10
20
30
40
50
60
70
80
90
SoC [%]

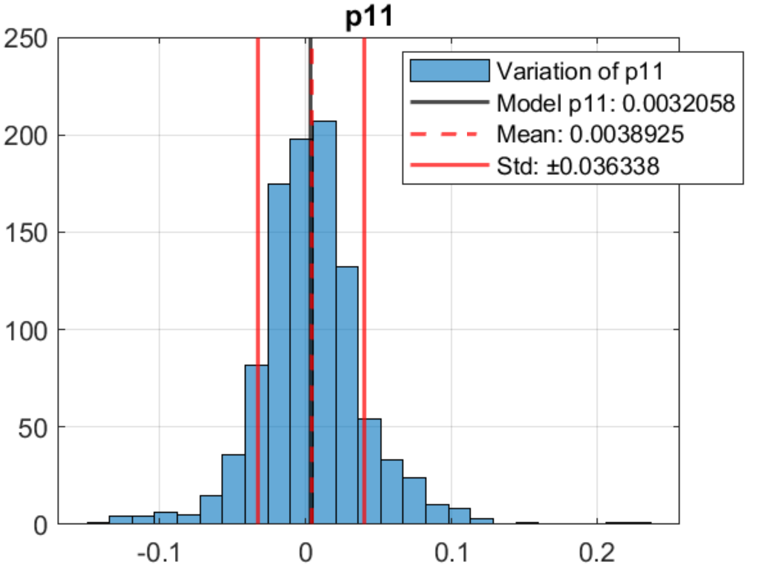

Travelled distance data
70
60
50
40
30
20
10
0
10
20
30
40
50
Travelled distance [km]

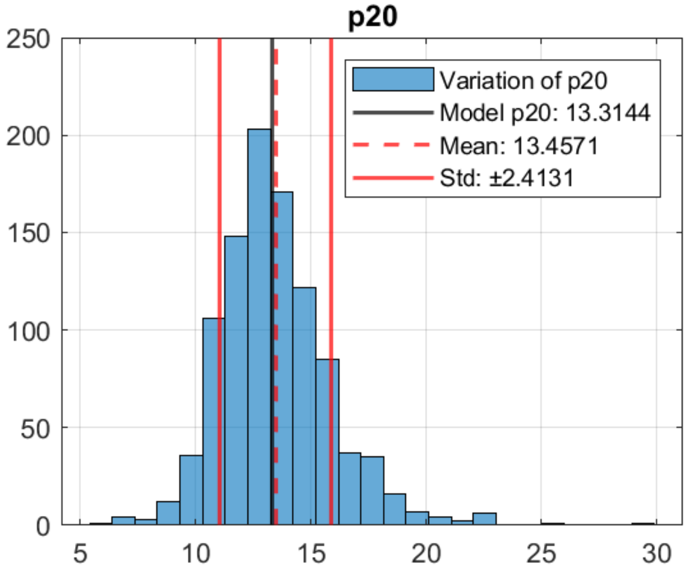
B

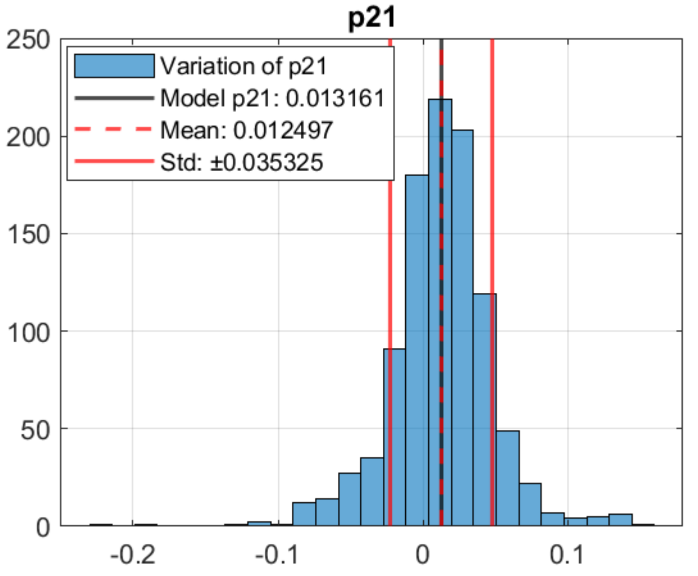
Bootstrap verification charging time model

