Czech Technical University in Prague
Faculty of Electrical Engineering
Department of Cybernetics

Charging Demand Models for Fleet Electrification

Bachelor thesis

Mária Cvečková

Bc. programme: Open Informatics
Branch of study: Computer and Information Science
Supervisor: Ing. Martin Schaefer

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Thesis Supervisor:
Ing. Martin Schaefer
Department of Informatics and Computer Science
Faculty of Electrical Engineering
Czech Technical University in Prague
Technická 2
160 00 Prague 6
Czech Republic

Declaration

I declare that the presented work was developed independently and that I have listed all sources of information used within it in accordance with the methodical instructions for observing the ethical principles in the preparation of university theses.

Prague, date........................ ....
signature

BACHELOR‘S THESIS ASSIGNMENT

I. Personal and study details

Student's name:	**Cvečková Mária**	Personal ID number:	**487000**
Faculty / Institute:	**Faculty of Electrical Engineering**		
Department / Institute:	**Department of Cybernetics**		
Study program:	**Open Informatics**		
Specialisation:	**Artificial Intelligence and Computer Science**		

II. Bachelor’s thesis details

Bachelor’s thesis title in English:

Charging Demand Models for Fleet Electrification

Bachelor’s thesis title in Czech:

Modely poptávky po nabíjení pro elektrifikaci flotil

Guidelines:

The companies that are considering electrification of their fleet make decisions on selection of the vehicles to be electric and how the charging infrastructure should be built. The modelling of the charging demand is important to evaluate the investment into the transition to EV. We would like to propose a charging demand model that might be parametrized by the expected fleet profiles composition. Moreover, we might analyze the charging demand of the already electric vehicles and calibrate the profiles with the historical data. The student is expected to experiment with several approaches to modelling of the charging demand and to compare the approaches in experiments.

1. Research the area of charging demand modelling.
2. Formulate the requirements on the desired models.
3. Propose and implement several models.
4. Design experiments to demonstrate the suitability of the considered models.

Bibliography / sources:

[1] Jeřábek, Vojtěch, “Data-driven sizing of electric vehicle charging stations”, Bachelor‘s thesis FEE CTU, Prague, 2020
[2] J. F. K. Thomas Franke, “Understanding charging behaviour of electric vehicle users”,Transportation Research Part F, 2019.

Name and workplace of bachelor’s thesis supervisor:

Ing. Martin Schaefer, Artificial Intelligence Center, FEE

Name and workplace of second bachelor’s thesis supervisor or consultant:

Date of bachelor’s thesis assignment: **08.01.2021** Deadline for bachelor thesis submission: **13.08.2021**

Assignment valid until: **30.09.2022**

Ing. Martin Schaefer Supervisor’s signature	prof. Ing. Tomáš Svoboda, Ph.D. Head of department’s signature	prof. Mgr. Petr Páta, Ph.D. Dean’s signature

III. Assignment receipt

The student acknowledges that the bachelor’s thesis is an individual work. The student must produce her thesis without the assistance of others, with the exception of provided consultations. Within the bachelor’s thesis, the author must state the names of consultants and include a list of references.

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Date of assignment receipt Student’s signature

Abstract

One of the consequences of nature protection is the electrification of the vehicle. Electric vehicles replace vehicles with combustion engines within the company fleet. Companies then have to set up their charging infrastructure.

This bachelor thesis offers a tool that will help to determine the charging demand within the corporate area. The thesis contains a solution to creating profiles of vehicles based on the parameters. The vehicle profiles are determined from the original data, which are examined by aggregation functions. Processed data by clustering then creates outputs profiles of vehicles. From the vehicle profile, it is possible to create a fleet of cars that corresponds to the fleet of a company that needs to electrify its fleet.

Subsequently, the work describes two approaches to generating vehicle management from the created fleet. The outputs of both approaches are the demand for charging and driving vehicles. These two approaches are based on the simulation of car driving based on the decision of Markov chains. There is an added approach where a general demand for charging is created. In our thesis, we do also research on related publications. We have compared the outputs of models on their basis.

Keywords: electric vehicle, EV, forecast model, charging demand, clustering fleet, modeling fleet, simulation of fleet

Abstrakt

Jedním z důsledků ochrany přírody je elektrifikace vozidel. Elektrická vozidla nahrazují vozidla se spalovacími motory v rámci firemního vozového parku. Společnosti pak musí navrhnout svou nabíjecí infrastrukturu.

Tato bakalářská práce nabízí nástroj, který pomůže určit poptávku po nabíjení v podnikové oblasti. Bakalářská práce obsahuje řešení pro vytváření profilů vozidel na základě parametrů. Profily vozidel jsou určeny z původních dat, která jsou zkoumána agregačními funkcemi. Pak zpracovaná data klastrováním vytvoří výstupní profily vozidel. Z profilu vozidla je možné vytvořit vozový park, který odpovídá vozovému parku společnosti, která potřebuje svůj vozový park elektrifikovat.

Následně práce popisuje dva přístupy ke generování chování vozidel z vytvořeného vozového parku. Výstupy obou přístupů jsou poptávka po nabíjení a řízení vozidel. Tyto dva přístupy jsou založeny na simulaci řízení automobilu na základě rozhodnutí Markovových řetězců. V této práci pojednáváme i o další přístup, kde je vytvořena obecná poptávka po nabíjení. V této práci provádíme také průzkum souvisejících publikací, na jejichž základě byli porovnány výstupy modelů.

Klíčová slova: elektrické vozidlo, EV, model predpovědi, nabíjecí stanice, zhlukování, modelování flotily, simulace flotily

Překlad názvu: Modely poptávky nabíjení pro elektrifikovanou flotilu

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EV electric vehicle. viii, ix, 1–8, 14, 16, 17, 20, 23, 29, 31–35

SOC state of charge. 4, 7, 14, 16

UBIS battery interaction style. 6

W2V wind to vehicle. 6

Contents

Chapter 1

Introduction

Nowadays, when non-renewable resources are running down, nature protection is more emphasised, we gradually move to environmentally friendly technologies. One of the current trends is that vehicles with combustion engines are supplanted by electric vehicles. This trend is followed even by corporations that own a fleet of cars.

The companies that are considering electrification of their fleet decide which vehicles to be electric and how the charging infrastructure should be built. The modelling of the charging demand is important to evaluate the investment into the transition to EV. Charging demand should not be based on the behaviour of any general type of vehicle. Therefore in the work there is a charging demand model proposed which is parametrized by the expected fleet profiles composition.

1.1 Motivation

Generally, the reason for modelling charging demand is that electric cars have a different range in comparison with oil or gas-powered cars, which means that they need to power more often. Also, EVs have different charging options than motor cars. Powering of EV is slower, so they can be powered for several hours. Therefore, it is a possibility to leave a car when it is powering. This possibility means that the driver's behaviour will be, to some extent, different. Based on this knowledge, we need to estimate the charging demand of representative groups of the corporate fleet. Imagine a company that wants to electrify its vehicle fleet. The simplest way to transform the fleet from combustion engines to electric engines for a given company is to determine the parameters of every vehicle.

One approach, how to model a vehicle's charging demand, is direct simulation. It means that the exact GPS locations from vehicles with combustion engines are used as GPS locations for electrified vehicles. After electrification, rides are identical. Subsequently, the charging demand of EV is at the end of every trip. In the thesis[1], this approach of electrification of the fleet was solved . We assume that if we do not simulate exactly the vehicle's rides, but approximately by parameters of the vehicles, so it will be less prone to some extraordinary situations.

Moreover, it is possible that the corporation does not have the GPS data needed for the direct simulation. Therefore, it is an advantage, to use data that we have already obtained for the simulation of other corporations fleets.

1.2 Goal

In this thesis, we set four goals. The first is researching the area of charging demand modelling. The second goal is to formulate the requirements for the desired models. The third goal is to propose and implement several models. The last is to design experiments to demonstrate the suitability of the considered models.

This work aims to propose a charging demand model for a given fleet. The fleet profile composition is selected according to preset parameters. Moreover, to study and analyze the charging demand of electric chargers. An essential aspect of the output is the demand for charging within the corporate area because companies that want to electrify their fleet also need to design charging infrastructure. Then the most likely prediction is based on traffic data is chosen.

1.3 Thesis Structure

The rest of this thesis is organized as follows. Chapter 2 contains related works. There is literature that deals with similar problems listed. There are approaches for solving the problem in other literature sources described, as well as the results of these approaches. In Chapter 3, methodology of the used solution is described. In addition, there is described theoretical background of used methods. In Chapter 4 there are specifics of implementation and experiments described. Chapter 5 summarizes results of the thesis, suggests improvements for future work.

Chapter 2

Related Work

Purchase of EV preferences has increased recently. As an example can be China. Nowadays in China, in six biggest Chinese cities, electric and hybrids represent about one-fifth of new car sales on average, according to data from the China Passenger Car Association [2].

Technologies associated with electric mobility have been changing exponentially. Directly, the academic field responded with a significant number of published articles developing around electric mobility. While writing the thesis, 38 242 results of research articles about EV and charging demand have been found. Studies cover various dimensions of EV adoption across countries, including charging infrastructure in [3], [4], policies and incentives in [5], [6], [7], business models in [8], [9], [10], among others. This chapter offers a survey and a description of existing scientific publications that laid the foundation for solving implementation problems used in the thesis (Chapter 4).

2.1 Generating electric vehicle load profiles

Before presenting our modelling charging profiles of electric vehicles, we give an overview of EV charge studies. First, we discuss other articles focused on EV and their characteristics of modelling fleet. Subsequently, we look into approaches of how to simulate EV loads at different aggregation levels. Finally, we give an overview of results that simulate EV fleet and given charging demand.

2.1.1 Schauble's approach

In the publication, [11] there is processed analysis of charging behaviour patterns of EV. As data sources there are used three electric mobility studies in Germany's southwestern region (CROME, Get eReady and iZEUS) which deliver comprehensive data of EV. This article analyzes and discusses the mobility and following charging demand characteristics. The model of generated EV fleet is based on statistical characteristics.

Figure 2.1 is showing weekly distribution of source data for charging demand. It is showing an approximately higher charging demand level, which is about it 15–20 % for all the studies during the weekdays. Subsequently, the charging demand of EV at the weekend is significantly lower. This plot Figure 2.1 validate our base data described in Section 4.4.1 obtained from charging stations.

