Unlocking the Potential of Public EV Charging: A machine learning approach for the prediction of individual public EV charging session flexibility

MSc Thesis, Delft University of Technology

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Unlocking the Potential of Public EV Charging

A machine learning approach for the prediction of individual public EV charging session flexibility

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Acknowledgments

Dear reader,

I am excited to share with you my master thesis to complete my master's in Complex Systems Engineering and Management. Over the past months, I have explored the world of (public) EV charging, machine learning and tried different approaches and techniques to predict the individual public EV charging session flexibility. Along the way, I have learned a great deal about data analysis, the Dutch EV charging infrastructure, and the potential of smart charging strategies at charging stations.

I want to take this opportunity to thank all those who have supported me throughout this journey. First and foremost, I would like to thank all the EV experts who shared their thoughts and expertise with me during the interviews conducted in the last few months. I would also like to thank the TotalEnergies Solutions team, who generously shared their EV charging data and expertise with me. Their willingness to contribute to this research is greatly appreciated, and their data has been essential in building and evaluating the predictive models. In particular, I would like to thank my external supervisor Jules for his knowledge of the EV industry and his enthusiasm during the process and brainstorm sessions.

Second, I would like to thank my first supervisor Amir for his guidance throughout the process. His insights and critical feedback during our meetings have been valuable in shaping this thesis. Furthermore, I would also like to thank my second supervisor Ron and my chair of the committee Maarten for the constructive feedback and pleasant meetings. Third, I am very grateful to my family and friends for their support during the process. Their encouragement and belief in me have been a constant source of motivation.

Finally, I am confident that this thesis will contribute to the growing body of knowledge on individual charging session flexibility and its applications. The insights gained from this research can benefit practitioners and researchers alike. I look forward to seeing how this work can be built upon in the future and eventually unlock the potential of public EV charging.

I wish you lots of reading pleasure.

Bart Dijkstra
Delft, April 2023

Executive Summary

Electric Vehicles (EVs) are becoming more popular within the Netherlands due to the switch from fossil fuel transport to zero emission transport in recent years. As a result, the number of EVs in the Netherlands has increased rapidly, as well as the EV Supply Equipment (EVSE) required for their charging. One challenge with the rapid growth of EVs and EVSEs is the pressure its energy demand puts on the electric power grid. In addition, the share of fluctuating Renewable Energy Sources (RES) in the energy mix is increasing rapidly in combination with the electrification of the industry. However, EVs can be used to ensure that the grid is more balanced on the feed-in and consumption side by smart charging strategies. The Charge Point Operator (CPO) can utilize smart charging at public Charging Points (CPs) by adjusting the charging power within the session based on the objective that it aims to achieve. Objectives include, but are not limited to, congestion management, CO2 reduction or charging when electricity prices are low. These objectives could ensure reliable, affordable, and sustainable energy access for EV users while reducing the environmental impact of electricity generation and use.

However, managing charging sessions without consideration of the EV driver may result in insufficiently charged batteries at departure times. This in turn may lead to unsatisfied EV drivers. Therefore, information about the individual charging session departure time and required energy is vital to stay within the boundaries of the EV user comfort requirements. These demands can provide the EV driver's flexibility. Based on the literature review conducted in this thesis, the following definition for DER flexibility was adopted in the context of EV charging session flexibility: *A device has flexibility if it is capable of shifting its production or consumption of energy in time within the boundaries of end-user comfort requirements and without changing its total energy production or consumption.* In an individual charging session, the flexibility can therefore be quantified by multiplying the time flexibility with the energy consumption within a session. The time flexibility is the time the EV is connected to the EVSE without charging and the energy consumption is the consumed energy during the session. However, information about the flexibility potential of individual charging sessions is not available at the start of the session from a centralized approach. In addition, currently, there is no communication between the EV user and the CPO, therefore predicting this flexibility in individual charging sessions is important for employing smart charging strategies on an individual level.

Previous research has already focused on predicting the individual charging behavior such as the session duration and energy consumption using Machine Learning (ML). These studies showed that it remains a challenge to do this accurately due to sometimes erratic characteristics of charging behavior. Moreover, these studies are done with only one CP or a few CPs and the characteristics of the CP in combination with the EV user data are neglected. Therefore, the research objective of this thesis is to incorporate such characteristics to improve the predictive performance for large sets of public CPs. Historical charging data, EV user info and other characteristics such as time of day weather data and urbanization degrees were used as data input for predicting the session duration and energy consumption for individual charging sessions at public CPs. In addition, each public CP was clustered based on historical charging sessions.

The main research question was formulated as:

How accurately can individual EV charging session flexibility be predicted, at public charging stations, with information available at time of connection?

First, a literature study was performed to define the problem and to explore the current literature on charging session flexibility and how to quantify it. In addition, current literature was reviewed regarding the prediction of charging behavior with ML, which ML algorithms resulted in good accuracies and which features are used for the prediction. In addition, interviews and a survey were conducted with experts in the EV domain to gain insight into their insights about important features to predict session duration and energy consumption.

Moreover, the research successfully utilized a rule-based clustering technique to categorize public CPs into subgroups based on their charging profile. These subgroups were identified as Hybrid, Home, Short Stay, or Work chargers. Figure 1 depicts the charging profiles of the ten largest clusters.

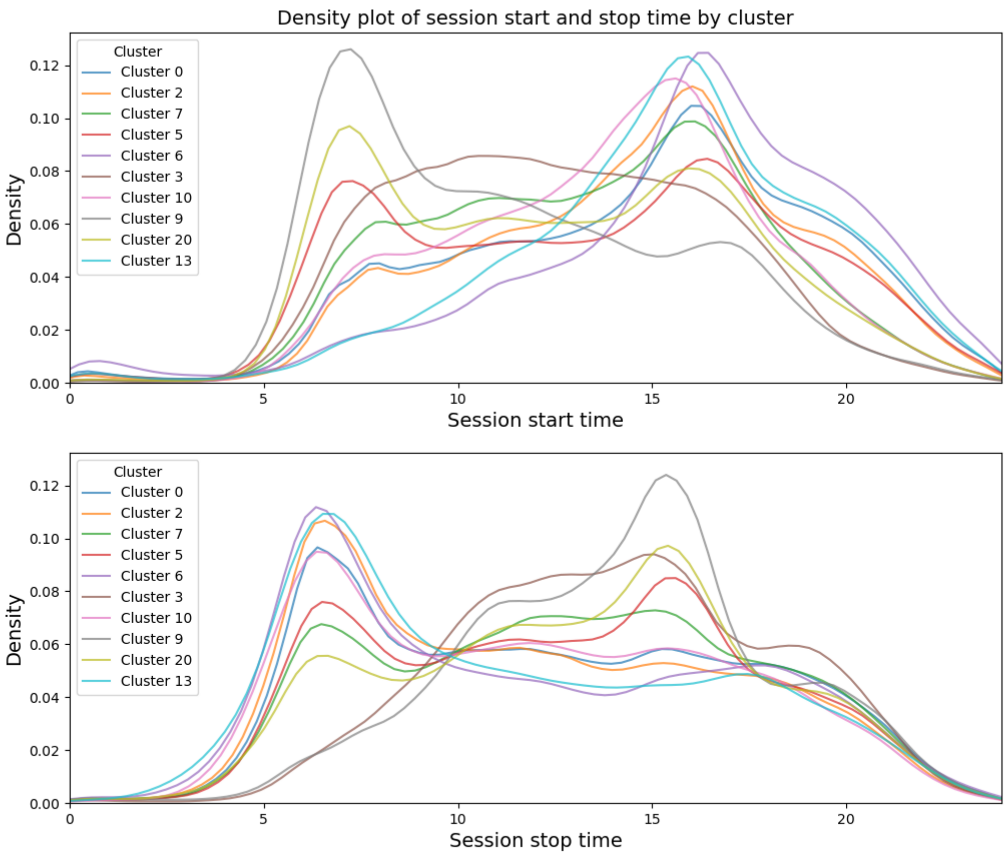

Figure 1: Density plot of the (a) start time and (b) stop time for each cluster

During the literature study, the XGBoost ML algorithm was identified and chosen due to the good accuracy results obtained in previous research. For the training and testing of the XGBoost algorithm, two different units of generalization were experimented with and evaluated for their ability to predict charging behavior: the Aggregated and the CP Cluster units. The CP Cluster unit utilized data segmentation of charging sessions within each cluster of CPs. The results showed significant prediction disparities among the subgroups within the Charging Pool of TotalEnergies for both the Aggregated and CP Cluster units. The CP Cluster unit produced more accurate predictions for charging sessions in the Short Stay and Work subgroups. Still, the overall accuracy improvement was limited due to many Hybrid and Home chargers in the used Charging Pool.

The study identified that the historical mean of EV users at a given CP was the most important feature for predicting session duration and energy consumption. The start hour of the charging session also proved to be important for predicting both variables. However, none of the other contextual features extracted from the available data were selected by the adopted feature selection approach and their exclusion did not impact the predictive performance. These contextual features, including weather variables, holiday indication, and urbanization degree, were irrelevant, in this study, for predicting session duration, energy consumption, and flexibility. Thus, the study concludes that the most relevant features for predicting session duration, energy consumption, and flexibility are related to the CP's usage history and that including contextual features does not significantly improve the accuracy of predictions.

This thesis concludes that it is possible to determine the flexibility of an individual EV charging session with the conditions mentioned in the main research question. However, it remains a challenge to accurately predict the individual EV charging session flexibility with the data available at the start of the EV charging session. Specifically, public charging stations categorized as Hybrid or Home chargers pose significant difficulty in anticipating the EV user's charging behavior in advance. The irregular patterns of behavior exhibited, such as extremely short or prolonged sessions, makes it challenging to predict the individual charging session flexibility with the available information from a CPO perspective. The errors for the prediction of the flexibility can be found in Figure 2.

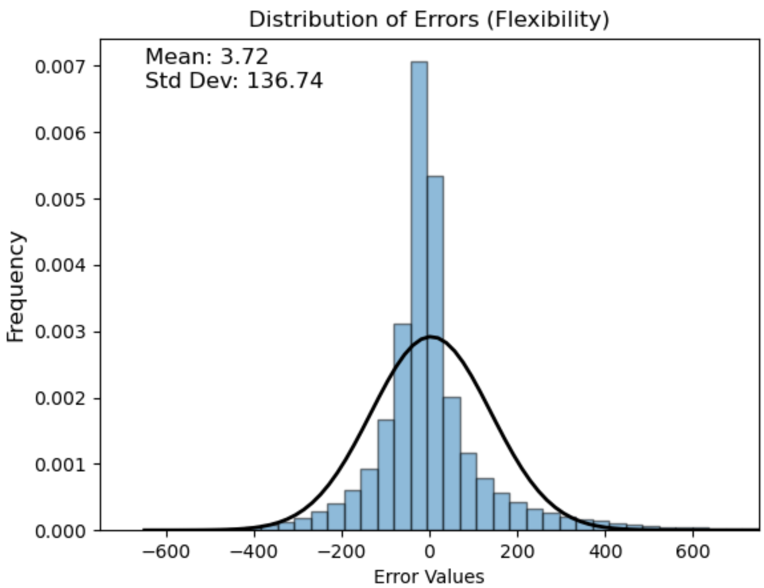

Figure 2: Histogram of the error distribution for the prediction of individual charging session flexibility (kWh^2)

The outcome of this thesis can be used by aggregators such as CPOs or policy makers to better understand the factors affecting charging behavior, which can ultimately lead to better allocation of resources. In addition, smart charging policies could be applied by taking into account the predictive errors that may arise. This can lead to improved scheduling optimization and more efficient use of charging infrastructure.