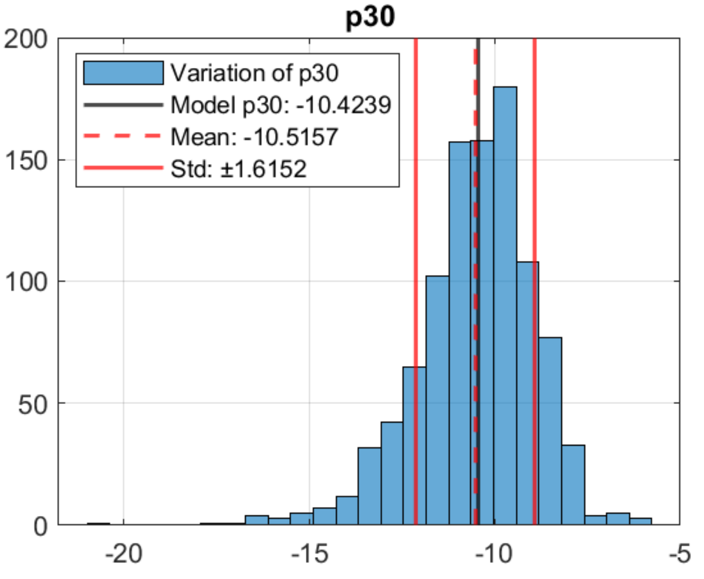

p00
Variation of p00
Model p00: 3.5921
Mean: 3.5918
Std: ±0.033423
0
20
40
60
80
100
120
140
3.5
3.55
3.6
3.65
3.7
p01
Variation of p01
Model p01: -0.017667
Mean: -0.017684
Std: ±0.0027532
0
20
40
60
80
100
120
-0.025
-0.02
-0.015
-0.01


p10
Variation of p10
Model p10: -6.4597
Mean: -6.5109
Std: ±0.82645
200
150
100
50
0
-12
-10
-8
-6
-4


p11
Variation of p11
Model p11: 0.0032058
Mean: 0.0038925
Std: ±0.036338
250
200
150
100
50
0
-0.1
0
0.1
0.2

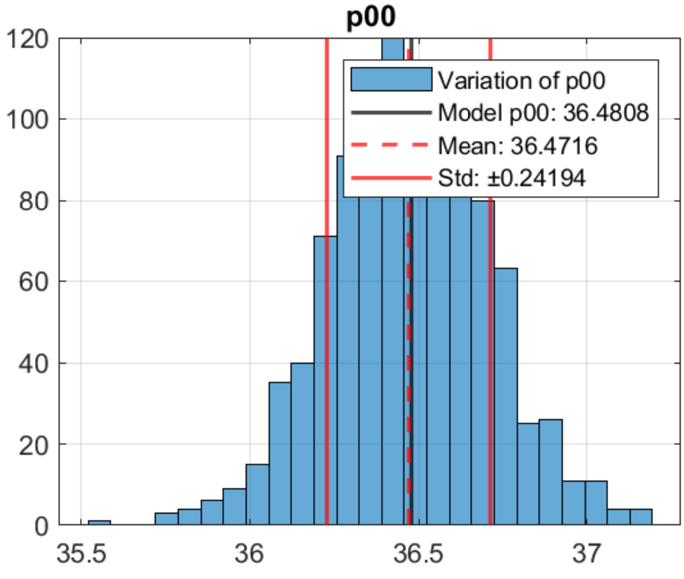

p20
Variation of p20
Model p20: 13.3144
Mean: 13.4571
Std: ±2.4131
250
200
150
100
50
0
5
10
15
20
25
30