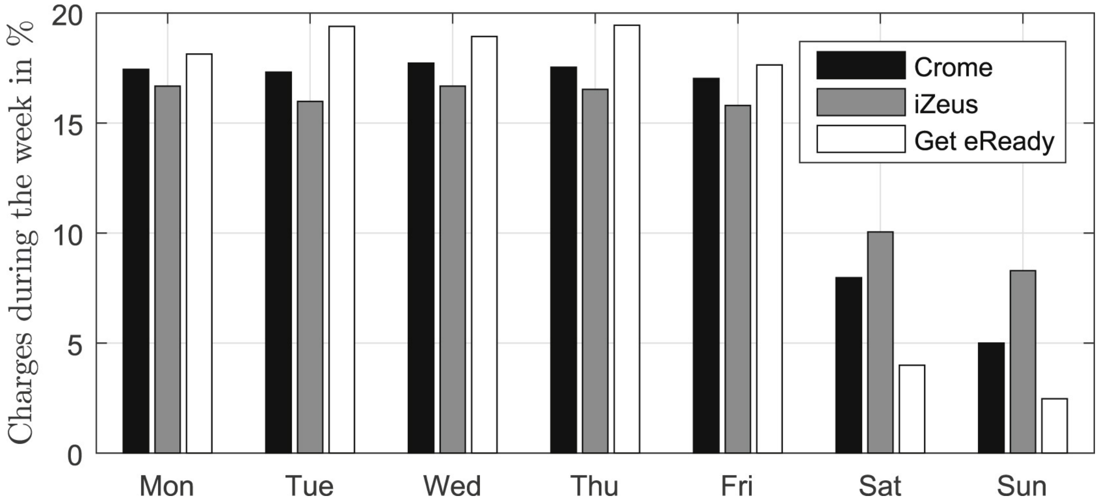

Figure 2.1: Percentage of charging processes per weekdays [11]

In publication [11] there is a direct and an indirect method used to create fleet profiles. Load profiles for any given time frame can be produced by both ways. The direct method uses all data of each charging process. However, data may originate from different sources like time-dependent state of charge (SOC). The indirect method requires information on the start and the end time of charging events and the corresponding (initial and final) SOC. The direct method is used to validate the quality of generated data of the indirect way. In Section 3.3.4 we used a combination of the direct and the indirect method for creating charging demand of fleet profiles.

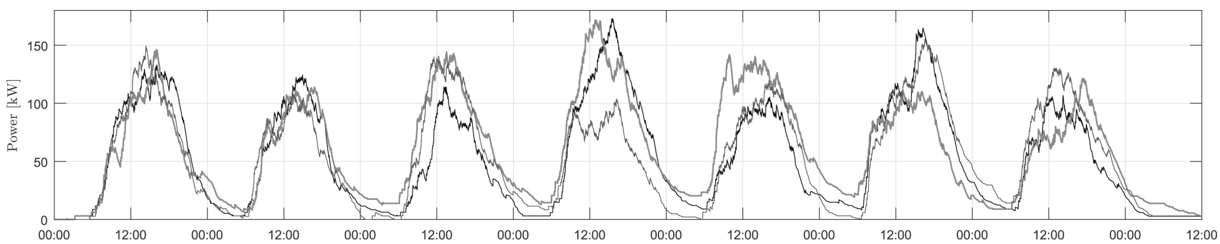

Figure 2.2: "Three simulated load profiles over a week, starting on Monday, for 100 EV that charge at least once every day with $p_{max} = 3.6kW$ using the mean number of charging events per vehicle and per weekday." [11]

One of the results of Schauble simulation is on Figure 2.2. This plot is used for comparison with our result of simulation the same composition of the fleet in Section 4.6.

2.1.2 Brandy's approach

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This approach solving generating EV load profiles use a stochastic simulation methodology. It is published in the article [12] and similar to the article [11] GPS travel data of EV are used as the basis for a fleet generation. Approaches in the data processing are different. Brandy's simulation use variables in function to distribute types of behaviour of EV driver. They used copula function, subsequently by Bayesian inference generate travel patterns. Parameters for patterns are departure time from home, the number of journeys taken during day, total distance travelled in a day. These parameters are taken during two days in a row and from them the movement of vehicles is generated. This approach serves as an inspiration in Section 3.1, there is not used copula function for distribution, although mentioned parameters for clustering fleet are used.

"Figure 2.3 illustrates the travel profiles for 20 days. The basic principle of a Monte Carlo simulation, uncertainty propagation, is evident in the resulting shapes of the travel profiles. The trend of a daily travel profile is reproduced for each day." [12] This result of simulation is used for comparison with our result of simulation the same composition of the simulation in Section 4.6.

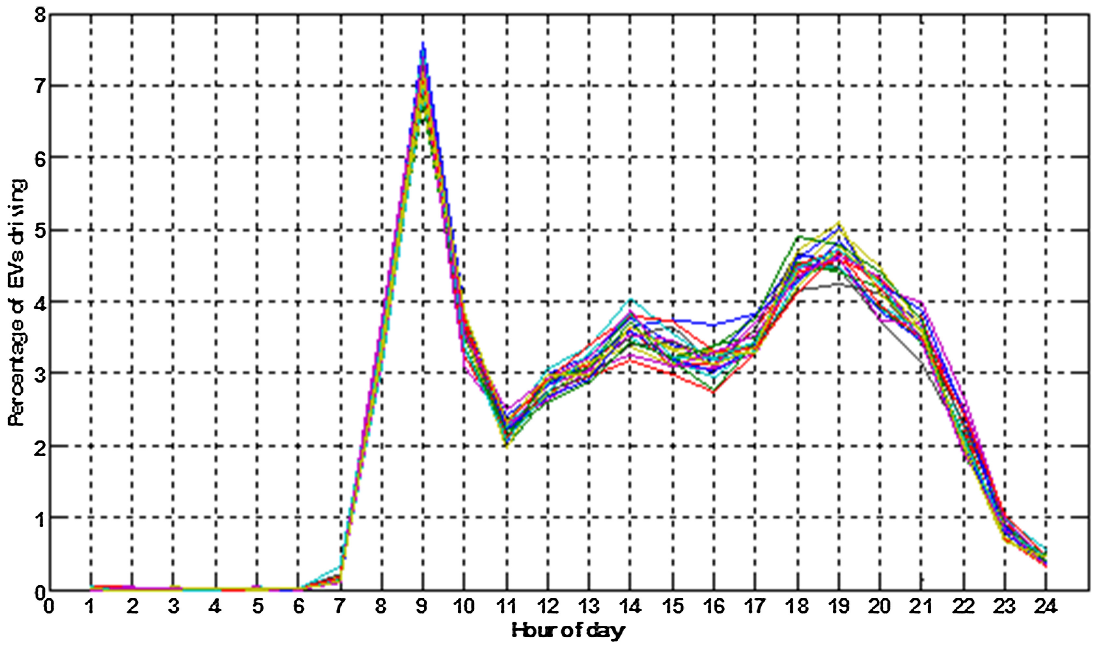

Figure 2.3: A 20 day simulation of the percentage of EVs driving per hour [12]

2.2 Charge timing choice estimation

Similar to the previous section, we give an overview of EV charge studies. First, we discuss other articles focused on EV and their charge timing choice estimation of the fleet. Subsequently, we look into approaches of how to simulate EV behaviour at different aggregation levels. In Section 4.6, we give an overview of results that simulate rides of EV fleet and given charging demand, if they have any.

2.2.1 Franke's approach

In the publication, [13] there is charging behaviour of EV users analysed. They attempted to understand the psychological dynamics underlying charging behaviour. Among other things, it is interesting how they research charging style among mobile phone users, and subsequently, they have a hypothesis that battery interaction style (UBIS) is similar to the charging behaviour of EV users.

Figure 2.4 depicts the model from the perspective of simulation behaviour of one EV user. To clarify wind to vehicle (W2V) means incorporated an algorithm that regulated energy input during charging to optimize the use of excess energy from the wind.

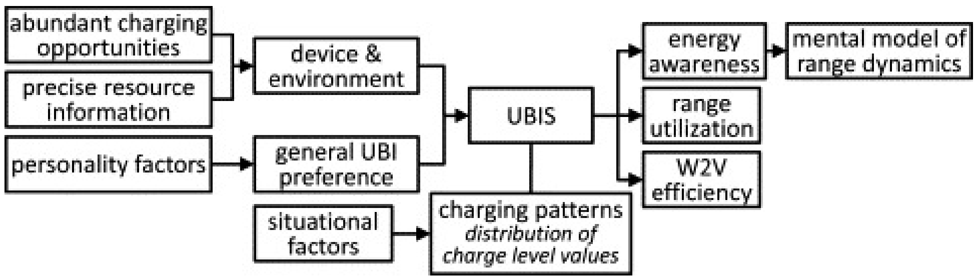

Figure 2.4: Simulation model [13]

W2V and UBIS are interesting, but from this study, we deal with the idea about limited energy resources. This issue is also addressed in [1]. The issue is called range-anxiety and it occurs when the remaining range is low or charging infrastructure is infrequent. Subsequently, it appears in a change of trips. We also solve this problem in Section 3.3, where vehicles need to change their rides because the remaining range is low.

2.2.2 Sun's approach

Publication [14] examines preference of behaviour of EV users in respect of the time when they charge their vehicles. In research, after a long journey they have opportunities to stay (no charging), charging immediately after arrival, nighttime charging, and charging other time. An important part of this research is that they examine the difference between commercial and private vehicles.

Model of charging behaviour suggest that SOC, from previous days before the travel day, and distance of kilometres which need to be travelled are the main predictors for the decision of EV driver whether choosing charging the vehicle or not. Probability of the decision of charging they can be different for commercial and private vehicles. This examined result is displayed on Figure 2.5.

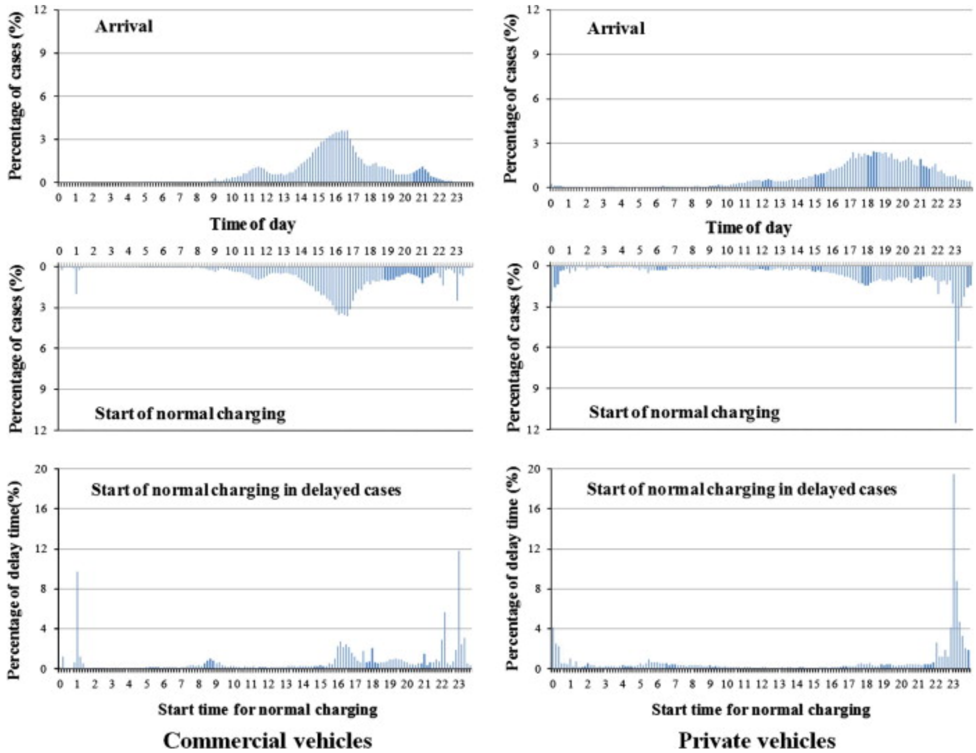

Figure 2.5: "Distributions of arrivals, start of normal charging, and start of delayed normal charging." [14]

We would like to remind the reader that in our study we focus only on commercial vehicles because we model company fleet. Thus, the previous Figure 2.5 serves only to show the study area of the left part of the plot which is aimed at commercial vehicles.