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Table 1: List of Abbreviations

Abbreviation	Meaning
AC	Alternative Current
ACEA	Automobile Manufacturers Association
AFIR	Alternative Fuels Infrastructure Regulation
BEV	Battery Electric Vehicle
CDR	Charge Detail Records
CP	Charge Point
DC	Direct Current
CPO	Charge Point Operator
DER	Distributed Energy Resources
DKDE	Diffusion-based Kernel Density Estimator
DSO	Distribution System Operator
DSRM	Design Science Research Methodology
EPA	Ensemble Prediction Algorithm
EU	European Union
EV	Electric Vehicle
EVCS	Electric Vehicle Charging Station
EVSE	Electric Vehicle Supply Equipment
FCEV	Fuell Cell Electric Vehicle
GHG	Green House Gas
GRU	Gated recurrent units
ICE	Internal Combustion Engine
IEA	International Energy Agency
LSTM	Long short-term memory
MAD	Median Absolute Deviation
MAE	Mean Average Error
ML	Machine Learning
PHEV	Plug-in Hybrid Electric Vehicle
PV	Photovoltaic
RES	Renewable Energy Sources
RF	Random Forest
RMSE	Root Mean Square Error
RNN	Recurrent neural network
SOC	State Of Charge
SVR	Support Vector Regression
TSO	Transmission System Operator
V2G	Vehicle to Grid
VPP	Virtual Power Plant

Contents

Chapter 1

Introduction

This chapter introduces the research by discussing the impact the energy transition has on the electricity grid and the need for flexibility services. Subsequently, the problem statement and the research gap that is addressed in this thesis will be presented. In addition, the linkage with the master program will be discussed and the objective with related research questions will be elaborated on. Finally, the research approach and the thesis outline are presented to conclude the introduction.

1.1 The energy transition and the need for flexibility

The energy transition is one of the most debated topics of the last few decades. To accelerate the transition, the Paris Agreement was signed in 2015 by 194 parties and the European Union (EU) to limit the global average temperature increase by reducing Green House Gas (GHG) emissions worldwide [9]. To reach this goal, the European Commission set the target of at least a 55% net reduction in GHG emissions in 2030 compared to 1990. The sub-goal of having a 45% share of Renewable Energy Sources (RES) by 2030 was also set to accomplish this [10, 11]. Therefore, it is expected that the European Union, which is still highly dependent on fossil fuels for electricity production, will change rapidly to more RES in the foreseeable future. In this pursuit of reducing GHG emissions, the global electricity system on the supply side, the demand side and the connecting power grid are undergoing significant changes.

On the supply side, fossil fuel-consuming power plants are being phased out and replaced by RES, such as solar and wind. With almost an 30% share of RES in 2021, the percentage of RES within the global electricity generation mix is increasing quickly [12]. A large part of this renewable energy production comes from hydro-power. However, the most significant growth in global electricity generation comes from solar and wind, which in 2021 increased by 18% and 17%, respectively [12]. The weather dependency of RES, such as solar and wind, causes fluctuations in their electricity generation. This growth of RES within the energy mix is expected to continue and even increase with the current energy crisis (2022/2023). In light of the current energy crisis, the European Commission presented REPowerEU in May 2022 [11], which aims to make Europe independent from Russian fossil fuels by 2030. This plan will further accelerate the energy transition within Europe by stimulating clean and affordable energy. One sub-goal of this plan includes installing more than 320 GW of solar PV by 2025, which is twice as much as present in Europe today [11].

From a demand perspective, there is an increase in electricity demand, which is the result of, among other things, the electrification of mobility and industry. The rise of heat pumps and data centers also contribute to the increase in electricity demand. In addition to the more considerable volume of electricity demand, there is an increase in fluctuations in the electricity consumption patterns. These fluctuations lead to increasing peak loads [13]. For example, simultaneously charging Electrical Vehicles (EVs) creates peak demand for electricity, which could cause congestion on the grid. Congestion on the electricity grid is when electricity flow is limited due to capacity constraints and the grid can not handle the required energy flows.

These changes in the supply and demand of electricity are a significant challenge for the electricity grids. Three potential problems arise with these changes: security of supply, balancing and congestion. The security of supply is defined as the availability of energy at all times for affordable prices [14]. When more intermittent RES is included in the electricity mix the security of supply can be challenged. The intermittent nature of solar and wind power could risk the continuous availability of electricity. On the other hand, the security of supply can be increased for countries that are now dependent on other countries for their energy production. Secondly, balancing supply and demand on the electricity grid is essential to maintain a stable system. The imbalance on the power grid would cause a change in the frequency or voltage, leading to poor power quality and ultimately resulting in power outages. Thirdly, the power transmission and distribution grid are a critical elements in the energy transition as they act as a connecting point for RES. Traditionally, to keep up with the growing peak supply and demand for electricity and avoid network congestion, the power grid is physically expanded and strengthened, but this is time consuming and expensive. It is estimated that the Distribution Grid Operators (DSO's) within Europe need to invest between 375 and 425 billion euros by 2030. This is an increase of 50-70% in the 2020s compared to the previous decade [15].

For that reason, at the same time as investments into expanding the grid are made, there is an increase in research that focuses on using the existing grid in a smarter way. One focus area is using flexibility to help reduce the overload on the grid and keep the grid stable [16]. Flexibility on the power grid is the ability to respond to changes in electricity supply and demand in real time, ensuring security of supply. Flexibility resources can provide this flexibility and are expected to be needed more in the near future due to changes in the supply and demand of electricity. In the following section, flexibility within the power grid will be explained in more detail and the resources that could provide this flexibility will be discussed.

1.2 Flexibility in the power grid

Multiple definitions of flexibility in the context of the power grid are used within research papers. For this research, the definition as given by the International Energy Agency (IEA) [1] will be used:

Definition 1 *Flexibility expresses the extent to which a power system can modify electricity production or consumption in response to variability, expected or otherwise.*

The definition from IEA defines that the flexibility of a power system can be determined by the ability it can adapt the electricity production or consumption when there is variability on the grid. There are several ways that grid services could provide adjustments of electricity production or consumption to provide flexibility to the power system. In Figure 1.1, several flexibility resources are mentioned on the right side. These flexibility resources are all able to increase or decrease their power in response to supply and demand variability.

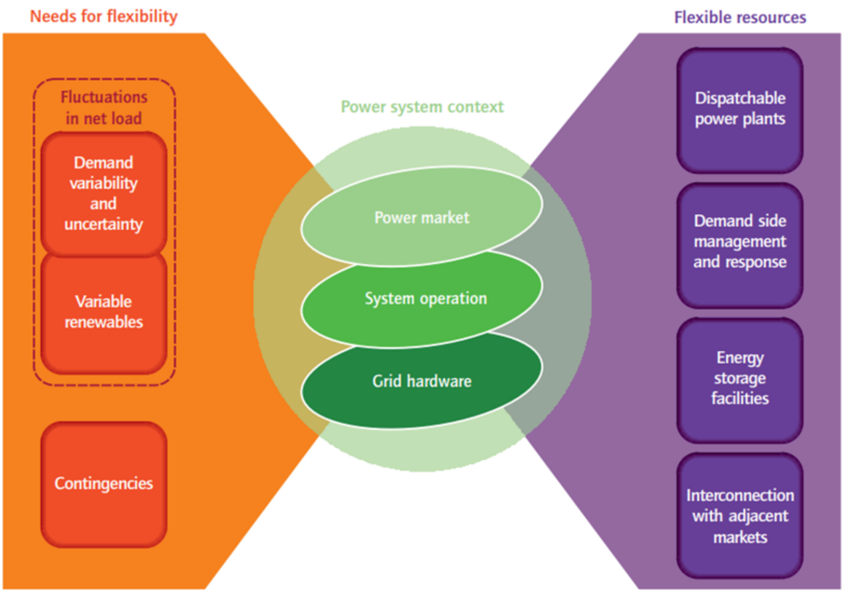

Figure 1.1: Overview of flexibility needs and resources [1]

Today, the largest flexibility providers in the traditional power grid, which has a low RES penetration, are dispatchable generation power plants such as gas turbines. These power plants are dispatched at times of high electricity demand. However, the disadvantage is that with the dispatching of power plants a ramp rate is present, which is the rate at which a power plant can increase or decrease output over a given period of time. The ramp rate indicates the speed at which a power plant can increase or reduce its power. Additionally, since there is a need for low-carbon flexibility solutions, this flexibility service is not desirable in the long term.

Interconnection with adjacent markets and regions is also an important flexibility resource on the current power grid. The interconnection between power systems in different regions can help balance the fluctuations caused by the intermittent nature of RES between regions. When there is little wind production in one region, another region with enough electricity production could provide electricity. In addition, interconnection can allow excess RES electricity production to be transferred from one region to other regions. This will increase the overall amount of RES that can be installed. With the increase in RES, the importance of interconnected power grids is expected to grow [17].

Flexibility can also be provided by demand-side management and response or energy storage facilities. This can be provided by electrical devices that are installed to the grid, which have the flexibility to generate, store or consume energy in the system. These electrical devices are referred to as Distributed Energy Resources (DER). Examples are: EV in combination with Electric Vehicle Supply Equipment (EVSE), Photovoltaic (PV), heat pump, lithium-ion battery and air conditioning. However, an individual small DER with low power can not provide flexibility to the power grid. This has to do with the limited quantity of flexibility that one small DER can provide. When multiple DERs are aggregated together, however, this will create a higher overall power and therefore flexibility potential, which creates the possibility to utilize this flexibility. Aggregated DERs can be controlled in a centralized IT infrastructure referred to as a Virtual Power Plant (VPP). [18]. An aggregator is a third-party stakeholder that acts as an intermediary between aggregated DERs and the electricity grid.

One DER that can provide a significant amount of flexibility to the power grid when used as a VPP is the EV in combination with the EVSE. Flexibility could be provided by increasing or decreasing the charging power within a charging session. This can be applied to avoid times of high energy demand on the power grid or steer towards times of high RES generation. With the electrification of the mobility sector, the number of EVs and therefore the aggregated flexibility present within EV charging sessions is expected to increase significantly in the coming years. This research focuses on the EV and EVSE as DERs and sources of flexibility

1.3 Problem statement

The problem addressed in this thesis relates to the need for more information about individual charging session flexibility when applying smart charging, specifically in the context of public EVSEs. While smart charging literature assumes that certain information about a charging session is available, such as the state of charge (SOC) or departure time of an EV, this information is rarely available for public EVSEs. Currently, the Charge Point Operator (CPO) can only determine the charging session flexibility when the charging session is completed. This absence of information can be attributed to the limited communication between the CPO, the EV and the EV user due to current communication protocols and the lack of direct contact with the EV user. The simplified communication situation is depicted in Figure 1.2. As can be seen, crucial information needed to determine the flexibility of an individual charging session at the time of connection is therefore unavailable. The lack of departure time and energy consumption information creates uncertainty about the available time window in which the CPO can alter the power of a EVSE without interfering with the EV users time and energy constraints.