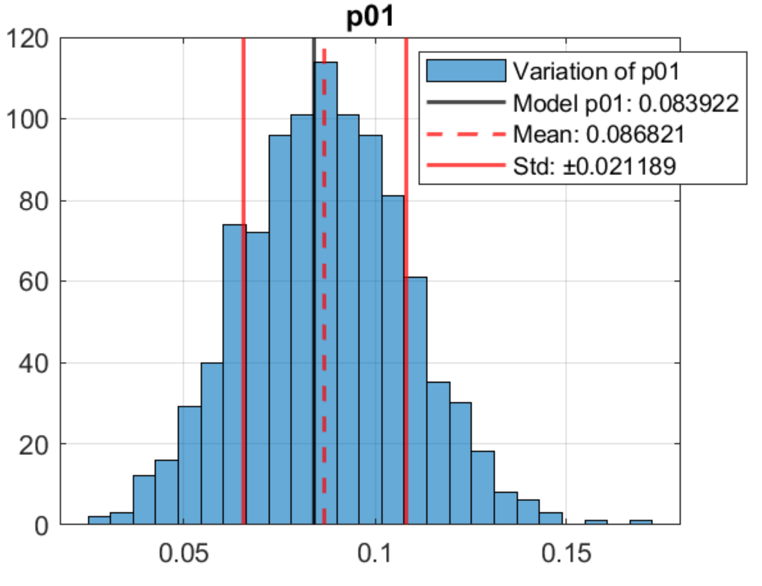

p21
Variation of p21
Model p21: 0.013161
Mean: 0.012497
Std: ±0.035325
250
200
150
100
50
0
-0.2
-0.1
0
0.1

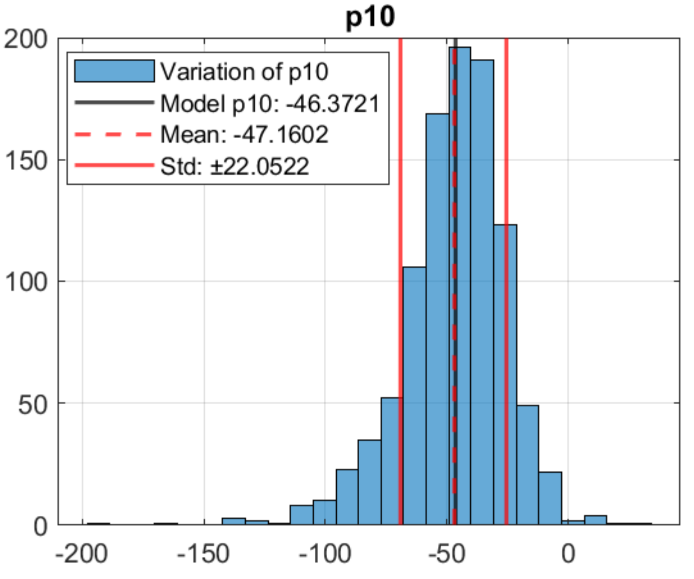

p30
Variation of p30
Model p30: -10.4239
Mean: -10.5157
Std: ±1.6152
200
150
100
50
0
-20
-15
-10
-5