Chapter 3

Methodology

In this chapter, the methods used to obtain the research results in this thesis are presented. Here we introduce the theoretical approaches which we use to solve the thesis problem. Sections are divided into theoretical fields for a better understanding of each step of the following implementation schema.

Firstly, we present a method of modelling fleet profiles. It consists of two parts, namely clustering and fleet composition. In clustering, it is about creating clusters of vehicles which are described by parameters. This allows us to simulate the rides of a vehicle by entering only the vehicle's parameters. Based on the parameters, the cluster to which the vehicle belongs is determined, and to it are added other properties of behaviour of vehicle from the given cluster. The fleet composition consists of profiles of vehicles created by us based on our parameters. The whole clustering makes it easier to create vehicles with driving parameters for someone who wants to electrify their fleet because it is easier to enter the general driving characteristics of the vehicles, which we then assign to the cluster than to solve each vehicle individually.

Secondly, we solve the charging behaviour of modelled fleet composition. The charging behaviour is solved on the basis of simulations. The input of simulations is fleet profiles, and this means labels of clusters corresponding to the vehicle we want to simulate. We also formulate the requirements on the desired models of charging behaviour. At the end of this chapter, we describe how we generate a stochastic model also used for generating of charging demand of EV. These approaches will be used in the next chapter in the implementation of several models.

3.1 Clustering

The first topic that must be solved before proposing a charging demand model generated from the fleet is composing fleet profiles. Considering we had access to the database of one corporation, which contains the vehicle fleet business rides, we decide to generate whatever corporation fleet from this input set. Of course, input sets can be different. The generation of the fleet is independent from the input data.

3.1.1 What is clustering?

Clustering is one technique of unsupervised learning method of machine learning. An unsupervised learning method is a method in which we pull input data from datasets without labelled responses. It is an exploratory data analysis technique that makes it possible to analyze multivariate datasets.

The clustering method is used for dividing the datasets into a specific number of clusters. That is used in a way that data points belonging to any cluster have similar properties. Thus, every cluster is only a group of data points with similar properties. On Figure 3.1 we can see that the distance between the data points within the clusters is minimal.

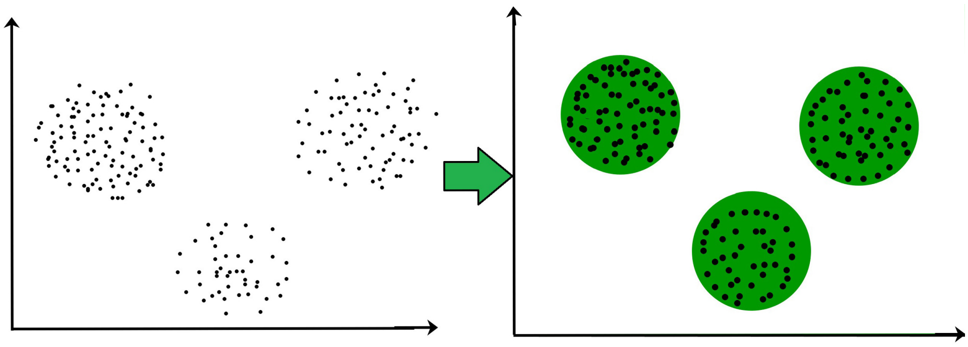

Figure 3.1: Example of merging data to clusters [15]

In other words, the clusters are areas with a higher density of similar data points. Clustering is a method of dividing the data points into a pre-selected number of groups such that data points in the same cluster are more similar to other data points in the same cluster and not so much similar to the data points in other clusters [16].

It depends on the type of algorithm selected for clustering how the clusters will be created. Types of clustering methods are following:

Density-based method states that the clusters are based on a presumption that area with the higher density has some similarities and differences are from the lower density area.

Hierarchical-based method, in this one, clusters are formed in this method by a hierarchy based on tree-type structure. New clusters are formed by the previously formed cluster. So it is formed from root to leaves.

The grid-based method is a method that divides the whole data space into form a grid-like structure. Of course, it is a finite number of cells that can be merged into the whole data space backwards.

The last one is a partitioning method. The partitioning method divides given input data into k clusters and each partition forms one cluster. This method is used when parameters corresponding to the point for division are objective so the function can classify points by distance [15]. To this clustering, method family belongs K-means algorithm, which is used in the implementation.

3.1.2 K-means

K-means clustering is one of the most widely used algorithms. As mentioned above data points divide into k clusters based upon the distance metric used for the clustering. The value of k is to be defined by the user and in the Section 3.1.4 it is described how to choose the optimal k. The distance is calculated between the data points and the centroids of the clusters. In our implementation we choose for simplification of writing code pre-programmed algorithm from Scikit library [17].

The K-means algorithm aims to choose centroids that minimize the inertia, or within-cluster sum-of-squares criterion:

$$\sum_{i=0}^{\infty} \min_{\mu_j \in C}(||x_i - \mu_j||^2) \tag{1}$$

Inertia makes the assumption that clusters are convex and isotropic, so it tries to form clusters to hyperspheres.

In our methodology approach we used MiniBatchKMeans from Scikit library [17]. It is a variant of the KMeans algorithm which uses mini-batches, this decision was made on reference [17]. They recommend using this variant for the small dataset size which we have.

The concept of how we solve clustering of vehicles corporate fleet is that we use some properties of every vehicle of fleet. Thus, every property is one dimension in space and by the clustering algorithm, we divide it into the clusters by mentioned sum-of-squares criterion (1). Subsequently, every cluster has its centroid with specifications.

3.1.3 Aggregation

For solving the problem with properties of fleet load we decide to use aggregation properties of each one vehicle. We presume that information about trips of cars can offer us the determination of profile vehicle of fleet. For clustering as the best choice appeared to choose as parameters length of trips vehicles. We have chosen more parameters for the most accurate classification. We studied the length of trips and time of trips. Because in every input data some errors can appear and it is better to have similar properties to prevent the transmission of the error to the results. Aggregation functions chosen for modelling are a means of trips, the $25th$ percentile is also known as the first quartile, the $50th$ percentile as the median and the $75th$ percentile as the third quartile. All mentioned aggregation function, based on SQL queries, they extract data from driving distance and duration from the original dataset. The longest car ride is also selected as the SQL query. This parameter in clustering helps to better differentiate cars to cluster with vehicles that are used for trips mainly abroad. In the implementation, it is called "vehicles planned for foreign trips".

3.1.4 Elbow method

As already mentioned, the K-means algorithm uses a pre-defined number of clusters from the user. The elbow method is the most efficient way to choose the number k of clusters effectively. This is a heuristic used in determining the number of clusters in a data set. Thus, this method iterates the values of k, calculates the distortions values for each value of k, and calculates the distortion or inertia for each value of k. This approach is highly inspired by the article [18].

To determine the optimal number of clusters, we have to select the value of k at the "elbow" or "knee of a curve", which is the point where diminishing returns are no longer worth the additional cost. Thus, for Figure 3.2, we conclude that the optimal number of clusters is 3.

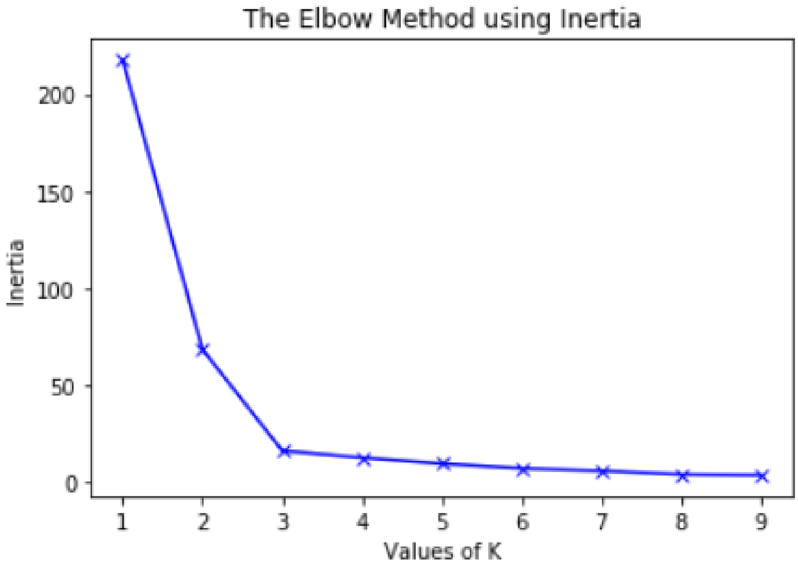

Figure 3.2: Example of elbow method [18]

3.2 Fleet composition

The fleet composition consists of profiles of vehicles that we want to create based on our parameters. The parameters indicate the driving characteristics of the vehicles for which we then want to generate the rides and charging demands. Then the vehicle is labelled to the clusters based on the parameters. Clusters are formed according to the criteria and algorithms described in the previous section. Our created fleet of profiles is an input to simulation, which finally generates the rides and charging demands. This part is described in the next section.

The fleet of vehicles is created according to clusters and their characteristics, how was mentioned. In addition, there is one more cluster that contains vehicles that run only within the factory areas. Because the additional cluster has particular properties, it was not possible to separate it from the rest of the data by the K-means algorithm. Thus, the data of this cluster was picked from input data before the K-means algorithm was run.

Description of fleet composition is as simple as possible. In the attached file code, there is the modelling of own fleet of vehicles programmed. The description is also included for clarification. So a potential fleet builder has as clear overview as possible. Thus, he does not have to do his own research among the vehicles he needs to include in the fleet.

To compose the fleet, we can use 2 approaches. Moreover, approaches can be mixed. The first approach is to choose the number of vehicles and corresponding cluster based on an approximate description of the cluster. Descriptions are listed in the implementation of clustering (Section 4.1.3). Subsequently, the number of vehicles and the label of the corresponding cluster is directly assigned to the generated fleet.

The second approach is to choose the number of vehicles and the approximate driving characteristics of the vehicles.

This approach, based on sum-of-squares criterion (1), selects the nearest centroid of the whole set of clusters and then assigns the selected number of cars to the resulting label of the cluster. Approximate driving characteristics of the vehicles can be chosen max-length-majority, min-length-majority, gen-length-majority.

Max-length-majority means that the majority of vehicle trips is less than a given value. It is the $75th$ percentile of the length of vehicle trips. Min-length-majority means that the majority of vehicle trips is greater than a given value. It is the $25th$ percentile of the length of vehicle trips. In the end, gen-length-majority means that the majority vehicle trip is about a given value. It is the median of the length of vehicle trips. In the case that characteristics are not complete, the label of the cluster is assigned based on rest values.

For the summary, the fleet contains numbers of vehicles of each assigned cluster and labels of clusters assigned to vehicles which we want to know charging demand. Chapter 4 compares the different compositions of the fleets if they consist of vehicles by description. Moreover, it examines how the rides and charging demands for these different fleets change.

3.3 Simulation model

This section has described the methodology of simulation and its theoretical background. Input is the fleet created according to previous Section 3.2 and output of the simulation is the charging demand of the fleet. Simulation of every vehicle of the fleet is one of the most used approaches in the given issue.