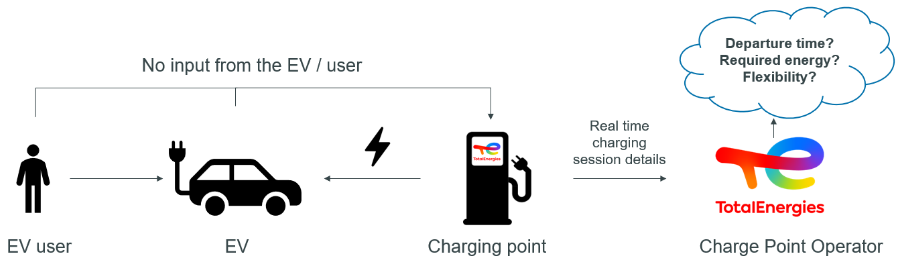

Figure 1.2: Lack of communication between CPO and EV user

1.3.1 Study context

The absence of this individual EV user departure time and energy consumption is one of the biggest challenges faced by CPOs today for utilizing this flexibility in charging sessions at public Charging Points (CPs). Therefore, the amount of flexibility in their portfolio is not known throughout the day. The flexibility can be used for scheduling and increasing the grid stability but also offer a more complete solution to the EV user. There could be two options to determine flexibility of a charging session. One would be to ask the EV user directly about their departure time and energy requirement and the second option would be to make predictions based on data that is available at the start of the charging session. One pilot project that was conducted in 2019 focused on utilizing the charging session flexibility is the European funded Interflex project [19]. In this pilot project the EV user could provide their flexibility to a commercial aggregator which would utilize this flexibility on the power grid. When an EV user plugged in their vehicle at a public CP it could provide their departure time and desired SOC through an app. This has two disadvantages. First of all, this would require an universal app that EV users actively use, which is not in place at the moment for public CPs. At present, the charging sessions at public CPs are started by the CP hardware and a charging card. Secondly, previous research indicates that EV users find it difficult to predict their own departure time and energy consumption. In a study that researched a CP at Caltech in California, the EV user could enter their estimates of energy consumption and session duration upon arrival [20]. It was found that the Mean Average Error (MAE) of predicting the energy consumption and session duration by the user are 11.8 kWh and 394 min, respectively. The MAE is a metric to indicate the sum of the absolute errors between the prediction and actual values [21]. On average, an EV user in this study wrongly predicts his departure time by more than 6.5 hours. This indicates the added value for predicting the charging session flexibility without asking EV users for input at the beginning of every charging session.

For the purposes of this thesis, only public chargers with a maximum power output of 22 kW will be considered. These are the chargers with the highest flexibility potential. There appears to be little charging session flexibility with fast chargers with higher charging power since these chargers are mainly used for charging purposes instead of the combination of charging and parking.

1.4 Research gap

The charging behavior of EV users plays a big role in determining the individual EV charging session flexibility. Due to the growth of charging session data and the open-source data sets that make this historical charging data available, previous research was conducted related to the prediction of the charging behavior of EV users. In the most recent literature, the prediction of this charging behavior is often done using Machine Learning (ML). ML turned out to be a suitable tool since it can recognize patterns in large amounts of historical data and predict new output based on these patterns.

However, in the current literature, the CP specific charging behavior is neglected during this prediction. This can be concluded since only one or two CPs are used or the focus lies on the historical charging sessions of the EV users without differentiating between the CPs. From previous research and interviews with EV domain experts, it was determined that public CPs are used differently throughout the day. Some public chargers are, for example, mainly used for long sessions such as overnight charging and other chargers are mainly used for short charging session during the day. In previous data analysis, CPs were categorized into several categories, such as Home, Work or Short Stay chargers. These categories are based on the connection time and duration of all the historical charging sessions on the specific CP. By differentiating between the CPs that an EV user connects to, it may be possible to improve the accuracy of predicting their charging behavior and flexibility, as different CPs may be used in varying ways.

In the current literature, no clustering of CPs has been done for the prediction of charging behavior. [22] provided a predictive model for individual charging session flexibility. However, in this predictive model, the CP specific information was not considered. This thesis tries to fill this gap by using a large historical charging data set with a substantial amount of public CPs in the Netherlands. In addition, a distinction will be made between different CPs by considering CP specific information such as the urbanization degree of the neighbourhood at which the CP is located.

1.5 Link with the Complex Systems Engineering and Management program (CoSEM)

The master CoSEM is centered around developing solutions for complex socio-technical problems. EV charging at public CPs is a system in which the electricity grid and the transport sector are both present. Looking at these sectors together results in a complex system with great potential for decarbonization when used in a smart way. In this complex system, multiple actors such as the CPO, DSO, Transmission System Operator (TSO) and the EV user are active. This thesis focuses on the latter and aims to develop and assess a prediction method for predicting individual charging session flexibility. The goal for the CPOs is to be as little of a burden to the EV user as possible while integrating smart charging policies. That is why for CPOs it in crucial to gain insight into the charging session flexibility before the session has ended. On the other hand, the EV user can provide flexibility to other stakeholders, for which they, in turn, can be compensated.

1.6 Research objective and questions

The objective of this research is to gain a better understanding of the factors influencing EV charging session flexibility and establish a benchmark for predicting such flexibility. This could lead to a better prediction of individual charging session flexibility, which reduces the uncertainties in smart charging strategies. Ultimately, this would improve the power distribution among EVSE. However, with a prediction, there is always uncertainty present. The evaluation of several metrics on the model can represent this uncertainty. The following research questions will be answered in this thesis.

Main research question: How accurately can individual EV charging session flexibility be predicted, at public charging stations, with information available at time of connection?

RQ1: How can charging session flexibility be quantified and what data are available at public charging stations at time of connection?

It is important to carefully define the problem and identify the data that can be used for the prediction. With this sub-question the charging session flexibility will be defined and quantified. This will help to apply focus and ensure that a specific, measurable outcome is reached. In addition, the data that is available at the start of the charging session that can be used for the prediction will be identified. This will be done based on current literature and interviews with EV experts.

RQ2: What are the most important independent variables that influence the individual charging session flexibility?

This sub-question aligns with the objective of understanding which independent variables influence the charging session flexibility most. First, it will increase the data understanding of the relationship between variables and the charging session flexibility. In addition, it improves the model's interpretability. This improvement in interpretability could help understand how a model is making its decisions and could be used to enhance the trust of EV users in the model. Identifying the most important independent variables will be done in multiple ways. First, a literature study on previous studies related to charging session flexibility and charging behavior will be conducted. Secondly, EV experts will be interviewed on their perspectives on important independent variables that could be used. The independent variables identified during these methods will be used within the predictive model and the importance can be indicated by data analysis through various packages in Python and a feature selection approach. In addition to the EV expert interviews, a survey will be sent to the EV experts about their perspective on the importance of the chosen variables.

RQ3: What machine learning model(s) can be applied for the prediction of individual charging session flexibility?

It is relevant to choose an appropriate prediction method based on the nature of the problem and the characteristics of the data. There are a variety of ML models to choose for the prediction of charging session flexibility. By conducting a literature search the ML model that provided the most accurate results throughout literature will be chosen.

RQ4: Does segmentation of the data through clustering charging points result in more accurate predictions for charging session flexibility?

Segmentation is the process of dividing a data set into smaller, more similar subgroups based on certain criteria. This can help to identify patterns or trends in the data that may not be apparent when looking at the data as a whole. One challenge in predicting the charging session flexibility at public CPs is that they are commenly used for both short and long charging sessions. By differentiating for what purpose a CP is commonly used, such as mostly for short charging sessions, it could be possible to increase the accuracy of the predictions. Based on a clustering approach the public CPs will be clustered based on their historical charging profiles. The segmentation of the data will be done based on the clustering of CPs. This way a seperate predictive model can be trained for each cluster of CPs with the same charging profile. To determine a suitable method to cluster the CPs a literature study will be conducted. In addition, in order to compare the accuracy between clustering CPs and no clustering a uniform model is compared to the clustered models. In ML, evaluation metrics are commonly used to evaluate the performance of a model on a given data set.

1.7 Research approach

In Figure 1.3 the research flow diagram of this research in presented which contains the steps that will be taken to obtain an answer to the research questions. The research approach that is used within this thesis is based on the Design Science Research Methodology (DSRM) provided by Peffers et al. [23]. This approach is chosen since the research question has a clear design component that has the goal to implement a new approach to a system. In the DSRM methodology, the following six objectives within a process model are provided: Problem identification and motivation, Definition of the objectives for a solution, Design and development, Demonstration, Evaluation, and Communication.

Step 1: **Problem identification and motivation**: The problem identification and motivation step consist of a literature study to provide background on the problem statement. A understanding of the changing power system and the need for flexibility was already provided in introduction. Secondly, the growth of EVs and EVSE in the Netherlands is researched. From this the need for smart charging will be explained. Thirdly, the parameters of a individual charging session are described and explained. To conclude the problem identification and motivation, it will be defined how individual charging session flexibility can be quantified.

Step 2: **Define objectives for a solution**: The second step is focused on defining the objectives for a solution. A literature review will be done into charging behavior in the context of this thesis. In addition, a literature search will be done focused on current ML prediction models related to charging behavior. Secondly, a literature review will be done on clustering within the EV domain. This has to goal to gain insight into the state-of-the-art methods that could be used for clustering CPs. Thirdly, interviews with EV experts will be conducted to gather insights into which features could be important for charging session flexibility prediction. The interviews will also be used to validate the intended prediction framework.

Step 3: **Design and development**: In this part of the research, the ML application will be designed and developed. The process start by answering RQ1 how to quantify charging session flexibility, and which data is available to a aggregator. Therefore, first different data sets will be identified that could be used for predicting charging session flexibility. Subsequently, this data will be preprocessed and cleaned to look at which data is available for aggregators. An important saying in ML models and other predictive models is the following: “the model is as useful as the data you put into it”. It is therefore important to properly evaluate and clean the data before training the ML algorithm. The next step in the design phase fits in well with this saying. The charging stations will be clustered on the basis of cluster techniques found in the previous phase. The cluster in which a charging station is located can then be used to segment the data or