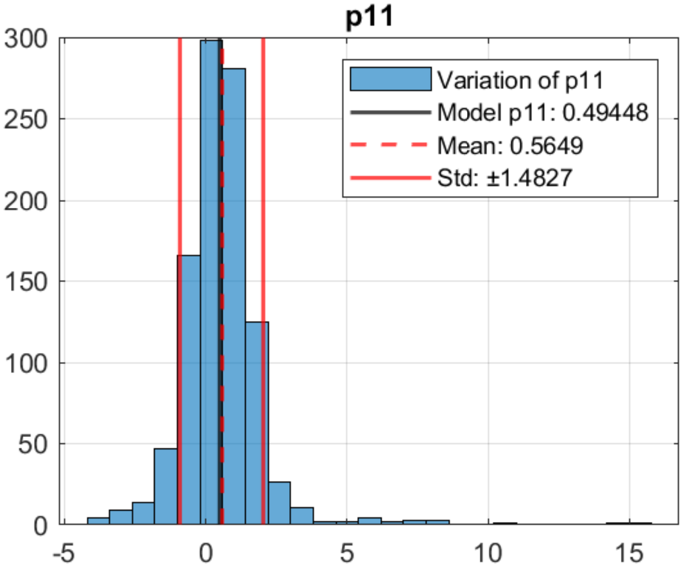
C

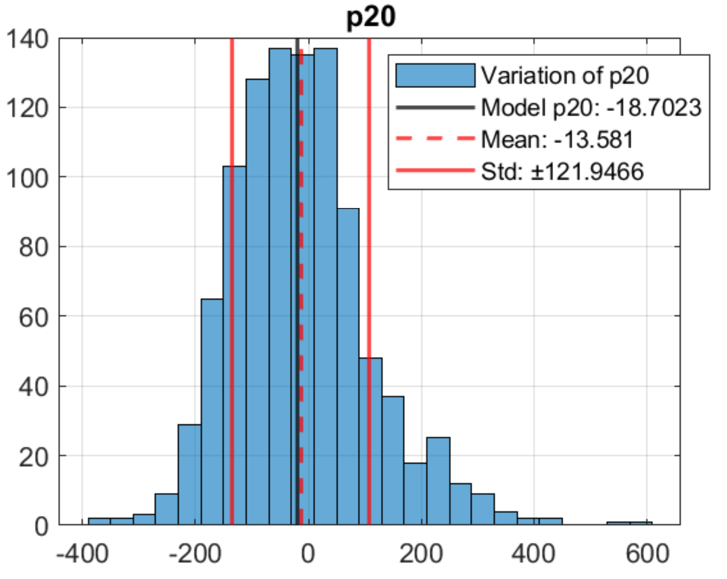
Bootstrap verification charge model

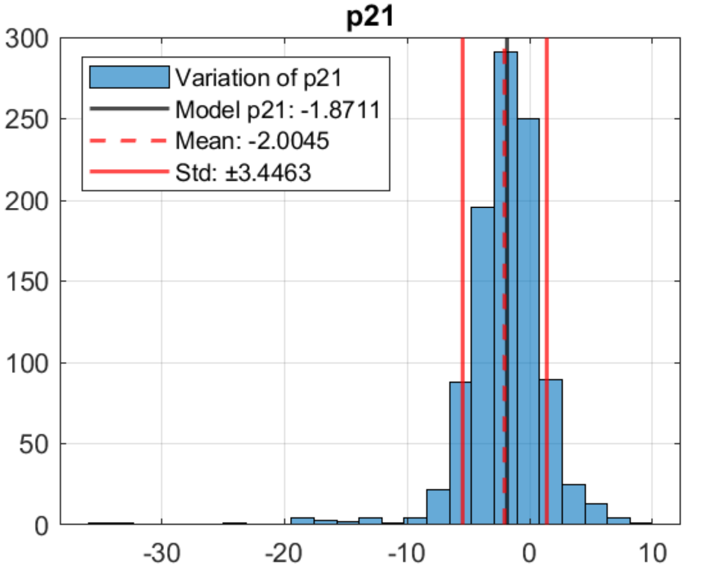

p00
Variation of p00
Model p00: 36.4808
Mean: 36.4716
Std: ±0.24194
120
100
80
60
40
20
0
35.5
36
36.5
37