3.3.1 Goal

The aim is to model the most accurate vehicle management of a given fleet. From the output of the simulation, we can determine the behaviour of EV. Thus, the fleet builder, who forms a fleet of EV, based on his requirements, will be able to determine at what times and in which places his fleet requires charging of the vehicle. Moreover, he will know if any vehicle he entered when creating the fleet has a demand for charging outside corporate areas or which vehicles have to adjust their driving due to insufficient battery capacity.

3.3.2 The base simulation description

Description of this approach of modelling charging demand of fleet contains an explanation of used algorithm and explanation of selected input values. Description belongs to the algorithm represented in the pseudo-code below.

How was mentioned the created fleet of vehicles enters as an input to the algorithm described in pseudo-code. It means that each vehicle of each cluster forms fleet, and it is needed to model its behaviour. Then, parameters are entered on input, namely the time period for which we want to model the behaviour of the vehicles, the initial date and time of modelling the simulation, then the initial location of the vehicle, and the SOC. Finally, optional constants enter the algorithm on input. These are the characteristics of EV which we want to model. Namely, the capacity of the battery and average consumption of EV. Concrete values are from [19]. According to the driving characteristics of any vehicle from [19] fleet can be model specifies for the selected vehicle.

The output of basic algorithm is set of actions of every EV from the fleet. Actions are charging, stay (non-charging), and movement. Moreover, a location is added to each action. The locations are not including exact GPS coordinates because we want to model general charging demand. Simulation of a corporate fleet distinguish whether the vehicle is located in factory areas or outside the factory. If several factory areas from input data can be distinguish, we can also distinguish between them.

Algorithm 1: Base simulation

```
Result: set of actions
initialization of constants;
while stateTime ≤ limitTime do
    action set by prob if moving;
    if moving then
        action set by prob where moving;
    else
        action set if charging is needed;
    end
    update state;
    append action to set of actions;
end
```

In the first step, the algorithm decides based on the probability (2) of whether the EV decide to move or stay. A specific probability formation is described in Section 3.3.3.

$$P(Moving \mid cluster,\ day\ of\ the\ week,\ hour) \tag{2}$$

The second step is divided into two parts. The first part is when the algorithm decides that vehicle at that moment is moving. In pseudo-code, it is the "if" clause. The probability (3) determine the location where the vehicle is moved. There is one more feature under this clause. It is called forced-charging. This happens when the SOC battery is insufficient to reach the target location. The proposed solution is stopped when the vehicle is charged. Subsequently, the time required for movement to the determined location is updated.

$$P(Location \mid cluster,\ location) \tag{3}$$

The second part of the second step occur when the algorithm decides that vehicle is not moving. In pseudo-code it is "else" clause. In this clause it is decided whether the vehicle will be charged or not. As the generated charging demand is proposed for the corporate fleet, we try to ensure , that vehicles are charged mainly in the corporate areas. There are two reasons for this approach. The first is that the corporations usually want to design their own vehicle-charger location in their areas. The second reason is that it is not known where are the locations of vehicle-charger outside the area. Thus, it is not known if the EV of fleet can charge in a given location. At present, although great efforts are being made to electrify vehicles, the charging infrastructure is still infrequent.

According to the study [12], most vehicles charge immediately upon arrival, so the charging demand is just at the time when EV park in a corporate area. In the same study [12], it is mentioned that their simulation for the behaviour of EVs is generated every 5 minutes. Because of probabilities (2), (3) which are generated at hour intervals, it is not possible to generate such frequent updates. The result would be that demands of rides would be generated much more often than in reality vehicles from clusters drove. Thus, it is chosen a 15 minute interval of charging or eventual non-charging. In case the SOC battery is almost full and so less time is needed to charge for full SOC. In this case, it is less than 15 minutes. Naturally, it also occurs situations when the EV is needed to be charged outside the corporate areas. For example, when the SOC battery is too low and it leads to range-anxiety, as it is mentioned in [1]. It should not occur often and any generated charging demand outside the area is also included in forced-charging. Finally, we assume that the vehicles always had access to charging facilities whenever parked.

3.3.3 Theory behind used probabilities

The studies presented in Chapter 2, as well as the initial data analysis, as well as the subsequent results in Section 3.4.2, show that the vehicles have a similar pattern of behaviour within days of the week. There is also a certain pattern of actions during hours within a day. Based on this fact, the probability of moving (2) is computed within the cluster per hour of days of the week. Probability (3) is derived from the typological behaviour of the vehicle within the cluster. The probabilities are shown here once again:

$$P(Moving \mid cluster,\ day\ of\ the\ week,\ hour) \tag{2}$$

$$P(Location \mid cluster,\ location) \tag{3}$$

Theoretically, we can write that the simulation is stochastic modelling of EV and charging profiles. The main decision probability (2) and also location probability (3) are based on the Markov chain. The Markov chain is a stochastic model defining a sequence of possible events in which the probability of each event is to continue from the current state.

The changes of state are called transitions. A transition matrix describes the probabilities of a particular every possible transition. In Section 4.1.4 there is the exact transition matrix for location probabilities shown.

Stochastic modelling of EV by Markov chain is also used and more described in [12] and [20].

3.3.4 Combined simulation

In this subsection, it is described a combined simulator which consists of base simulation described in Section 3.3.2 and probabilities of charging. Probabilities of charging drawn from the approach described in the next section (Section 3.4.2). The difference between base simulation and combined simulation is marked in pseudo-code below with red text. Thus, algorithm does not decide to charge whenever it is possible, but on given probabilities.

Algorithm 2: Combined simulation

```
Result: set of actions
initialization of constants;
while stateTime ≤ limitTime do
    action set by prob if moving;
    if moving then
        action set by prob where moving;
    else
        action set by prob charging;
    end
    update state;
    append action to set of actions;
end
```

3.4 Forecast model

In this section we describe methodology of generating of charging demand based on historical charging data obtained from charging stations. This approach in reality generates a forecast model. This method, in contrast with the method used in simulation mentioned in previous section, does not generate charging demand on the basis of a given fleet of vehicles. Therefore, the output of this approach is just a general summary of the charging demand.

3.4.1 Goal

A general charging demand is set as a goal on output. The general charging demand contains the number of charges in a selected time period when the charging starts, consumption how much energy is consumed during charging, and time period how long the car is standing on the charging station.

3.4.2 Prophet

Every approach or output of the approach marked as forecast in this thesis is modelled by the tool developed by Facebook and called the Prophet. Detailed description of this tool is in [21]. In simplicity, Prophet is a forecasting tool based on an additive model where non-linear trends fit with seasonality. Seasonality is based on the Fourier series. Default settings are yearly, weekly and daily seasonality. Simply written form:

$$y(t) = g(t) + s(t) + h(t) + e(t) \tag{4}$$

where:

$g(t)$ - trend (non-periodic changes)

$s(t)$ - seasonality (periodic changes)

$h(t)$ - holiday effect

$e(t)$ - noise

3.4.3 Theory behind Prophet

The initial data analysis of charging stations showed that the vehicles have a similar pattern of behaviour within days of the week. According to this fact, it was decided to use for modelling charging demand based on the periodicity of actions. The own implementation did not work so precisely. Thus, we decided to use the Prophet, mainly due to the seasonality function included in the formula (4). A Fourier series is a technique how to represent a periodic function as a sum of sine and cosine functions, an example is shown on Figure 3.3.

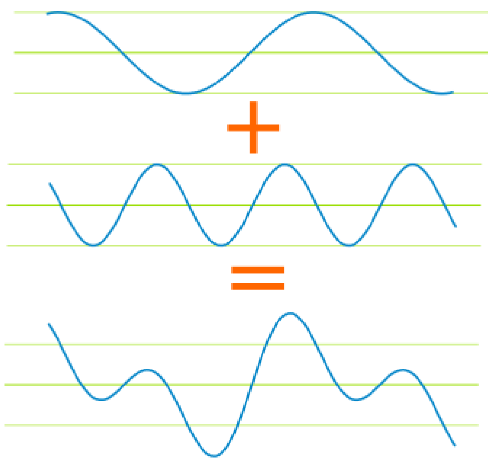

Figure 3.3: Fourier series: $sin(x) + sin(2x)$ [22]

The seasonality function is simply a Fourier series as a function of time. It is the sum of sines and cosines, each multiplied by some coefficient. A Fourier series is a technique how to represent a periodic function as a sum of sine and cosine functions. Constant P is the regular period we expect the time series to have. Thus, for yearly seasonality $P = 365$ and for week $P = 7$. Seasonality formula (5) is described in [21].

$$s(t) = \sum_{n=1}^{N} \left(a_n cos\left(\frac{2\pi nt}{P}\right) + b_n sin\left(\frac{2\pi nt}{P}\right)\right) \tag{5}$$

Chapter 4

Experiments

This chapter contains a description of our solution based on the theory in Methodology (Chapter 3). We are explaining how approaches work on exact input data. What exactly our input data looks like. If any optional values are used, we describe our selection. At the end of each approach, we summarize the results. We compare different approaches to each other. Finally, we evaluate each modelled charging demand which different approaches generated.

4.1 Representative models of vehicles

The first step in creating a charging demand for some optional composition of EV fleet is to create representative models of vehicles. The methodology is described in Section 3.1. In this section, there are listed all operations that take place at the level of cluster processing.

4.1.1 Input data

The input data from the data set processed according to Section 3.1.3 enter the clustering algorithm. In short, it is the data of the vehicle drives of the already existing fleet, and subsequently, their characteristics are processed by aggregation functions in SQL.

Data set

All data are from private data sets. Because of the data provider's policy, we provide only processed data that does not contain private data of the vehicle user. Contact thesis supervisor Ing. Martin Schaefer for complete input data.

The input table contains rides from the company's fleet. Provided data contains records of six months. Trajectories are recorded by GPS location. The table contains only business rides, so there is no driving to work, driving from work or private driving included. Every mentioned trajectory contains the start of the ride, end of the ride and identification number of the car. All rides are from gasoline-powered cars.

4.1.2 Implementation of clustering

Processed data from input by the aggregation functions are only vehicles with their characteristics. These characteristics of vehicles enter the Minibatch algorithm from Scikit library [17].

Then, the elbow method to find the optimal number of clusters is used. The output of the elbow method of our input and aggregation parametrization is shown in the Figure 4.1 and the Figure 4.2.