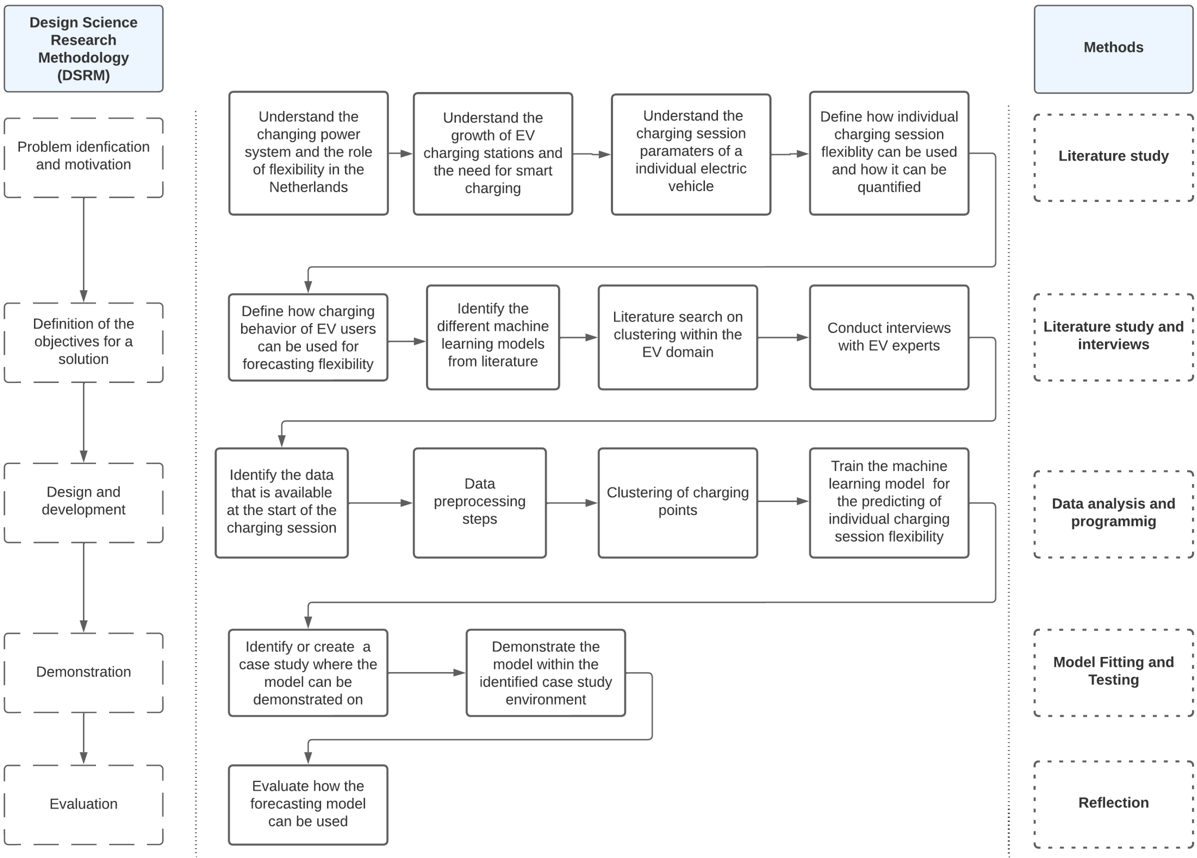

Figure 1.3: Research flow diagram

an extra feature can be added in which the cluster is presented. To conclude, a suitable ML method will be identified from literature.

Step 4: **Demonstration**: In the demonstration phase the use of the designed ML framework to solve the problem identified in step 1 will be demonstrated. This will be done by identifying or creating a case study based on real life charging session data that is provided by TotalEnergies. The ML model will be trained, validated and tested in Python to see how accurately the flexibility of an individual charging session can be predicted at public EVSE. In addition, within the demonstration phase RQ4 can be answered, where a evaluation will be made if the segmentation of data based on charging station clustering has a positive effect on the accuracy.

The demonstration of the ML models will be done by analyzing the accuracy of predictions that are done by the models. There are several metrics available to evaluate the performance of a prediction model. From the literature study, the metric outcomes of other predictive models can be compared, however, the different research contexts should be taken into consideration when comparing the outcomes of this research to the literature.

Step 5: **Evaluation**: In this phase it is important to see how accurate the predictions are and how they can be used by an aggregator such as a CPO. It could be important, for example, to see what kind of impact this have on the EV user and what strategies could be applied to minimize this?

1.8 Thesis outline

This thesis is organized as follows: First, in Chapter two, background information will be provided about the growth of EVs and EVSEs in the Netherlands and the need for smart charging. In Chapter three, a literature review is conducted on core concepts that are related to charging session flexibility. In Chapter four, the methodology of the research will be presented. Chapter five will present the results of the methodology. To conclude, in chapter six and seven the discussion and conclusion about the research will be presented.

Chapter 2

Background

In the previous chapter, the research objectives with corresponding research questions and approach of this thesis were outlined. This chapter aims to provide contextual background information by highlighting the necessity of smart charging in light of the growing EVs and EVSE market. In addition, an overview of different EVSE will be given to provide a better understanding about different EVSE based on their maximum charging power, accessibility and charging profile. This will help identify differences between EVSE and thereby cluster different public CPs to answer RQ4.

2.1 Electrical vehicles and charging infrastructure

As stated in the introduction, one focus area of the European Union to achieve GHG emissions reduction is the electrification of the mobility sector. Although the GHG reduction that EVs can offer depends on different factors such as the electricity production mix and the materials that are used within the battery, there is broad consensus that EVs have a positive impact on the environment compared to conventional internal combustion engines (ICE) [24]. Many countries, including the Netherlands, are therefore encouraging private and business transport to switch from ICE to electric transport [25]. These incentives from the government, in combination with electric driving becoming more financially attractive, and driving satisfaction are making electric driving an increasingly popular alternative. This increase in EV passenger cars in the Netherlands is illustrated in Figure 2.1. It is expected that by 2030 there will be around 2 million active EVs on the road in the Netherlands. In addition, all new cars sold in the Netherlands must be electric by 2030 [26, 27]. As can be seen in Figure 2.1, Battery Electric Vehicles (BEVs) and Plug-in Hybrid Electric Vehicles (PHEVs) are gaining much more ground in the Netherlands compared to Fuel Cell Electric Vehicles (FCEVs). One reason for this is the availability of EVSE for BEVs and PHEVs, and the lack of refueling infrastructure for FCEVs. In general, BEVs have a higher battery energy storage capacity than PHEVs. However, it is important to note that in the context of this thesis, which is based on the perspective of the CPO, the distinction between BEVs and PHEVs is not made. Therefore, within this thesis, when the term "EV" is mentioned, it refers to either a BEV or PHEV.

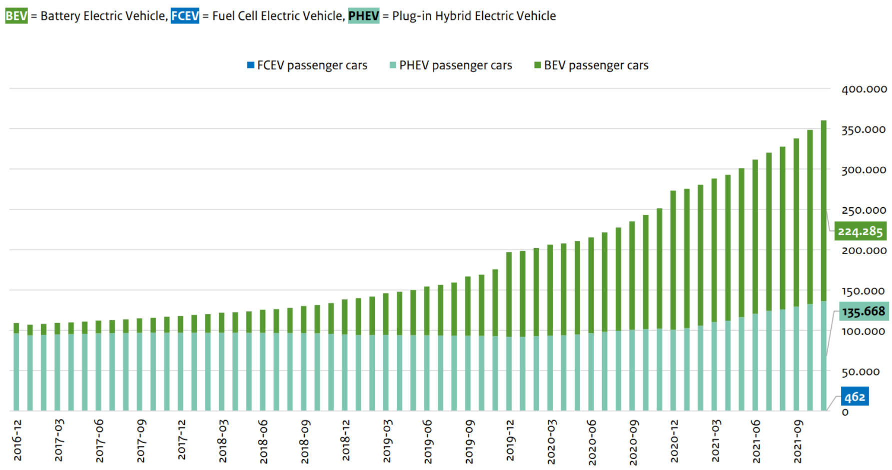

Figure 2.1: Registered EV passenger cars in the Netherlands [2]

With the growth of EVs and the need from EV users to charge their vehicle the installed EVSE infrastructure needs to grow as well to keep up with the demand. The charging of EVs can be in the form of private charging at home, public charging stations or charging stations provided at work. Many EV users, especially in densely populated cities, do not have the possibility to charge their cars at home due to the lack of private parking spaces and are therefore dependent on public or work chargers. Because of this, an extensive public EV charging network will have to be available in the Netherlands and Europe as a whole to make charging possible for everybody. To accelerate the implementation of the public infrastructure for alternative fuels such as EVs, the Alternative Fuels Infrastructure Regulation (AFIR) was implemented by the European Commission [28]. Due to the high demand for more public EVSEs in Europe in order to accommodate the significant growth of EVs, as well as the government stimulation packages, it is anticipated that the expansion of EVSEs will persist. The European Automobile Manufacturers Association (ACEA) published a study which showed that each week up to 14,000 CPs need to be installed in Europe to facilitate the 55% CO2 reduction for passenger cars [29]). The Netherlands already has a good amount of public CPs as can be seen in Figure 2.2 and is the leader worldwide in placing public CPs. With 90,000 public CPs, 29,4% of all public chargers within Europe are located in the Netherlands [30].

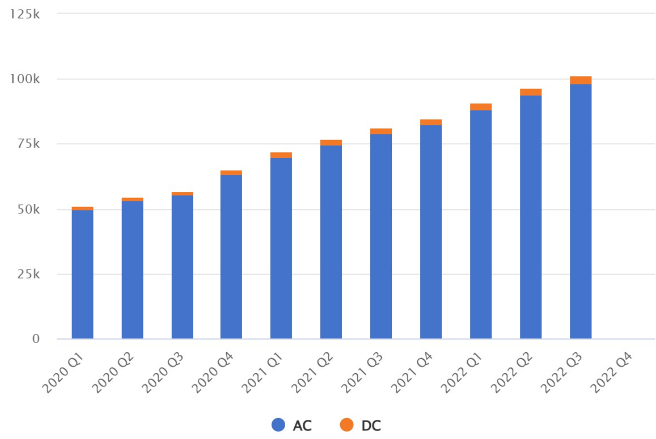

Figure 2.2: Total number of public charging points in the Netherlands [3]

2.1.1 The need for smart charging

Besides the logistical challenge of deploying a large amount of CPs, the electrification of transport has also become a challenge for the electricity grid. Charging a large amount of EVs simultaneously creates peak demand for electricity, which could cause congestion. With the current charging patterns the charging sessions are mainly concentrated in the morning and evening. These peaks of EV charging sessions coincides with the peaks of (other) household electricity consumption creating a large demand peak for electricity. Another often mentioned drawback of electrical charging is the long charging duration in comparison with refueling an ICE. The refueling of a ICE can be done quickly at gas stations while charging an EV can take several hours, depending on the type of charger and the EV battery capacity. However, it is common practice to use an EVSE in a different way as a gas refueling system. An EVSE is often used simultaneously for parking as well as charging. This change in user behavior with a EV compared to a ICE and the fact that on average 95% of the lifetime of a car is parked[31] offers opportunities to optimally utilize EVSEs and provide flexibility to the electricity grid.

This field of study is widely studied and is called smart charging. Smart charging is used, amongst other objective, to manage the charging of EVs in order to optimize the use of the electric grid and reduce the impact of EVs on the grid. This is done by charging or discharging, assuming Vehicle to Grid (V2G) technology, EVs at various rates when they are connected to an EVSE. Smart charging applications can be focused on reducing pressure on the electricity grid or minimizing the charging costs related to electricity prices. In addition, smart charging could be applied to charge more sustainably by increasing charging power when there is a lot of renewable energy generation. In the absence of smart charging, EVs will typically begin charging as soon as they are connected to an EVSE, continuing until the battery's maximum State of Charge (SOC) is reached.This charging process does not take into account variables such as electricity costs or the overall demand on the grid, as discussed in greater detail in Section 3.1. However, with knowledge of the charging session's flexibility, smart charging techniques can be employed within the parameters of the EV user's needs. This may include reducing the charging power at the charging point, shifting the charging time, and potentially even utilizing V2G technology to invert electricity back into the grid. However, since most public EVSE currently do not support V2G technology, the focus in this research will be on smart charging whereby the charging rate of an EVSE is increased or decreased based on a smart charging objective.

To conclude, the electrification of the mobility sector within the Netherlands is a challenge to the electricity grid but smart charging provides opportunities to balance the grid and prevent congestion with the flexibility potential charging sessions can provide. In the next section the different types of EVSE infrastructure categories are explained.