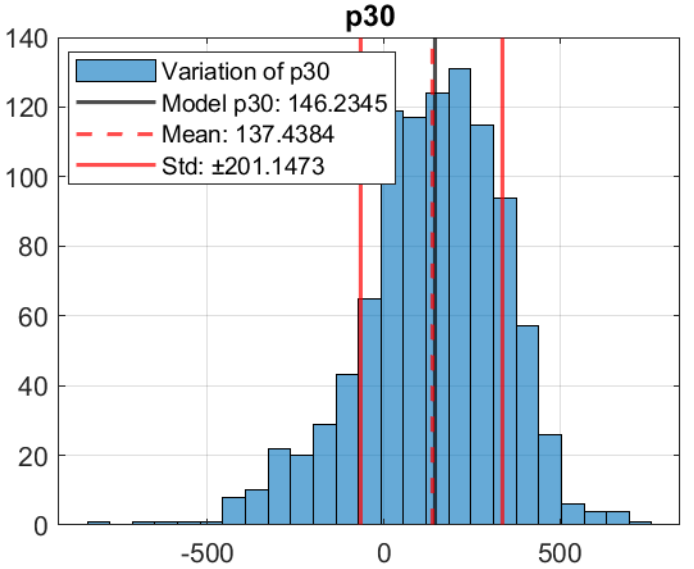

p01
Variation of p01
Model p01: 0.083922
Mean: 0.086821
Std: ±0.021189
120
100
80
60
40
20
0
0.05
0.1
0.15

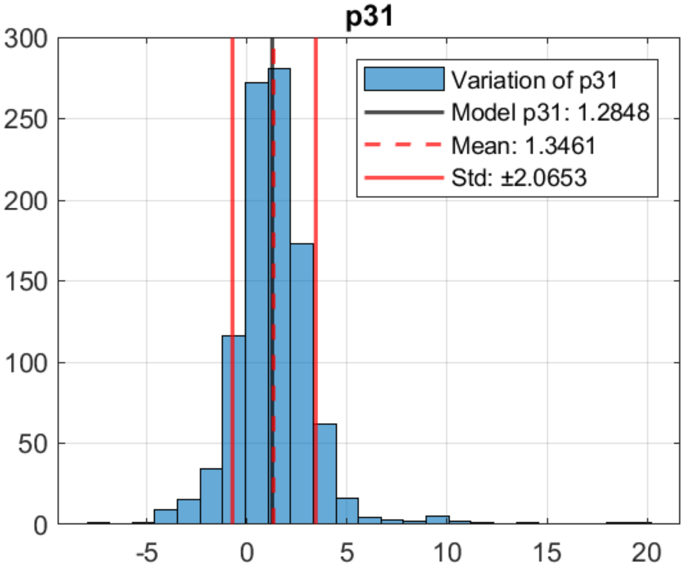

p10
Variation of p10
Model p10: -46.3721
Mean: -47.1602
Std: ±22.0522
200
150
100
50
0
-200
-150
-100
-50
0

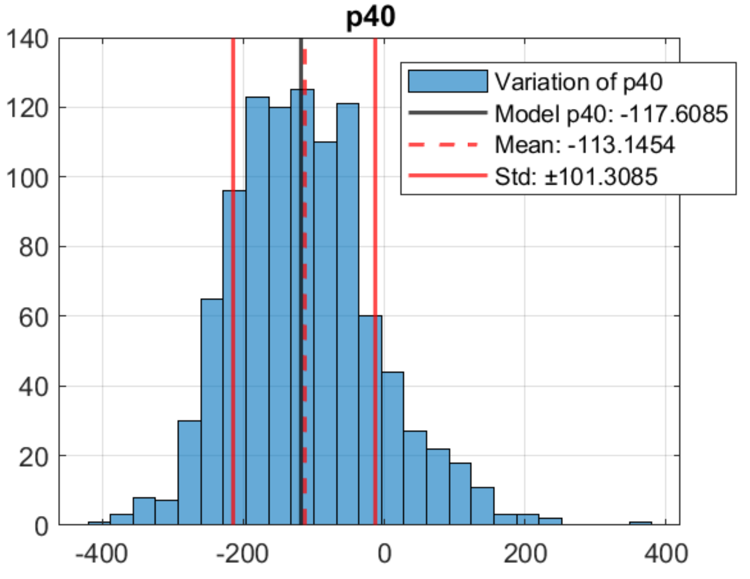

p11
Variation of p11
Model p11: 0.49448
Mean: 0.5649
Std: ±1.4827
300
250
200
150
100
50
0
-5
0
5
10
15