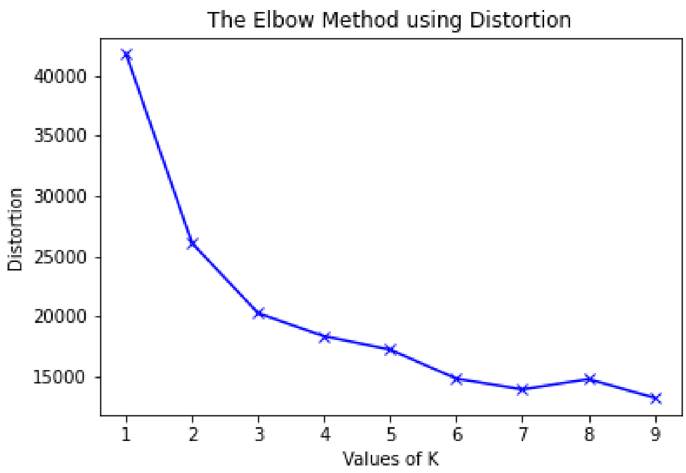

Figure 4.1: Elbow method for Distortions

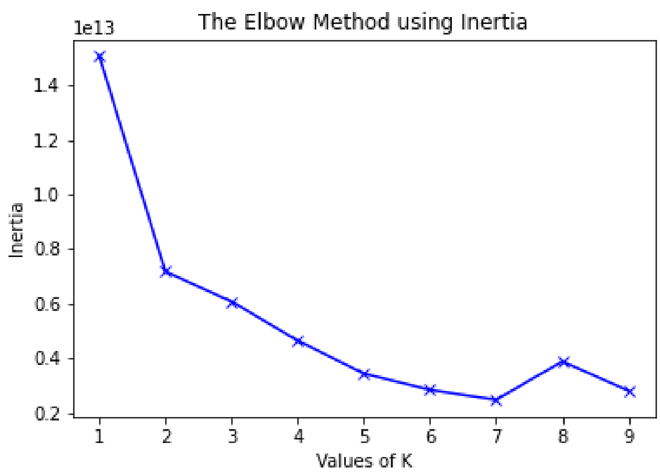

Figure 4.2: Elbow method for Inertias

We model 7 clusters for given input data according to elbow method (Section 3.1.4) as shown in the Figure 4.1 and Figure 4.2. We offer an overview of the centroids of the given clusters with the properties according to which clusters were modelled and in the Table 4.1. In the table, all values of length are in kilometres, and it contains processed all rides of vehicles. For clarification, $Q1$ means the first quartile ($25th$ percentile), $Q2$ means the second quartile (median), and $Q3$ means the third quartile ($75th$ percentile).

The clustering classification can also be seen on the Figure 4.3, Figure 4.4 and Figure 4.5. Because only 2 dimensions can be shown on the plot, it represents the only sample of characteristics of vehicles of clusters.

Table 4.1: Centroids of clusters

	avg length	Q2 length	Q3 length	Q1 length	avg time	max time	Q2 time	Q3 time	Q1 time	num of cars
0	5.9	2.7	4.3	1.9	00:12:09	01:27:20	00:08:12	00:13:23	00:05:34	1841
1	88.1	67.2	130.9	24.2	01:12:16	03:26:27	01:00:09	01:44:53	00:27:38	139
2	178.6	135.6	300.2	48.0	01:54:49	04:43:22	01:31:19	02:58:59	00:40:37	41
3	20.0	2.9	6.2	1.8	00:21:57	04:02:56	00:08:40	00:18:16	00:05:13	535
4	31.9	6.8	26.5	3.4	00:30:56	03:05:17	00:14:41	00:33:05	00:08:14	285
5	48.0	12.3	71.4	4.0	00:42:31	03:14:13	00:21:57	01:01:14	00:10:00	290
6	55.3	56.9	70.8	22.2	00:50:17	02:29:20	00:48:45	01:04:46	00:26:05	191

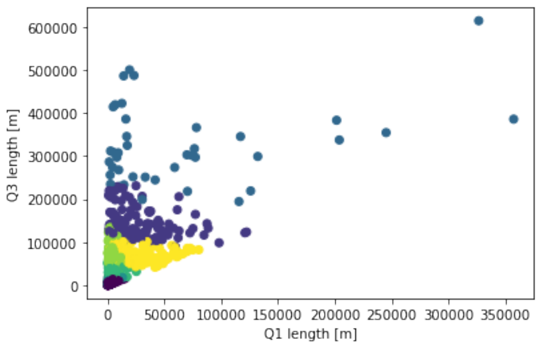

Figure 4.3: Comparing of the first quartile and the third quartile of trips length

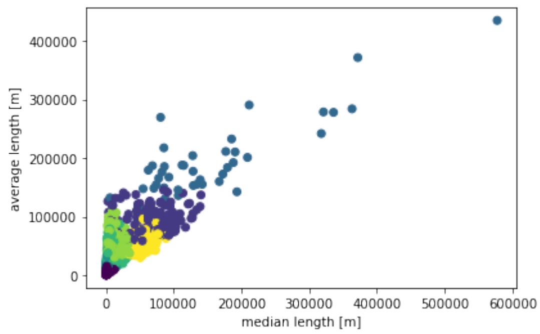

Figure 4.4: Comparing of average and the median of trips length

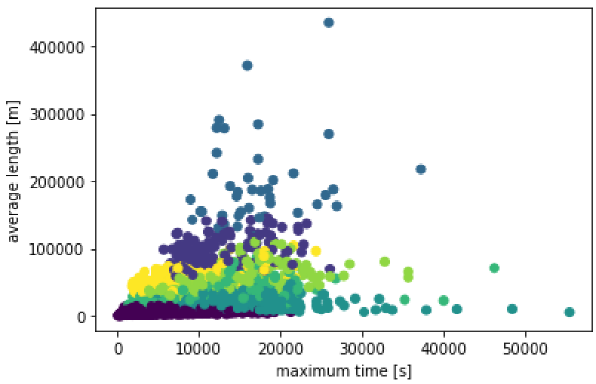

Figure 4.5: Comparing of average and the maximum of trips

Finally, we add to the generated clusters from the Minibatch algorithm one more cluster of vehicles separated from the original set because vehicles have more than 90%

of trips inside of corporation areas. This cluster is separated based on SQL query. This cluster is not shown in Figure 4.3, Figure 4.4, Figure 4.5 and Table 4.1.

4.1.3 Result

Classification of vehicle types and the following description of the category is the output of the whole clustering. Characteristics are derived from the analysis of clusters outlined above in Table 4.1. This output enables us to create our own fleet very clearly.

Approximate characteristics of clusters are following:

0. Vehicles ride only in the factory and near the factory.
1. Vehicles ride mainly longer business trips (ca. 90 km).
2. Vehicles planned for foreign trips (the longest trips within the clusters).
3. Vehicles ride mainly in the factory and near the factory but can occur longer trips (for example, business trips abroad).
4. Vehicles ride mostly regular rides within the district.
5. Vehicles ride around factories or not too long business trips (ca. 70 km).
6. Vehicles ride mainly business trips (ca. 55 km).
7. Factory vehicle (rides only in the factory).

Category number 7 is generated directly from the database. The others are classified by the K-means method.

*Once again we remind you that the characteristics are approximate and in case it is not able to classify the car according to the given characteristics it can be classified according to the driving characteristics.

4.1.4 Probabilities within the clusters

As it is mentioned in Section 3.3.3, we use probabilities based on clusters to generate a motion of EV in simulation. As a result of this substep, we gave an overview of probabilities within two clusters. The cluster shown on the left side of Table 4.2 contains vehicles that ride only in the factory and near the factory. The cluster shown on the right side of Table 4.2 contains a factory vehicle that rides mainly in the factory.

The probabilities are shown in transitions matrices. The Table 4.2 shows the percentage probability of transition from one state to another. It is a transition between numbered factories and the surroundings outside the factory labelled as "other".

Table 4.2: Transition matrices

Table 4.3: Cluster 0

	to other	to f1	to f2	to f3
from other	63.1	36.4	0.5	0.1
from f1	36.5	63.4	0.1	0.0
from f2	16.4	3.3	80.3	0.0
from f3	40.6	22.0	0.0	37.4

Table 4.4: Cluster 7

	to other	to f1	to f2	to f3
from other	15.0	59.1	22.7	3.2
from f1	2.8	97.2	0.0	0.0
from f2	2.2	0.2	97.7	0.0
from f3	0.3	0.0	0.0	99.7

4.2 Fleet composition

In this section we examine fleet composition approaches. Methodology is described in Section 3.2. There are two approaches to fleet composition. The first approach is to choose the number of vehicles and the corresponding cluster based on an approximate cluster description. This approach is not necessary to test because of triviality.

We test only the second approach. The second approach is to choose the number of vehicles and the approximate driving characteristics of the vehicles. Subsequently, by the driving characteristics of the vehicles, the vehicle is assigned by the label of corresponding cluster.

We validate input shown in Table 4.5 of the second approach with the description of the cluster mentioned in Section 4.1.3. In the table, all values of length are in kilometres. For clarification, $Q1$ means the first quartile ($25th$ percentile), $Q2$ means the second quartile (median), and $Q3$ means the third quartile ($75th$ percentile).

Table 4.5: Input of parameters of fleet

Q3 length	Q1 length	Q2 length	num of cars
'None'	1	2	1
100	70	90	2
200	100	150	3
10	2	'None'	4
30	5	10	5
100	0.3	0.5	6
100	30	50	7

For simplicity for the reader, 'num of cars' is set by the cluster where cars with driving characteristics should belong according to the cluster description. So 'num of cars' = 1 belongs to the first description of the cluster mentioned in Section 4.1.3 and so on.

The fleet is composed exactly according to our assumptions. We conclude that fleet composing is successful because of this one experiment. Moreover, this composed fleet is used in Section 4.7 to compare several fleets composition in simulation.

4.3 Base simulation model

One of the approaches how to generate charging demand is to simulate the behaviour of the fleet. In this section, there are listed settings of the parameters used in the simulation and then the simulation result. The methodology is described in Section 3.3.2.

4.3.1 Implementation

The fleet's composition according to the characteristics of the cluster from the previous section is an input for the base simulation. Probabilities of car movement are used for generating motion. Probabilities and fleet's composition are outputs of processing data by clustering. The input fleet consists of 13 vehicles of the first 4 clusters and 12 of the rest of the clusters. Energy consumption set on $194Wh/km$, battery capacity set on $60.5kWh$ and average speed of vehicle set on $80km/h$, are selected as an optional simulation parameters in all experiments. Listed values are averages from [19].

4.3.2 Result

The demand for charging and the place and time assigned to it are the results of the simulation. An example of the experiment with set inputs of one day is shown in Figure 4.6. The rides of vehicles of the experiment are shown in Figure 4.7.

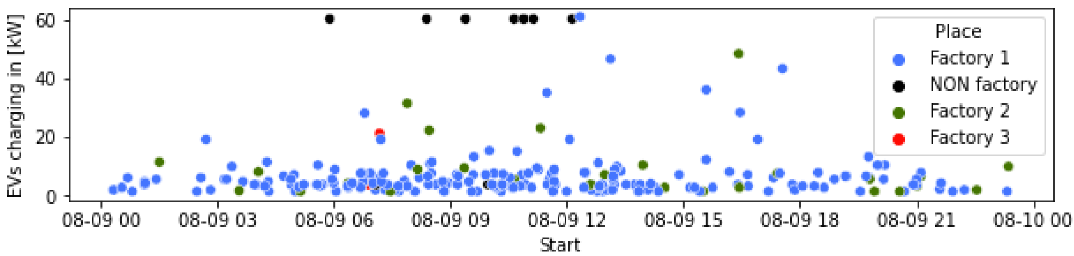

Figure 4.6: Chargings by locations

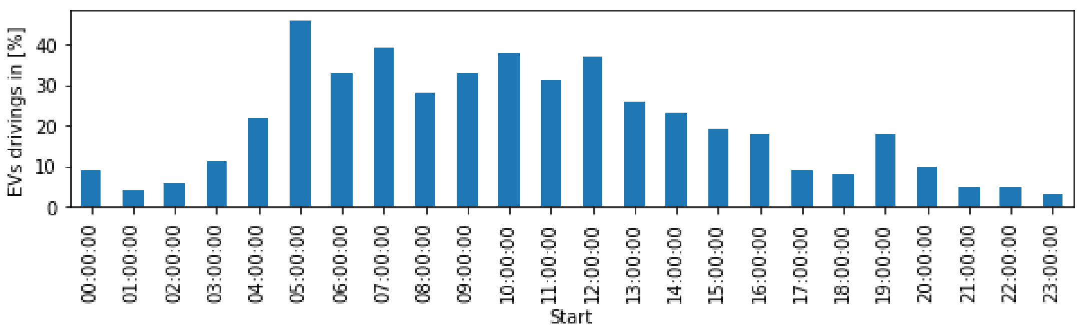

Figure 4.7: EVs driving

4.4 Forecast model

One of the approaches to generate charging demand is to predict future events based on historical data. In this section, there are listed settings of the parameters used in the model and then show results. The methodology of this approach is described in Section 3.4.