2.2 EV infrastructure

The growth of EV adoption and the rapid deployment of EVSE is accompanied by evolving technologies. As a result, there is not always a clear consensus on a definition for a particular technology. This section will explain the different EVSE infrastructure to provide an overview of the definitions used in this thesis. This is relevant for the thesis since these definitions are used repeatedly. The definitions from the EU Sustainable Transport Forum will be used for the EVSE components [3]. In Figure 2.3 the different components are illustrated.

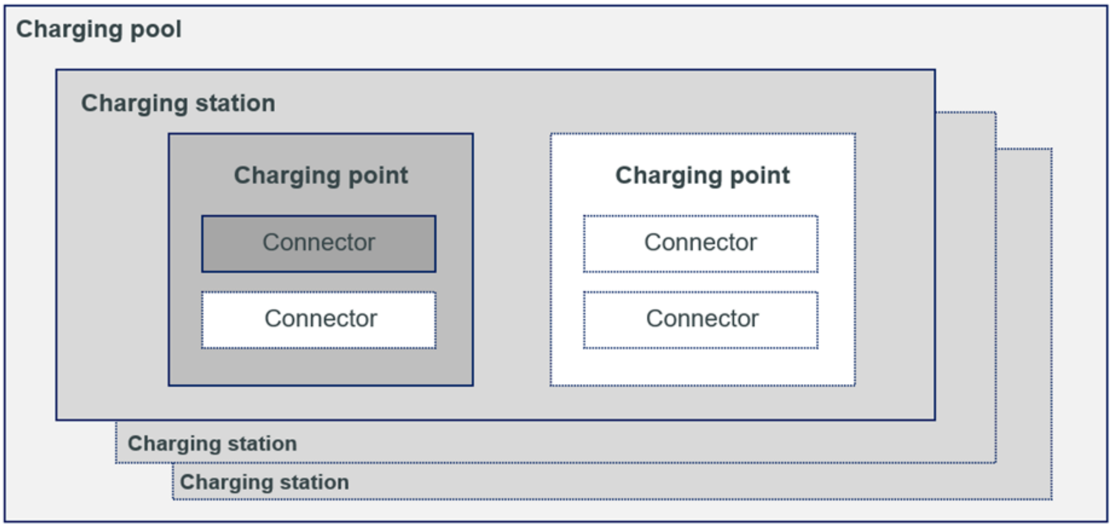

Figure 2.3: Visualization of charging infrastructure definitions. In this visualization, one Charging Pool, three Charging Stations, six Charging Points and twelve Connector or EVSE are present. Source: Image redrawn from [3]

The concept of an EV Charging Pool refers to a collection of Charging Stations that are managed and operated as a unified entity by a single CPO. A Charging Pool can consist of one or more Charging Stations but is defined by a specified location scope, such as a street, city, or country. It is imperative to note that Charging Stations situated at distinct locations can only be categorized under the same Charging Pool with a clear demarcation of the location scope. An Electric Vehicle Charging Station (EVCS) or Charging Station is a physical infrastructure offering one or more CPs. A CP is recognized as a tangible object where the standardized user interface for accessing the EVSE is situated. The EVSE comprises one or more Connectors that enable the transfer of electricity from the CP to the EV. Typically, only one Connector can be used at a time. However, to serve to different types of EVs, multiple Connector technologies may be available. The EVSE is the physical link between the CP and the EV, through which electricity is supplied. Several types of Connectors and connector technologies exist, such as cables, induction plates, or pantographs. Therefore, the charging process depends on the type of connector used by the EV and the related technology employed by the EVSE.

2.2.1 Categories of EVSE

Different kind of EVSE can be further categorized based on their maximum charge power, accessibility and charging profile. First the different EVSE charging powers will be discussed.

Maximum charge power: There are three main charging modes based on the power output provided by the EVSE. Category 1 is called 1-phase Alternative Current (AC) charging, category 2 is 3-phase AC charging and category 3 is Direct Current (DC) charging. Category 1 provides charging using a single-phase AC power supply, typically up to a maximum power output of 7.4 kW. Category 2 provides charging using a three-phase AC power supply, typically up to a maximum power output of 22 kW. This category is commonly used at public charging stations. Category 3 provides electricity to the EV by DC with a maximum power output of 350 kW or more. This charger category is commonly placed at places with low parking time, such as highway stops [32].

Accessibility The EVSE can be further classified into different accessibility categories, which include public, semi-public, or private access. Public EVSE's are 24/7 available for everybody and can be found at locations such as parking garages and on streets. Public charging stations typically fall into category 2 or DC fast charging stations, and may require a subscription or payment to use. Semi-public EVSE are accessible to everyone, but they may have restricted public access due to factors such as limited parking or operating hours of a shopping mall. Private EVSE's are installed at private residence or business, and are only available for use by the owner or employees [33].

Charging profiles: The density profiles presented in Figure 2.4 offer insights into the temporal charging behavior of EV drivers at various types of EVSEs, including home, work, public chargers. On the x-axis the connection time of the charging session is present and on the y-axis the percentage of all the charging sessions. The figure contains data from charging sessions that were conducted between 2018 and 2020.

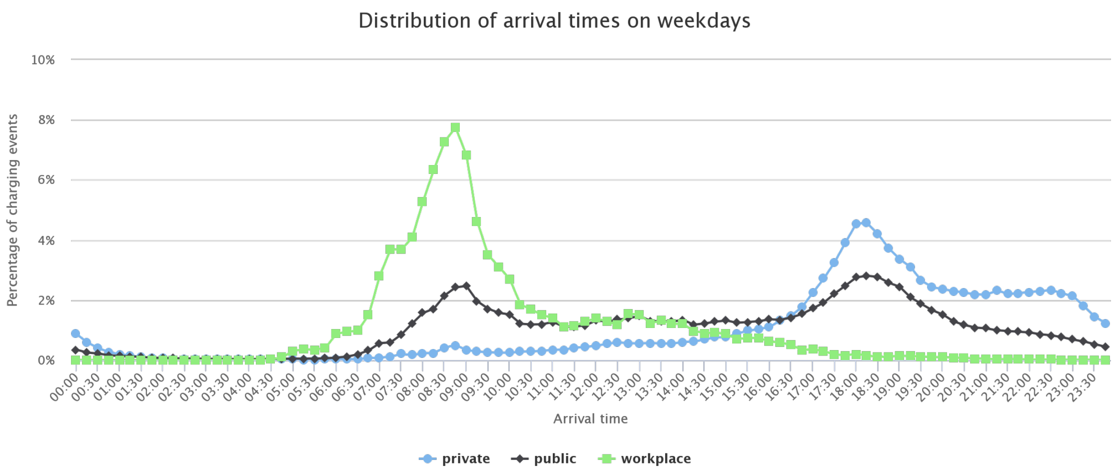

Figure 2.4: Connection start time per type of charge point on weekdays. Source: Open data platform from ElaadNL [4]

The connection time at CPs serves as a key indicator of EV charging behavior, which is inherently linked to EV drivers' daily mobility patterns. These density profiles, derived from connection times and onset of charging sessions on weekdays, provide crucial information for understanding the charging patterns of EV drivers in each of these charging environments. Figure 2.4 shows that most people tend to start using work chargers at around 8-9 am due to 9-5 work patterns. With home chargers a peak in connections can be observed around 6-7 pm. Public charging points have two peaks, one in the morning and one in the evening, depending on where they are located. In addition, a higher percentage of sessions occur during the day relative to work and private chargers.

In addition to start times, it is important to also take into account the peak power supplied by an EVSE. In Appendix A charging profiles for 100 EVs are illustrated, which are categorized by EVSE type and include their respective power output (measured in kW). The graphs illustrate that the profiles show similar peaks as in Figure 2.4.

This research explores a public accessible Charge Pool comprising over more then 5,000 CPs or 10,000 public EVSEs, all of which are AC chargers with a maximum power of 22 kW. The EVSEs are capable of providing single-phase AC or three-phase AC charging, depending on the type of EV that is connected. Typically, PHEVs utilize single-phase charging, while BEVs can charge three-phased, although certain older BEV models may also rely on single-phase charging. Even though only public CPs are considered in this study, different subgroups within the public CPs will be identified based on the charging profiles as shown in Figure 2.4. For example, it can be seen that charging sessions that are started at workplace CPs mainly start in the morning and at private CPs mainly in the evening. This information will be used when clustering the public CPs into subgroups.

2.3 Chapter summary

This chapter provided background information on the growth of EVs and EVSE in the Netherlands and the need for smart charging. Definitions have also been given about the various components of EVSE and the various categories into which EVSE can be categorized. It was identified that CPs can be categorized based on their maximum charge power, accessibility and charging profiles.

In the next chapter, a literature review will be performed to provide more insight into an individual EV charging session, how flexibility in a charging session can be defined, the quantification of this flexibility, the charging behavior of EV users and how previous literature tried to predict this charging behavior.

Chapter 3

Literature review

The previous chapter provided background information about the need for EV smart charging strategies and the different categories of EVSE. In this chapter, a literature review will be performed in which the aim is to find state-of-the-art literature on charging session flexibility. Another goal is highlighting the knowledge gap within individual charging session flexibility prediction using ML. First, insight into the different parameters of an individual charging session will be provided. Secondly, a literature search will be done regarding studies that define the flexibility of DER and EVs. Subsequently, literature will be reviewed about transforming this defined flexibility into a quantitative metric, which contributed to answer RQ1. This quantitative metric can be used to prioritize charging sessions within smart charging strategies. Thirdly, the current literature on EV charging behavior and the prediction of this behavior will be reviewed, which contributed to answer RQ2 and RQ3. Finally, the current literature on the EV domain's clustering will be discussed. This will contribute to finding a method to divide the different public CPs into subgroups based on their location or charging profile and answer RQ4. The literature databases Scopus and Google Scholar were used to find the literature using keywords that will be mentioned for each concept.

3.1 Individual electric vehicle charging session

An EV charging session can be described as the time period during which an EV is connected to a EVSE. However, there are many more parameters involved which are important to consider while researching the flexibility of an individual charging session. In this section the concept individual charging session will be discussed to gain knowledge about the different parameters what an EV charging session consists of. This will be done based on the simplified individual charging session example that can be found in Figure 3.1.

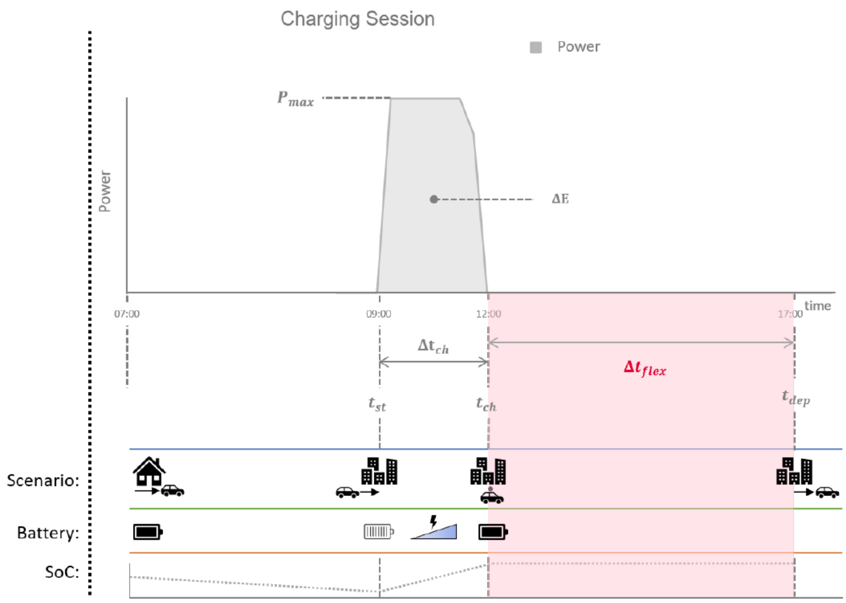

Figure 3.1: Example of a electrical vehicle charging session [5]

The individual charging session depicted in Figure 3.1 can be described as a uncontrolled charging session at an office location. With uncontrolled charging, the aim is to charge the EV as quickly as possible without taking into account external factors such as the electricity price or grid congestion. This means that no alternations are made to manage the charging power while the EV is connected to the EVSE. Therefore the EV will start charging at the maximum charging power it can provide when the EV is connected to the EVSE until the maximum SOC is reached [34].