p20
Variation of p20
Model p20: -18.7023
Mean: -13.581
Std: ±121.9466


p21
Variation of p21
Model p21: -1.8711
Mean: -2.0045
Std: ±3.4463


p30
Variation of p30
Model p30: 146.2345
Mean: 137.4384
Std: ±201.1473
140
120
100
80
60
40
20
0
-500
0
500


p31
Variation of p31
Model p31: 1.2848
Mean: 1.3461
Std: ±2.0653
300
250
200
150
100
50
0
-5
0
5
10
15
20


p40
140
120
100
80
60
40
20
0
-400
-200
0
200
400
Variation of p40
Model p40: -117.6085
Mean: -113.1454
Std: ±101.3085

Bibliography

[1] Volvo Cars Sweden. Volvo recharge. https://www.volvocars.com/se/om-volvo/innovation/elektrifiering Accessed 2020-05-19.

[2] Mergim Dushku and Julius Kokko Ekholm. Charge into the future grid : Optimizing batteries to support the future low-voltage electrical grid. Master's thesis, Linköping University, Vehicular Systems, 2019.

[3] Markus Knutfelt. Charging cost optimization of plug-in hybrid electric vehicles. Master's thesis, Linköping University, Vehicular Systems, 2015.

[4] Mitsubishi Motors. Outlander phev. https://mitsubishimotors.se/uploads/cars/423318_SE_PHEV_MY14_Garanti.pdf. Accessed 2020-05-20.

[5] Chargestorm. Csr100. https://chargestorm.se/wp-content/uploads/CSR100_ENG_180216.pdf. Accessed 2020-05-20.

[6] Kong Soon Ng, Chin-Sien Moo, Yi-Ping Chen, and Yao-Ching Hsieh. Enhanced coulomb counting method for estimating state-of-charge and state-of-health of lithium-ion batteries. *Applied Energy*, 86:1506–1511, 2009. https://doi.org/10.1016/j.apenergy.2008.11.021.

[7] Jinhao Meng, Lei Cai, Daniel-Ioan Stroe, Guangzhao Luo, Xin Sui, and Remus Teodorescu. Lithium-ion battery state-of-health estimation in electric vehicle using optimized partial charging voltage profiles. *Energy*, 185:1054–1062, 2019. https://doi.org/10.1016/j.energy.2019.07.127.

[8] Jay L. Devore. *Probability and Statistics for Engineering and the Sciences*. Cengage Learning, eighth edition, 2012.

[9] MathWorks. Evaluating goodness of fit. https://se.mathworks.com/help/curvefit/evaluating-goodness-of-fit.html. Accessed 2020-05-25.

[10] Bradly Efron. Bootstrap methods: Another look at the jackknife. *The Annals of Statistics*, 7:1–26, 1979. https://doi.org/10.1214/aos/1176344552.

[11] Francesco Marra, Chresten Træholt, Esben Larsen, and Qiuwei Wu. Average behavior of battery-electric vehicles for distributed energy studies. In *2010 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT Europe)*, pages 1–7, 2010. https://doi.org/10.1109/ISGTEUROPE.2010.5638920.

[12] Zheng Chen, Xin Shu, Renxin Xiao, Wensheng Yan, Yonggang Liu, and Jiangwei Shen. Optimal charging strategy design for lithium-ion batteries considering minimization of temperature rise and energy loss. *International Journal of Energy Research*, 43:4344–4358, 2019. https://doi.org/10.1002/er.4560.