4.4.1 Input data

The input table contains publicly accessible charging stations in the factory area. This table contains electricity consumption, the time when the car was plugged in, time of disconnection of the car. Data are collected from three months in 2020. As example of data is in Figure 4.8. It shows one random selected day from all given charger stations.

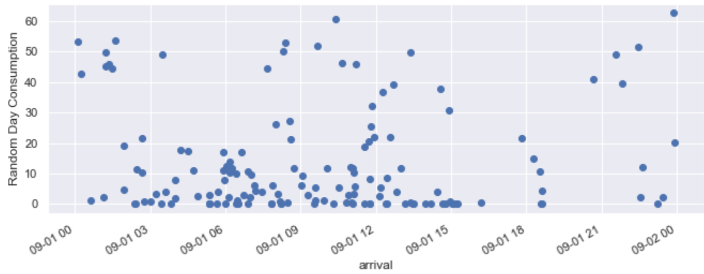

Figure 4.8: Day sample of charging station consumption

4.4.2 Implementation

We used a forecast based on historical data to determine the time of start vehicle charging. For prediction we used Prophet [21], with parameter "seasonality mode" set on "multiplicative". The prediction was set on every hour of one week, and as input was the sum of chargings of every hour from historical data. Processing the prediction of this model is in Figure 4.9.

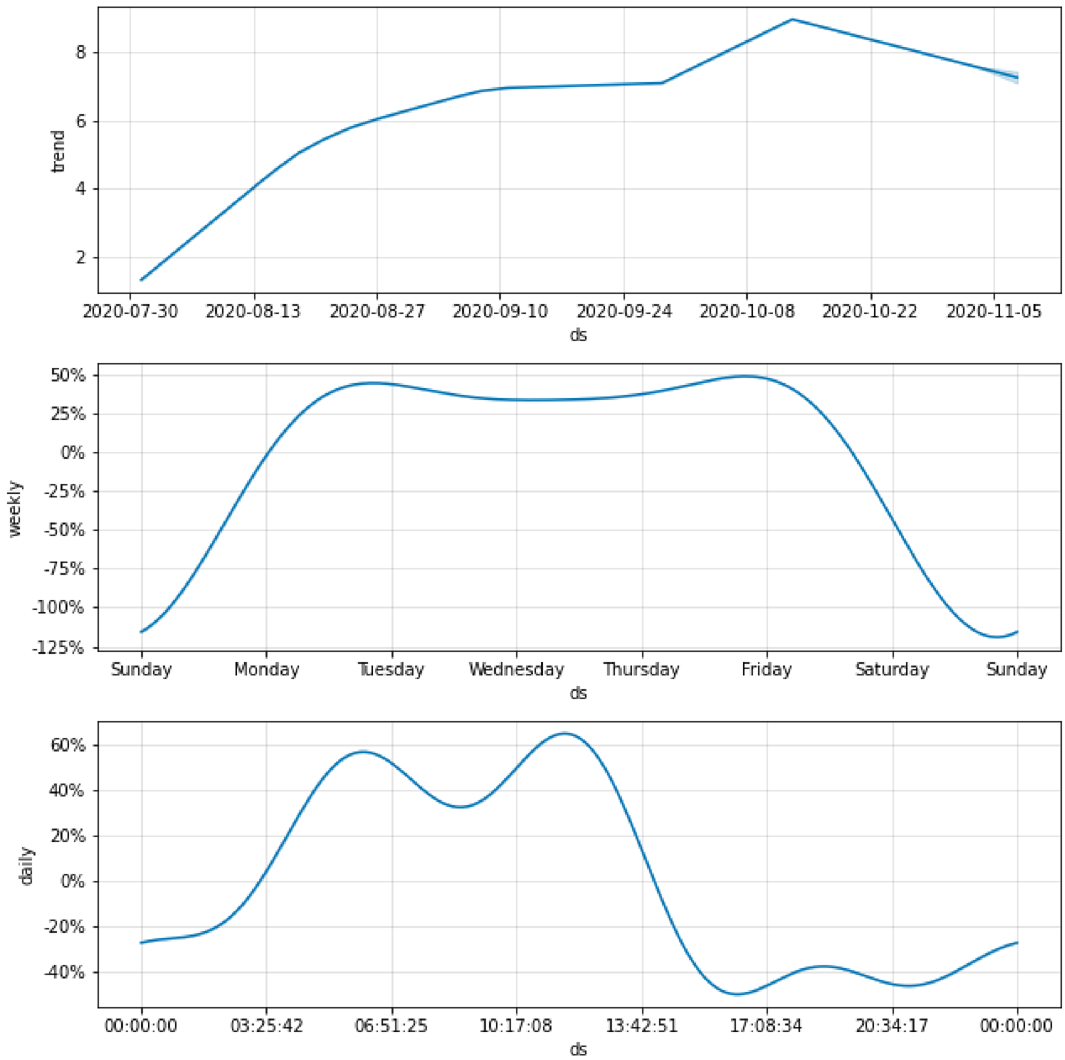

Figure 4.9: Prediction of number of chargings

4.4.3 Results

Prophet prediction of general charging demand can be used as a stochastical approach to solving the thesis problem. Moreover, after modifications of the datatypes from the Prophet output, we determine the probabilities of charging. The probability of charging is shown in percentage per every hour on days of the week in the figure. We used this probability in the combined model experiment described in the next chapter based on week periodicity.

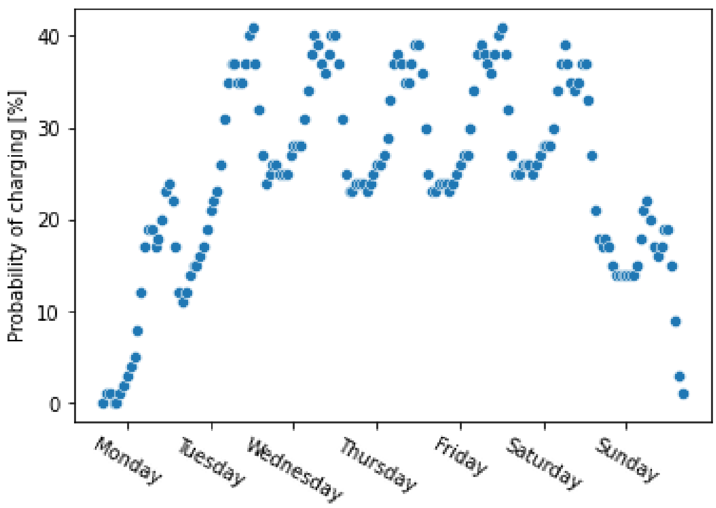

Figure 4.10: Percentage probability of charging demand per weekdays

4.5 Combined simulation model

By added the probability of charging to the base simulation model, we create a combined simulation model. The methodology of combined simulation is described in Section 3.3.4. Settings of the parameters used for the experiment are the same as in the base simulation model.

4.5.1 Result

The demand for charging and the place and time assigned to it are the results of the simulation. An example of the experiment with set inputs of one day is shown in Figure 4.11. The rides of vehicles of the experiment are shown in Figure 4.17.

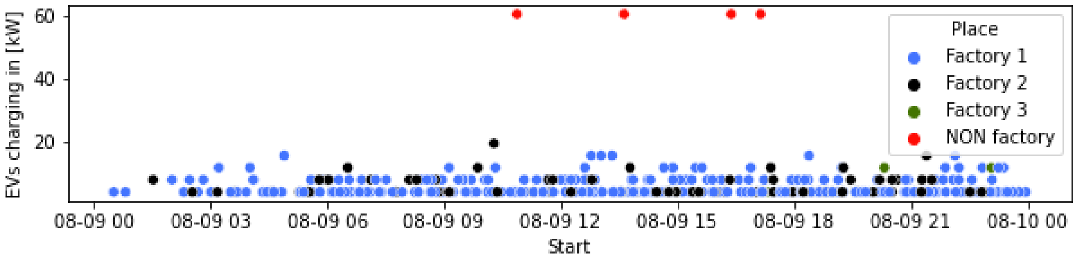

Figure 4.11: Chargings by locations, combined simulation

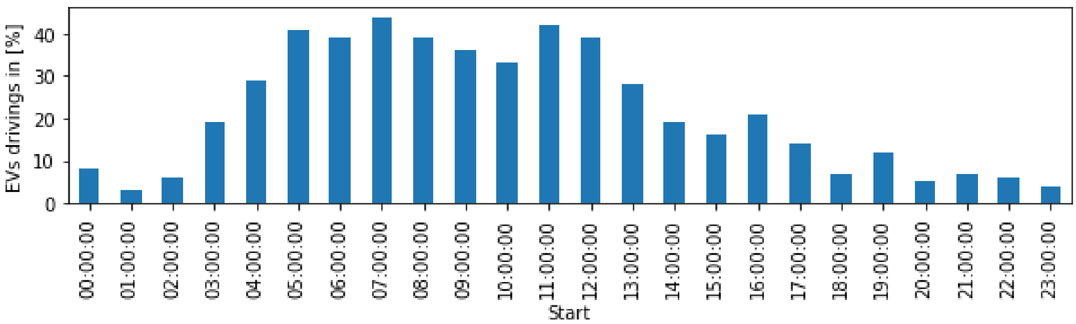

Figure 4.12: EVs driving, combined simulation

4.6 Validation and comparing with literature

Firstly, we compare our input values and input values used in other research. In Section 2.1.1, research and Figure 4.13 are described. Both Figure 4.13 and Figure 4.14 shows an average of percentual charges for week. Plots shown similar values.