Table 3.1: EV charging session parameters

Parameter	Definition
t_{st}	Start of charging session
t_{ch}	End of charging
t_{dep}	End of charging session
Δt_{ch}	Charging duration (hours)
Δt_s	Total session duration (hours)
Δt_{flex}	Total session time flexibility (hours)
P_{max}	Maximum amount of energy for EV (kW)
ΔE	Amount of electricity charged by EV (kWh)

In the charging scenario from Figure 3.1, the EV user leaves their home at 7:00 in the morning and drives to work, which lowers the SOC of the battery. At work, the EV user connects the EV to the EVSE at 9:00 which is indicated by t_{st}. The EVSE then starts delivering electricity to the EV with the maximum power that the EVSE can deliver to the specific EV until the battery is full. The maximum power that the EVSE can deliver is indicated by P_{max}.

When the battery is fully charged the EVSE will stop providing electricity to the EV which is indicated by the parameter t_{ch}. Subsequently, when the EV user leaves the workplace the EV is unplugged from the EVSE which is indicated by the parameter t_{dep}. The total electricity that was consumed by the EV during the charging session is denoted by the parameter ΔE.

The total time which the EV is connected to the EVSE is called the session duration or sojourn time. The session duration can be calculated by subtracting the start time of the charging session from the departure time. This can be found in Equation 3.1.

$$\Delta t_s = t_{dep} - t_{st} \tag{3.1}$$

The total time the EV is charging, under the assumption of uncontrolled charging, is defined in Equation 3.2 and is called the charging duration.

$$\Delta t_{ch} = t_{ch} - t_{st} \tag{3.2}$$

The time flexibility of a charging session is the time that the EV is connected to the EVSE without charging, also called idle time, and is defined in Equation 3.3.

$$\Delta t_{flex} = t_{dep} - t_{ch} \tag{3.3}$$

Here t_{flex} represent the time flexibility within a individual charging session. The parameters that are described in Table 3.1 are needed to create a load profile of a charging session and quantify the individual charging session flexibility potential.

EV users tend to plug in their vehicle to a public EVSE and simultaneously use it as a parking spot. This means that often the connection duration exceeds the charging duration which results in idle time. To provide insight into how much flexibility is in a charging session it is important to quantify this flexibility. In the next section the quantification flexibility will be discussed.

3.2 Electric vehicle charging session flexibility

As with the definition of flexibility on the power grid, there has yet to be a consensus on the definition of charging session flexibility. This section will provide an explanation of the definition used in this thesis and how this definition results in the quantification of charging session flexibility. This will answer part of RQ1:" How can charging session flexibility be quantified?". The following keywords were used to search for literature: 'EV charging session flexibility', 'EV flexibility', 'DER flexibility' and 'Charging session flexibility quantification'.

3.2.1 Defining electric vehicle charging session flexibility

The EV in combination with the EVSE can be defined as a category of DER, which can be used as a flexibility resource to the power grid. In previous research, various flexibility definitions from a DER perspective are provided.

Eid et al.[35] researched how DERs can be used as a flexibility service to the power grid. It was determined that the flexibility that a DER can provide is the power adjustment stained at a given moment for a given duration from a specific location.

Sadeghianpourhamami et al. [36] defined the flexibility of an EV as the extent to which a charging load can be coordinated. With this, the maximal load that could be deferred for a specific duration at any time of the day is intended.

Aunedi et al. [37] refer to the flexibility of a charging session as the terms of the amount of load shifted in time from the peak consumption while considering the minimum amount of energy required for the EV user to take a trip.

Gerritsma [38] provided a method for analyzing the time-dependent flexibility of EV demand. Here, flexibility is defined as the difference between the connection time and charging duration. This is in line with the definition from Kera et al. [39], which state that the flexibility of an EV is the fraction of the connection time that is not spent on charging. The load flexibility is a ratio calculated by dividing the idle time (t_{flex}) by the total connection duration (t_s). In this study, a differentiation is made between two different control mechanisms to realize smart charging, namely direct and indirect control. Direct control is when the aggregator manages the charging sessions without the EV user being involved in the control loop, which results in critical information such as departure time and energy requirements being unknown. This control mechanism is often used to aggregate the load and increase the quantity of the flexibility potential. With indirect control, the EV user manages the charging session by a decentralized strategy that is chosen by the EV user. With indirect control, the EV user manages the control mechanism with their own strategy.

Schlund et al. [40] proposed a methodology for modeling flexibility for DER, such as EV charging. In the paper of Schlund et al., the separation between energy flexibility and time flexibility is made. Here energy flexibility is defined as the difference between the maximum and minimum energy to be charged. The comment was made that the flexibility related to EVs is complex due to the charging behavior of EVs. This is the same flexibility definition that De Witte [22] uses. In this work the time flexibility is defined as the difference between the latest start time and the earliest start time to provide the EV with the required energy when the charging point can deliver at P_{max}.

Roossien [41] stated that a DER has flexibility if it is capable of shifting its production or consumption of energy in time within the boundaries of end-user comfort requirements and therefore not changing its total energy consumption or production. With production vehicle-2-grid technology is assumed with EV charging. The definition can be found in Definition 2.

Definition 2 *A device has flexibility if it is capable of shifting its production or consumption of energy in time within the boundaries of end-user comfort requirements and without changing its total energy production or consumption [41].*

From the discussed papers, several parameters can be derived that define EV charging flexibility. The power, the duration of power delivery and the amount of energy delivered. This thesis will adopt these parameters and the DER flexibility definition that is mentioned in the study from Roossien [41], which can be found in Definition 2.

Section summary:

- The individual charging session flexibility can be perceived in the three dimensions energy, time and power.
- Both the time flexibility and the amount of power adjustment for a given duration are essential for the flexibility of individual charging sessions.
- Two different kinds of control mechanisms for smart charging utilization where identified. In this thesis the focus is on the direct control approach where the EV user is not in the control loop.
- Definition 2 will be used in this thesis which considers the end-user boundaries of EV users.
- When the session duration t_s of a charging session is longer than the charging duration t_{ch} it can be assumed that there is time flexibility in the charging session. However, for an aggregator that wants to use this flexibility, it is important to quantify this flexibility. Therefore, in the next subsection, literature will be searched on how to quantify the individual charging session flexibility.

3.2.2 Quantification of charging session flexibility

From Definition 2, it can be derived that the shifting of the charging load needs to be within the end-user boundaries. With EV charging, this can be interpreted as follows, the EV user should not experience the undesirable consequence that the battery of the EV is not charged to their desired SOC. The amount of energy that is consumed (ΔE) by the EV should be equal with both the controlled and uncontrolled variant at the departure time. In [40], a distinction is made between the minimum E and the maximum E. The minimum E is defined as the minimum energy that is needed to satisfy the mobility demand. The maximum E is defined as the maximum energy that the EV can consume until the maximum SOC is reached. In this thesis, with the direct control mechanism, which allows no contact with the EV user, the maximum E will be used as the desired charged energy.

The definition from Roossien [41] for the quantification of charging session flexibility is adopted.

Definition 3 *The amount of power increase or decrease with respect to its current power consumption, that can be sustained for a given period.[41].*

Based on the the definition above and in [5], the flexibility of a charging session can be quantified by multiplying the total amount of energy charged by the additional available time. The method to calculate the flexibility can be found in Equation 3.4. Following this equation the flexibility within a charging session is the energy consumption within a session multiplied by the session's time flexibility. By using this equation only high values of flexibility are assigned to charging sessions that have high values of energy and the the required time window to shift that specific energy. As the quantification of charging session flexibility in this thesis is the product of time and energy, the unit of flexibility is kWh^2. It must be noted that this unit for flexibility is not an official unit but serves as an interpretive unit for flexibility [5].

$$\Delta f = \Delta E \cdot t_{flex} \tag{3.4}$$

Here, Δf is the flexibility within a charging session, ΔE is the consumed energy and t_{flex} is the time flexibility. To determine how much time flexibility there is within a session first the charging time needs to be derived. In current literature a common way to derive the charging time within a charging session is by using the P_{max} and the energy consumption ΔE [36, 22, 40]. This approach assumes that the P_{max} is constantly available during the charging. The equation for the approach can be found in Equation 3.5.

$$\Delta t_{ch} = \frac{\Delta E}{P_{max}} \tag{3.5}$$

Subsequently, with the addition of the total session duration (t_s), the idle time (t_{flex}) can be derived by substracting the charging time from the session duration. This can be found in Equation 3.6.

$$\Delta t_{flex} = t_s - t_{ch} \tag{3.6}$$

Section summary:

- The definition and quantification methodologies vary within literature. The equation that will be used within this study to quantify flexibility is presented in Equation 3.4.
- To quantify the charging session flexibility, knowledge or an prediction of departure times or session duration and energy consumption is needed.
- To derive the charging time from the energy consumption the maximum charging power (P_{max}) within the charging session is needed to use Equation 3.5.
- The flexibility of a charging sessions is besides the P_{max} highly dependent on the charging behavior of the EV user [40]. Namely the session duration and the energy consumption. In the next section the concept charging behavior will be discussed.

3.3 Charging behavior

The previous section concluded that knowledge about EV charging behavior is crucial for deriving flexibility within a charging session. Therefore the next concept that is explored is EV charging behavior. The goal is to understand what exactly charging behavior entails and what variables it consists of. This will provide insights into which independent variables are important indicators for predicting charging behavior and therefore help with answering RQ2. In addition, literature will be searched about the impact of the COVID-19 pandemic on charging behavior. The following keywords were used: 'EV charging behavior', and 'EV charging behavior COVID-19'.

The EV charging behavior can be described simply as the behavior of an EV user towards the charging of his EV. In the context of this thesis, it can be described by means of the following components: the arrival time, departure time, the time during which the EV is charging at the charging station and the total amount of energy supplied. This involves looking at the connection time and the disconnection time [20]. Due to the maturation of the EVSE infrastructure and EV usage as described in Section 2.1, recent studies increasingly use real-life charging sessions for exploring and analyzing charging behavior. In the study of Quiros-Tortos et al [42] a statistical analysis of charging behavior from the EV perspective in the UK was conducted which looked at the number of connections per day, start charging time and the initial and final SOC. The analysis showed that 70% of EVs start a charging session at least once every day and that it does not matter whether it is a weekday or weekend. It did appear, however, that the start time in the weekend is typically later than during the week, which can be attributed to the work schedules of EV users. In another paper it was researched how EV users behave at different EVSE types [43]. It was found that EVs spend a lower amount of time at fast chargers compared to slow chargers. This is no surprise since fast chargers are often placed in locations where people are in need for charging and want to continue their commute quickly, such as a location next to a highway.