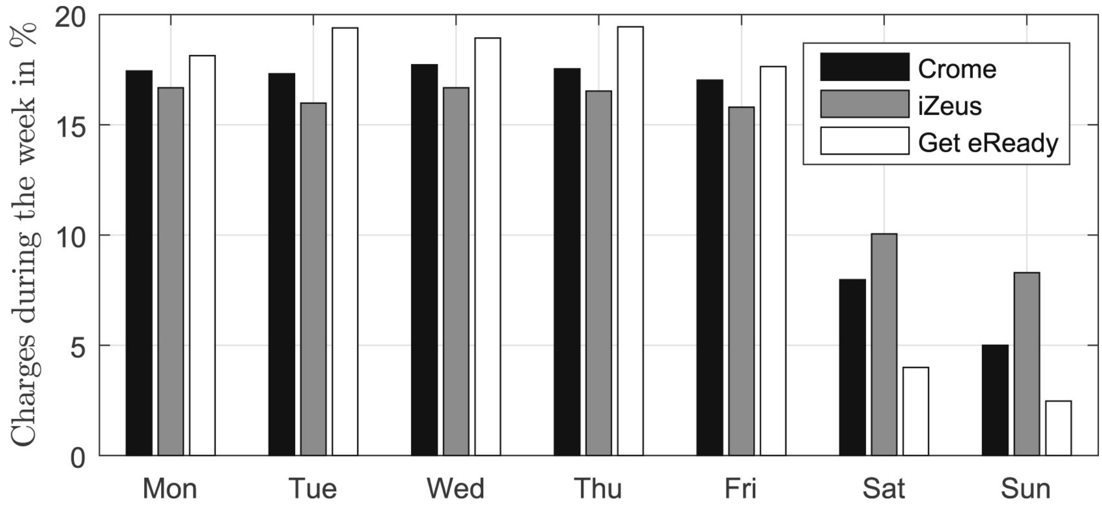

Figure 4.13: Percentage of charging processes per weekdays [11]

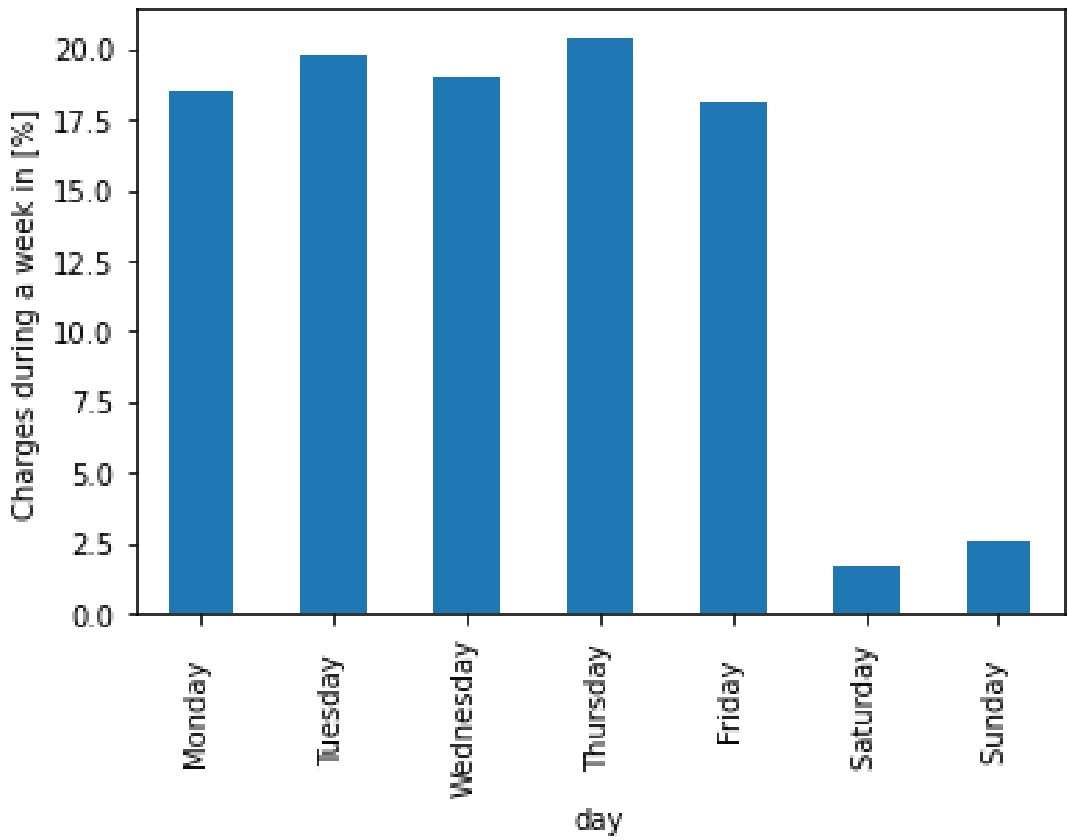

Figure 4.14: Percentage of charging processes per weekdays, our data set.

Secondly, we compare output of our simulations and output values from simulation in other research. In Section 2.1.2, research and Figure 4.15 are described. Results from Figure 4.16 and results from Figure 4.17 is about 5 times higher results from Figure 4.15. Weattribute this difference to the fact that we generate rides for corporation fleets where the probability of driving is generally higher than for private cars. The curve of values of all figures are similar to general business hours.

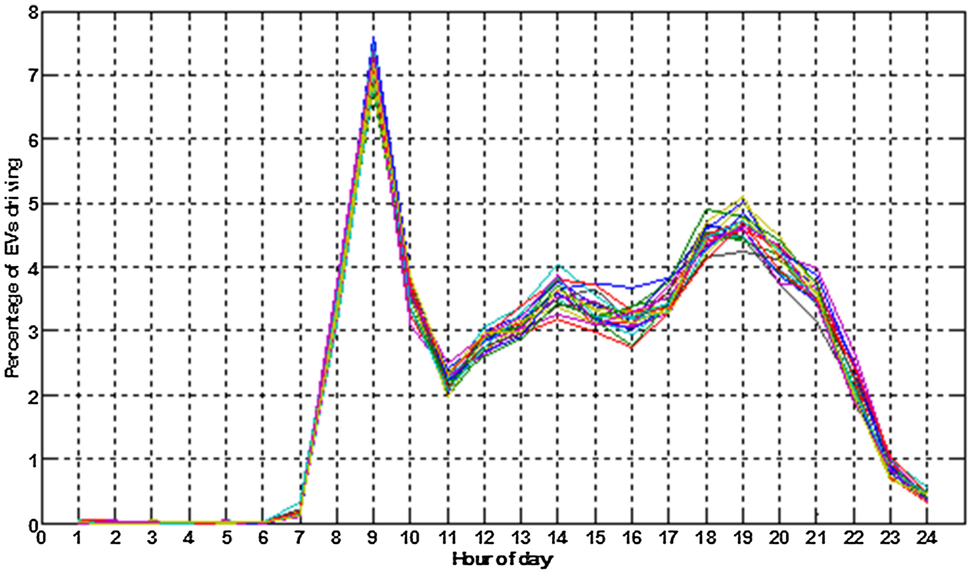

Figure 4.15: A 20 day simulation of the percentage of EVs driving per hour [12]

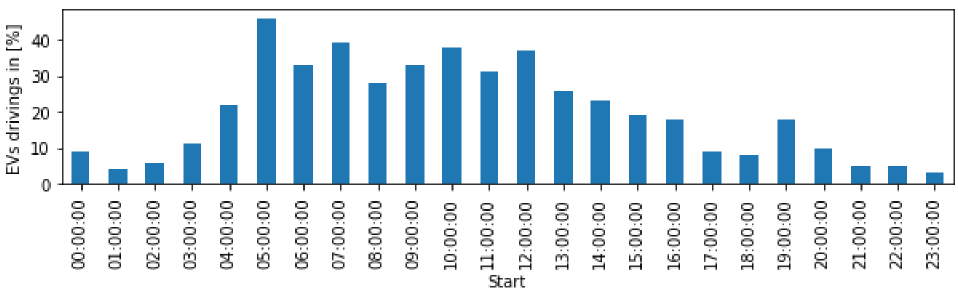

Figure 4.16: A base simulation of the percentage of EVs driving per hour

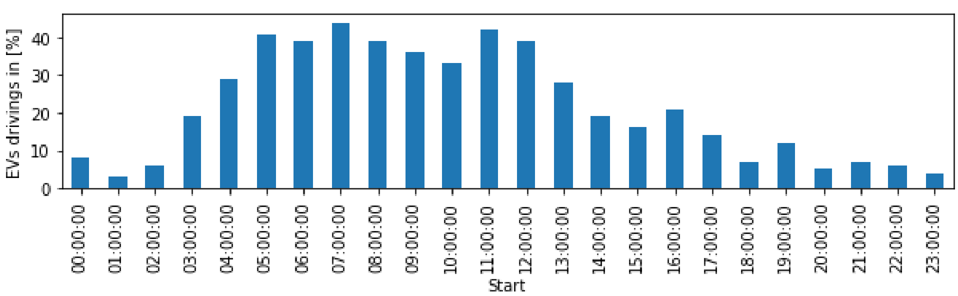

Figure 4.17: A combined simulation of the percentage of EVs driving per hour

Thirdly, we compare simulated charging demand over a week between our results of simulations and simulation of related work described in Section 2.1.1. Set on the input parameters described in the Figure 4.18 is the same for Figure 4.19 and Figure 4.20. Results of simulation in Figure 4.18 after comparing with our models (Figure 4.19, Figure 4.20) are not as accurate as they seem. The reason for this conclusion is vehicles behaviour on the weekends. Because both in our approach and the Schauble approach [11], input values of charges are lower on the weekends. Additionally, vehicles have a lower percentage of travel on the weekends, so the demand for charging should be lower.

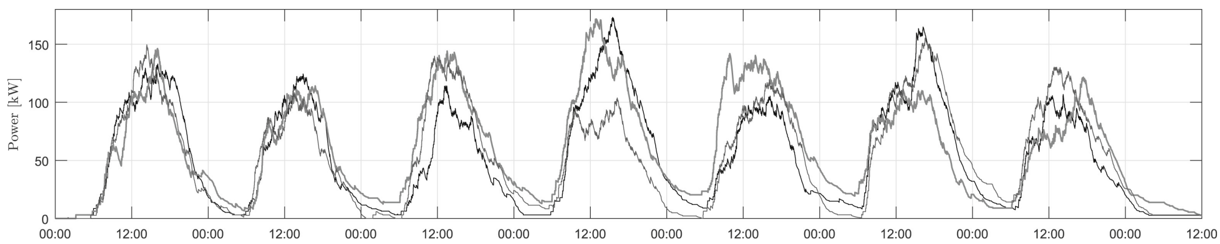

Figure 4.18: "Three simulated load profiles over a week, starting on Monday, for 100 EV that charge at least once every day with $p_{max} = 3.6kW$ using the mean number of charging events per vehicle and per weekday." [11]

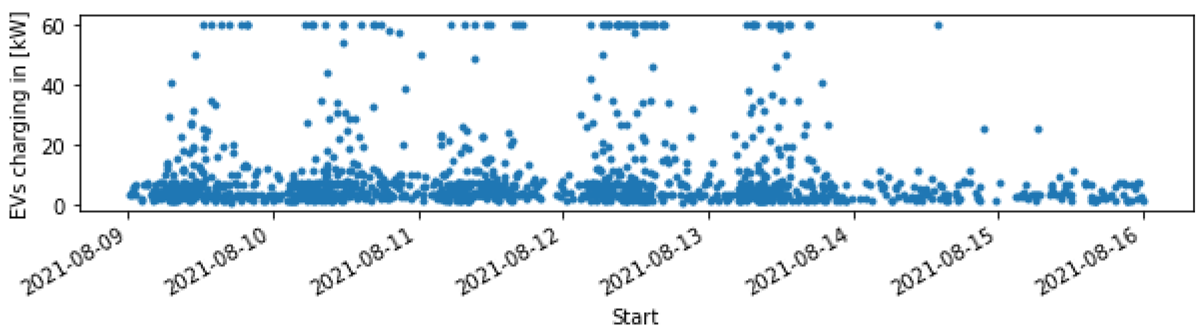

Figure 4.19: A base simulation for charging demand over a week.