Research has also been conducted into which factors have the most influence on charging behavior. A study based on empirical data collected from charging stations in the Netherlands investigated the variables that influence the session duration. Results indicate that the time of day and type of charging station are the most significant factors affecting the duration of charging connections. [44]. Another study supported these findings and found that the location as well as the start time have the greatest influence on the connection duration [45]. In addition, the same study shows that 23% of the time the EV is connected to a charging station it is used for charging, the other 77% is used for parking, also referred to as idle time. This high percentage of idle time can have a negative impact on charger availability, preventing other EV users from using the public CP. However, this also creates opportunities to shift the charging session to a later point and start with the idle time and end with the charging of the EV.

3.3.1 Impact of COVID-19 on charging behavior

The data analysis studies that were mentioned previously were conducted before the COVID-19 pandemic. During the pandemic, there was a significant change in people's travel patterns due to lockdowns. Similarly, after the lockdowns, there have been changes in people's commuting, both private and work-related, and therefore also in the charging behavior of EV users. Several articles have been published which researched both the changes in charging behavior during a lockdown and the long-term impact [46, 47, 48, 49]. Although there is a change in charging behavior due to COVID-19, the growth in charging stations and EVs in the Netherlands does not seem to be decreasing. The growth of EVs in the Netherlands from Chapter 2 shows that the purchase of EVs has not decreased due to COVID-19. The choice has been made to discuss the paper that uses data from the Netherlands and provides a long-term analysis, however it was found that other literature studies have similar conclusions.

The research by Van der Koogh et al. [49] with a data set from the Netherlands shows that COVID-19 has had a significant impact on charging behavior. During the lockdowns, where people stayed at home more often, this led to a significantly longer connection duration but at the same time a reduction of more than 50% in the energy that was charged. In the same research, an analysis was performed on data from early 2022, when almost all the COVID-19 restrictions were lifted. This shows that a nine-to-five pattern has disappeared from many employers. This has led to longer connection times at chargers, which is beneficial for the flexibility of charging sessions since this increases the time flexibility. At the same time, the decreasing energy consumption within individual sessions reduces the quantity of the flexibility potential.

Section summary:

- The two charging behavior dependent variables that are essential for determining the charging session flexibility are the session duration/departure time and the energy consumption.
- The start time of the charging session, the location and the type of charging station are important for determining session duration.
- Data analysis shows that charging sessions that are conducted in the weekend typically tend to be start at a later time which can be attributed to the absence of work commute.
- The long-term effects of COVID-19 are that the session duration is typically longer and the energy consumption is lower which can both be attributed to less distance travelled.

3.4 Charging behavior prediction

In the previous section, it was established that knowing the charging behavior of EV users is necessary to determine charging flexibility. This section will research existing literature regarding EV charging behavior prediction, specifically the prediction with ML. This will lay the foundation to answer the research questions: RQ1, RQ2 and RQ3. The literature search showed that ML methods are already applied for predicting the two variables that define the charging behavior of EV users, session duration and energy consumption. The articles were chosen if a ML method was used to predict the charging behavior or one of the two variables. The following keywords were used in the search: 'EV energy consumption prediction', EV connection duration prediction,' 'EV idle time prediction,' 'EV session duration prediction' and 'EV charging demand prediction.'

Research by Shahriar et al. [20] predicts the session duration and energy consumption of individual charging sessions. The ML algorithms used are Random Forest (RF), Support Vector Machine (SVM), XGBoost and Deep Neural Networks. The paper uses the ACN data set for historical charging data, which is publicly available. The ACN data set is commonly used when data from a CP is required. This data set consists of two CPs located at Caltech in California. These chargers also allow the user to provide additional information through a mobile app. By scanning a QR code, the EV user can predict their energy consumption and departure time. The prediction results by the EV user show that the prediction of the user and the actual session duration and energy consumption are far apart. Shahriar et al. [20] indicate that this may be related to the lack of interest of the EV user. This emphasizes the importance of a ML algorithm if the user finds the estimation challenging to do or is not motivated enough to do it accurately. In addition to historical charging session data, weather, traffic and events data are added as features to increase the model's accuracy. Ultimately, the ensemble model proved to be the most accurate for both the prediction of session duration and energy consumption. The used model resulted in an MAE of 3.38 kWh for energy consumption and an MAE of 66.5 minutes for the session duration prediction.

Research by Mouaad et al. [50] focused on predicting the charging time of EVs at two public charging stations in Morocco with a maximum charging power of 11 kW and 22 kW. The data used are historical charging data of the CP, where the user ID is also known. For the prediction of charging session duration, the different Deep Learning models, Recurrent neural network (RNN), Long short-term memory (LSTM) and Gated recurrent units (GRU) were used. GRU provided the most accurate predictions with an normalized MAE of 0.686%. However, the prediction was made on the aggregated session duration focused on one CP instead on the individual level.

Pezim [51] researched the prediction of energy requirements and departure time with tree-based classification algorithms. Within the research, two different approaches were taken. One approach trains one model for each CP and the other trains a separate model for each anonymized user ID card. It turned out that, on average, the approach based on the CP resulted in more accurate results. For the session duration prediction, the most important features were: time of day, day and the rolling mean. For the energy consumption prediction, the most important features were: cumulative, time of day and rolling mean. Cumulative is the kWh delivered to the vehicle until the current time step. The rolling mean is the mean of the session duration or energy consumption for the specific EV user or CP of the historical charging sessions. The rolling mean is updated after every charging session.

Frendo et al. [52] tested the different ML models XGBoost, Linear Regression and Neural Networks where historical charging session data sets from a heterogeneous EV fleet were used to train the models. The parameters that were used included the type of car and the SOC. The XGBoost ML model came out to be the most accurate in predicting the charging profile of EV users.

Research by Almaghrebi et al. [53] predicts the charging demand (energy consumption) of EV users after the charging session starts using the supervised ML models XGBoost, RF and SVM. The historical charging data set of Nebraska was used with chargers that could provide a maximum charging power of 9.6 kW. In the study the unique user ID was available within the data set. However, the decision was made to not include the variable to create a model that is more easily generalized to large populations. The XGBoost model outperforms the other models with an MAE of 4.57 kWh, but the accuracy is still moderate, accounting for roughly 50% of the variance in EV user behavior.

De Witte [22] is the only research that was found in literature that looked at the charging behavior prediction in combination with quantifying it to the charging session flexibility. Besides the commonly used historical charging session data also weather data was used. The work concluded that the weather features turned out to be not relevant for the prediction of charging behavior, which is in contrast with the research from [20]. The three ML algorithms, XGBoost, an Artificial Neural Network and K-Nearest Neighbors, were used for the prediction. XGBoost performed the best on both the session duration and the energy consumption prediction. The MAE for session duration prediction was found to be 3.23 hours and the MAE for the energy consumption prediction 5.6 kWh. However, this study only derived features from the EV user perspective and neglected the difference between CPs. The most important feature for predicting session duration was the mean session duration from all the previous sessions based on the user ID. The mean energy consumption of the user was the most important for predicting energy consumption. With the mean of the session duration or energy consumption the same is meant as the rolling mean in the research from Pezim [51].

Research by Chung et al. [54] uses several ML models, SVM, RF, Diffusion-based kernel density estimator (DKDE) and an Ensemble Prediction Algorithm (EPA) to predict both the session duration and energy consumption. The study used two historical charging session data sets, one being on the UCLA campus and the second data set includes residential charging data in the UK. The EPA model turned out to predict with the highest accuracy with an Median Absolute Deviation (MAD) for session duration of 1.16 hours and 2.52 kWh for energy consumption. The MAD is similar to MAE however is calculated as the median instead of the absolute differences between predicted and actual values. The data entropy and sparsity ratio were used within this paper to increase the accuracy of the EPA model. In addition to the prediction of charging behavior, the predictions are also used directly for smart charging strategies.

Research by Lucas et al. [55] predicts the idle time of an EV charging session. This is the time the EV is connected to a charging point without charging also called the time flexibility in this thesis. The supervised ML models Gradient Boosting, RF and XGBoost were used. The XGBoost model was the best performing model with an MAE of 1.11 hours. The historical charging session data set came from the Dutch knowledge center ElaadNL and consisted of 1747 public CPs located in the Netherlands that can provide electricity with a maximum charging power of 22kW. The parameters that influence the prediction of idle time the most are the time of day when the charging session starts, and the total energy supplied to the EV. However, the total energy supplied to the EV is not available to the CPO at the start of the session. In addition to predicting the idle time, the paper also discusses several policy interpretations to use these predicted outcomes.

Research by Ullah et al. [6] predicts the EV charging duration using an ensemble ML algorithm. The data that is used comes from 500 EVs in Japan and is from the perspective of the EV user. In the paper the authors use data that is not available from a direct control mechanism, such as SOC, a/c compressor and heater usage. The feature importance also shows that the start time and end SOC are the most important parameters for the prediction of charging duration. The XGBoost model achieved the highest accuracy with a MAE of 1.29 hours.

Research by Singh et al. [56] clusters and predicts the energy consumption and idle time ratio using RF and LSBoost. The historical charging session data set that was used originates from charging session in the Netherlands and was provided by ELaadNL. As in the paper by Lucas et al. [55], the idle time is predicted, only the article by Singh et al. (2022) refers to idle time ratio. The idle time ratio is defined as the ratio between idle and sojourn time. By providing this ratio, the load shifting potential is meant. Ultimately, LSBoost gives the most accurate prediction for idle time ratio and energy consumption of MAE 0.023 and 1.27 kWh. With these predicted charging behavior attributes, a heuristic charging scheduling approach was proposed.

Research by Almaghrebi et al. [57] aims to predict the idle time of EV users using several supervised ML methods. For the prediction of the idle time features such as the total energy consumption and the charging duration of that charging session are used. The authors concluded that it is hard to predict the idle time based on the low accuracy that was observed. The XGBoost model outperformed the other models with a MAE of 0.58 hours where the mean idle time of dataset was 0.95 hours. However, the same as [55] for the prediction of the idle time connection duration and energy consumption are used as independent variables. This information is not available to the CPO at the start of the session. The feature importance also show that these two features are significantly the most important, besides the start time of the charging session.

Research by Straka et al. (2022) [58] focuses on the prediction of session duration and specifically on the influence of asynchronously updating the predictions. The EVnetNL historical charging session data set from ElaadNL was used which contain 1731 public and semi-public CPs. The LightGBM method was used for the prediction of session duration. The features that were updated include the current hour of the day, weekday, month, total charged energy since the start of the session, charged energy in the last time period and connection duration since the beginning of the session. It was concluded that regular updates significantly improved the accuracy of the predictions.

The relevant papers with the used ML model and data source can be found in Table 3.2.

Section summary:

- Most articles conclude that the ML algorithm XGBoost can make the most accurate predictions for charging behavior variables.
- The rolling mean of the session duration or the energy consumption is an important feature for predicting these target variables.
- The start time at which a charging session is started was found to be an important feature to include.
- Idle time prediction papers use variables not available at the start of the charging session, such as session duration and energy consumption.
- The MAE for session duration ranges between 1.2 and 3.23 hours and the MAE for energy consumption ranges between 1.27 and 5.6 kWh.