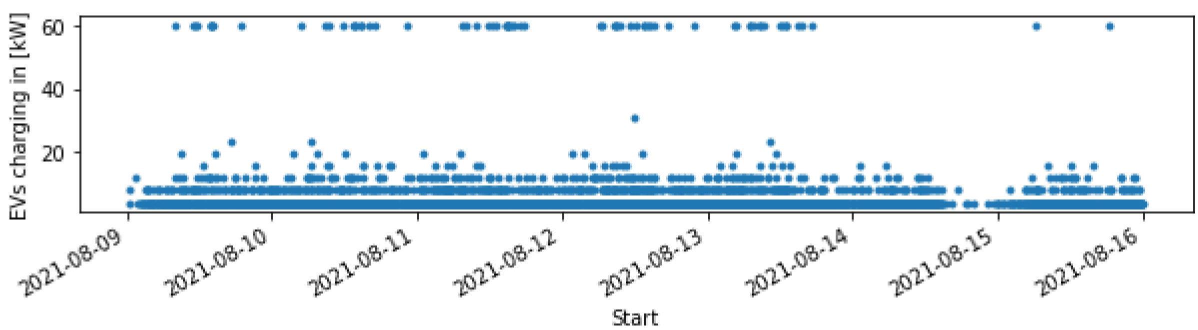

Figure 4.20: A combined simulation for charging demand over a week.

The result in Figure 4.20 is more structured. This problem occurred when each pause is set to 15 minutes. In this period vehicle can be charged. This fact also contributes that not always is vehicle charged whenever possible but based on probability charging. So charging does not occur as often, and then there is a larger capacity of the discharged battery, which is mentioned 15 minutes. However, the result of Figure 4.20 is more accurate than fFigure 4.19, because it is closer to the real behaviour of EVs.

4.7 Validation and comparing different fleet compositions

In this section we compare different fleets compositions. We decided to simulate the behaviour of EVs of different fleet compositions and, based on this, determine how the rides have changed and how the charging demand has changed when the fleets are differently composed. The vehicles contents of the fleets we compare are shown in the Table 4.7.

Table 4.6: Input labels of EVs fleet

name of fleet	0	1	2	3	4	5	6	7
mixed fleet	1	2	3	4	5	6	7	0
fleet with long trip EVs	0	0	28	0	0	0	0	0
fleet with factory EVs	0	0	0	0	0	0	0	28
triple mixed fleet	3	6	9	12	15	18	21	0

The combined simulation is used for generating charging demands. The optional simulation parameters are the same values set to the simulation as in the previous simulations. Specifically, energy consumption set on $194Wh/km$, battery capacity set on $60.5kWh$ and average speed of vehicle set on $80km/h$. In Table 4.7, there are simulated load profiles shown over a week, starting on Monday. The first column of the Table 4.7 shows the total number of charging demands. The second column shows the number of charging demands inside the factory area. The last column shows the total number of rides.

Table 4.7: Summary output of different fleets

name of fleet	num of chargings	num of chargings inside of area	num of trips
mixed fleet	122	106	335
fleet with long trip EVs	40	0	101
fleet with factory EVs	2565	2565	3399
triple mixed fleet	393	322	1012

According to Table 4.7 we conclude that simulations of different fleet compositions generate different outputs. For comparison, the' triple mixed fleet' model is three times greater than the 'mixed fleet' model output. This is working correctly. The 'fleet with factory EVs' generates all charging demands inside of the factory area. The 'fleet with long trip' generates all charging demands outside the factory area. Therefore the car is discharged outside the area and can not travel to the factory area for charging. We conclude that simulation of the fleet is successful because of this experiment.

Moreover, below there are chargings demands of these fleets shown on Figure 4.21, Figure 4.22, Figure 4.23 and Figure 4.24.

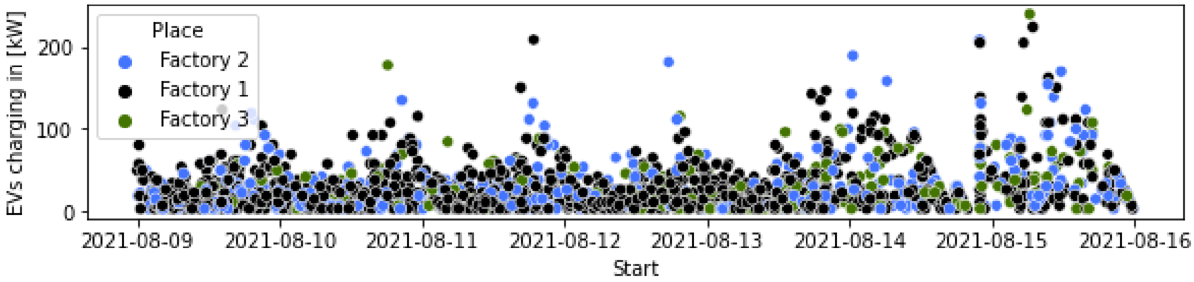

Figure 4.21: A simulation of the fleet with factory EVs

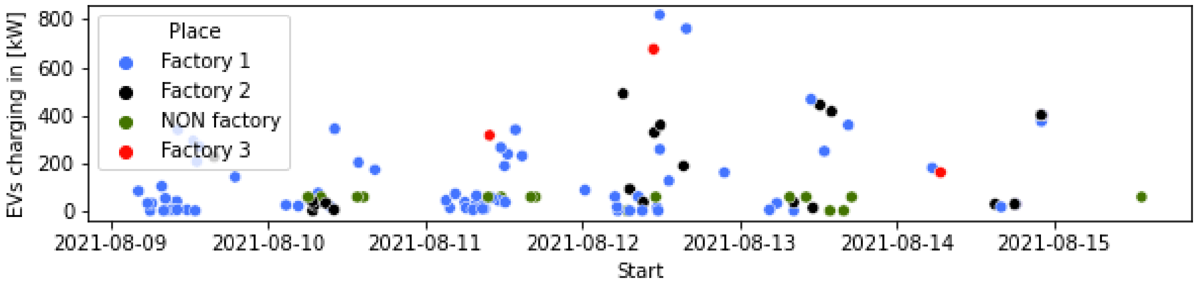

Figure 4.22: A simulation of the mixed fleet.

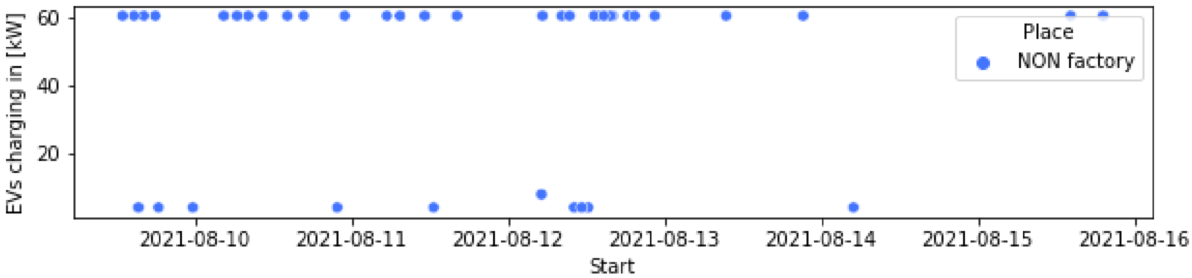

Figure 4.23: A simulation of the fleet with long trip EVs.

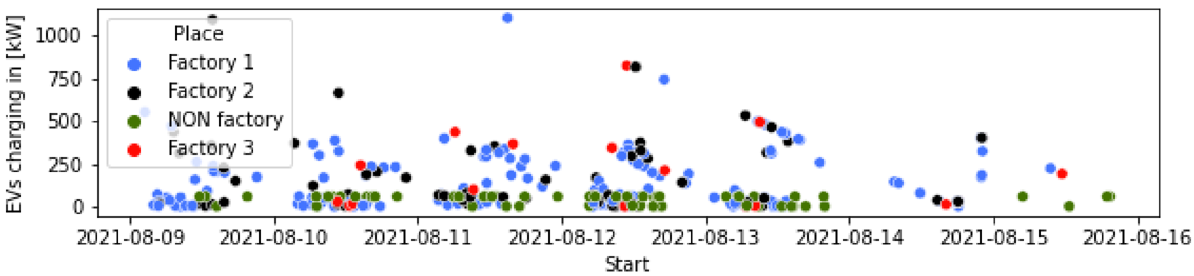

Figure 4.24: A simulation of triple mixed fleet.

Chapter 5

Conclusion

We have investigated charging demand models for fleet electrification. Firstly, we examined literature that deals with related problems as we researched. We defined the similarities and differences of the approaches solved in related literature. An appreciable inspiration was generating rides and subsequently generating the demand for charging, such as studying the behavior of EVs riders. After that, we designed a solution based on knowledge from related publications. The solution consists of three approaches that generate demand for charging EV.

Firstly, we would summarize the forecast model. It is stochastical model based on historical data. Simplified, we take historical data of charging actions, and we generate future by approximation functions. This model is suitable for any existing EV fleet, and we only want to change it. Simply if we double the number of vehicles in the fleet, we double the demand for charging. The problem with our data was that we did not know the number of vehicles included in the historical data. So we just estimated the general behavior of a given fleet of EVs.

Secondly, we would summarize the base simulation model. The approach is based on generating action for fleet vehicles. Actions are generated based on probabilities that are different for different groups of vehicles. This model has the advantage of simply choosing a vehicle with some driving characteristics, and then its drivings are simulated. So it is not a general vehicle. Related literature states, the most EVs will start charging immediately after parking. Therefore this fact was included in the basic simulation model. We can certainly say that a simulation model is more suitable than probabilistic for modelling a new fleet of EVs.

Thirdly, we summarize the combined simulation model. The approach is based on generating action for fleet vehicles. It is a combination of the basic simulation model and forecast model. The main functionality is same as in the basic simulation model but decision charging it is other. The charging decision is base on statistical probabilities of the general chargings. Output of this approach is the most precise in comparison with other approaches. Because of charging probabilities from forecast model results are more reliable.

Simulations are not working as precisely as necessary. It is needed to work on this problem in future. The idea for the future is to use proper simulation with more statistical probabilities used in it.

Other problem was not complete information in vehicles rides. It would be a piece of very useful information to know when the vehicle is at home, so we could determine the night charging. Night charging is one of the important data when setting up an electric vehicle simulation. Unfortunately, due to insufficient initial data, we had to omit this approach.

Appendix A

User Guide

In this appendix is structure of attached files together with description of each part.

```
Cveckova_thesis_attachment
│
├── thesis_text
│
└── code
    │
    ├── input
    │
    ├── output
    │
    ├── analysis.ipynb
    │
    ├── fleet_simulation.ipynb
    │
    └── stochastic_simulation.ipynb
```

thesis_text PDF version of this thesis.

code Contains source files of our Python project

input Contains data used as input to Jupyter notebooks.

output Contains images used in thesis. Images are result of Jupyter notebooks.

analysis.ipynb Jupyter Notebook contains data analysis of clustering and experiments. Notebook is fully run-able.

fleet_simulation.ipynb Jupyter Notebook contains making a fleet and simulation of the fleet. Notebook is fully run-able.

stochastic_simulation.ipynb Jupyter Notebook contains data analysis of chargings. Notebook is fully run-able.

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