Author (year)	**Dependent variable(s)**	**Independent variables data source**	**Machine learning model**
Shahriar et al. (2021)	Session duration and energy consumption	Historical charging data, weather, traffic, events	Random forest, SVM, XGBoost and Deep Neural Networks
Mouaad et al. (2022)	Charging duration	Historical charging data	Deep learning models: Recurrent Neural Network, Long Short-term Memory, Gated Recurrent Units
Pezim (2018)	Session duration and energy consumption	Historical charging data	Random Forest, Gradient Boosting, Decision Tree, Logistic Regression, Linear Support Vector Classifier
Almaghrebi et al. (2020)	Energy consumption	Historical charging data	XGBoost, Random Forest and Support Vector Machine
De Witte (2021)	Session duration, energy consumption and charging flexibility	Historical charging data, weather data	XGBoost, an Artificial Neural Network and K-Nearest Neighbors
Chung et al. (2019)	Session duration and energy consumption	Historical charging data and entropy/sparsity ratio	Support Vector Regression, Random Forest, Diffusion-based kernel density estimator and Ensemble Prediction Algorithm
Lucas et al. (2019)	Idle time	Historical charging data and Road Segment	Random Forest, Gradient Boosting, XGBoost
Ullah et al. (2022)	Session duration	EV information	Ensemble: Random Forest, XGBoost, categorical boosting and light gradient boosting machine
Singh et al. (2022)	Session duration and energy consumption	Historical charging data	Random Forest and LSBoost
Almaghrebi et al. (2021)	Idle time	Historical charging data	XGBoost, Random Forest and SVM
Straka et al. (2022)	Session duration	Historical charging data with asynchronously updating	LightGBM
Frendo et al. (2020)	Session duration	Historical charging data and EV data	XGBoost

Table 3.2: Overview of charging behavior ML prediction models identified in the literature review

3.5 Gaps in the current literature

The literature on predicting charging session behavior with an ML algorithm has several research gaps. The previous research has neglected the CP specific charging behavior during the prediction of charging session behavior, focusing solely on historical charging sessions of EV users without differentiating between different characteristics of public CPs. It has been determined that public CPs are used differently throughout the day, and differentiating which CP an EV user connects to could improve prediction accuracy. First, research has yet to be conducted on the influence of the urbanization degree of the neighborhood where the CP is located. Urban areas typically have more public CPs available than rural areas, and different lifestyles, demographics, traffic patterns, and commuting behaviors can influence the session duration and energy consumption of charging sessions.

Secondly, no clustering of CPs has been done for the prediction of charging behavior. Section 2.2.1 clarified that CPs could be categorized based on their accessibility as private, work or public chargers. Each of these CPs has its distribution of arrival times. However, the location of a public CP could impact the charging sessions that are started at the CP and, therefore, these arrival times. For example, historical data determined that public CPs near large office buildings are mostly used during working hours and less during the weekends. However, a residential area is also close to the public CP, which means that after working hours, it will be used as a home charger for residents. This is just one example of how a public CP could be used. Clustering within the EV domain has been done in previous literature for charging sessions, EV users and CPs. However, no clustering of public CPs is used in literature for the predicting charging session duration, energy consumption or flexibility. Therefore, this thesis aims to fill these gaps by segmenting a large historical charging data set based on CP clustering and developing separate ML models tailored to the specific characteristics of each CP cluster to predict charging behavior. By analyzing and training each cluster individually, the specific patterns and characteristics of each cluster can be identified, allowing for more accurate predictions of charging behavior.

3.6 Conceptual model

The conceptual model for this research can be found in 3.2 and includes three types of input variables: CP based independent variables, EV user based independent variables and contextual variables. One of the identified research gaps is addressed by incorporating the urbanization degree and variables based on historical sessions of the CP as CP based independent variables.

The other research gap will be addressed by clustering the CPs into distinct groups based on the the historical charging sessions of each CP. For each cluster, a separate ML model will be trained and analyzed to predict charging behavior. This approach will allow for a more tailored analysis of the data, as each cluster will have its own specific characteristics and usage patterns. This also ensures that the different feature importance can be analyzed for each cluster of CPs.

In the next section of the thesis, various clustering approaches within the EV domain will be explored to determine the most appropriate method for clustering the CPs in this study. By using an effective clustering approach, the resulting ML models will be more accurate in predicting charging behavior for each cluster, and ultimately provide valuable insights for improving the charging infrastructure in urban areas.

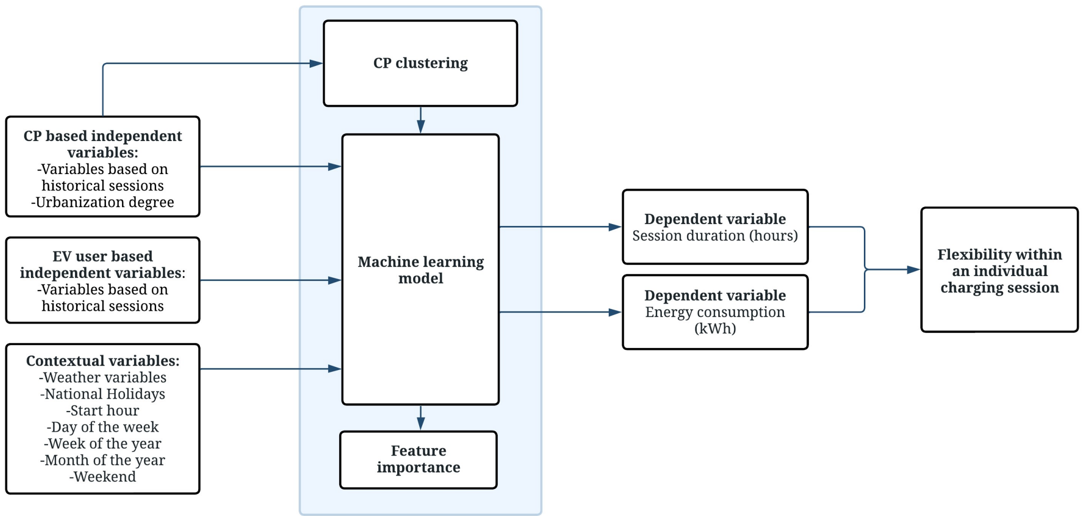

Figure 3.2: Conceptual model for the research

3.7 Clustering within the EV domain

The preceding section provided a literature review on ML models for forecasting charging behavior and session flexibility and highlighted the research gaps that will be researched in this thesis. In this section, a literature review focused on clustering methods that are used within EV domain will be conducted. First, an introduction to clustering will be provided and subsequently the current literature on clustering in the EV domain will be discussed. The current literature concerning charging behavior clustering will be divided into clustering of charging sessions, EV users and charging stations. The following keywords were used to search the literature: 'EV charging behavior clustering', 'EV charging stations clustering' and 'EV user clustering.'

Clustering is the unsupervised classification of a set of patterns or objects into groups which are called clusters where the characteristics are similar to each other but dissimilar to patterns or objects in other clusters [59]. The output of clustering could provide hidden patterns or insights from data. In smart charging applications clustering has been widely used to identify hidden patterns such as electric load patterns for forecasting purposes [60]. From the perspective of this thesis it would be useful to cluster CPs based on historical charging sessions on a specific CP. This way a CP will be placed into a group with other CPs that have a similar charging profile.

3.7.1 Charging sessions clustering

In this subsection the clustering of historical charging sessions will be discussed. Al-Ogaili et al. [61] provides a literature review of clustering strategies for controlling EV charging. In this review several types of clustering were identified namely spatial, temporal or spatial-temporal. Spatial clustering looks at the data that is associated with the location and temporal clustering is associated with clustering based on time dependent data points.

Tang and Wang (2016) [62] clustered different charging patterns into three clusters namely: Home, Work and Other. The clustered were formed based on random trip chain and Markov decision process. However, with this clustering information was used that is not available to a CPO such as the trip distance or the initial SOC and departure SOC.

Singh et al [56] clustered the charging sessions based on the connection time and the connection duration, which can be defined as temporal clustering. The clustering algorithm Gaussian Mixture Models was used for the clustering. Four different clustered were obtained: Morning Hour With Medium Duration (also called Work and Charge), Daytime With Short Duration (also called Stop and Charge), Afternoon/Evening With Medium Duration (also called Park and Charge) and Afternoon/Evening With Long Duration (also called Home and Charge).

Sadeghianpourhamami et al. [36] clustered the arrival time and departure time of charging sessions to identify characterization of EV charging behavior.

Märtz et al (2022) [63] used the Gaussian Mixture Model as well as K-means for the temporal clustering of charging processes. Here, it was also researched if the same users are in different charging clusters based on their user ID. They concluded that the users switched a lot from one charging session cluster to another. However, it was also seen that the charging load patterns at the charging locations such as home, workplace, public or fast chargers showed similar results. These are similar charging patterns that were developed by ElaadNL and can be found in Appendix A.

3.7.2 User profile clustering

Clustering has also been done for EV users based on their historical charging sessions.

Cañigueral and Meléndez [64] used Gaussian Mixture Models for the clustering of EV user profiles. Eventually seven different user clusters were formed for the scheduling of charging sessions. For the clustering the start time and the duration of the connection for every charging session was used.

Develder et al. [65] used the two variables start time and end time with the density based clustering method DBSCAN. Based on this clustering method they identified Office chargers, home chargers, and visitors.

Helmus et al. [66] clustered three types of office hours users, three types of overnight users and three types of non-typical users. Gaussian Mixture Model with four variables was used, namely session start time, connection duration, hours between sessions and distance between sessions. However, the variables hours between sessions and distance are not available in the direct control approach. The hours between sessions could not be determined with certainty since a CPO does not have a complete overview of all the charging sessions that are conducted by one EV user or a different charge card is used.

3.7.3 Charging point clustering

Previous research also focused on the clustering of CPs based on different characteristics.

ElaadNL has determined three categories of CPs namely 'Home charger', 'Work charger' and 'Public charger'. For every category a standard loading curve for a CP was provided in Figure 2.4. However, this categorization was done based on clustering from historical sessions but mainly on predefined accessibility of the CP.

Straka and Buzna [67] clustered public CPs based on the popularity of CP, utilization of CP and on the temporal usage pattern. For the temporal usage pattern, the mean start time and the mean end time of the charging sessions at the station were considered. The clustering techniques K-means, agglomerative hierarchical and DBSCAN were compared. This resulted into four clusters of charging stations. Both approaches lead to the same interpretive clusters.

Straka et al. [7] used a matrix approach for the clustering of public CPs. A matrix was made with the arrival time of the EV at the CP and the session duration at the CP. In the paper, all the CPs that were closer than 30 meters were merged, assuming that the charging patterns of these CPs were similar. Two different approaches were used for the clustering: Rule-Based approach and hierarchical clustering. With the Rule-Based approach, the clustering was done on pre-identified clusters and time intervals with a threshold value. With the hierarchical clustering, the dissimilarity between CP matrices was used. Hierarchical clustering first places all the patterns in their cluster and gradually merges similar patterns.

Section Summary:

- Historical charging sessions were clustered based on their start time and session duration to be Short Stay sessions, Park and charge sessions, Work sessions or Home sessions.
- K-means clustering, Hierarchical clustering and DBSCAN clustering are widely used clustering methods in the EV domain.
- Charging session clustering is done based on historical charging session. The same EV user or CP can have a variety of different historical charging session clusters. Therefore this kind is not useful for prediction purposes.
- Charging profiles at specific CPs show similar patterns [63]. For our research this similarity indicates the potential usefulness of clustering public CPs into subgroups that indicate their main usage.
- The Rule-Based matrix approach in the article from Straka et al.[7] has the potential to cluster the temporal behavior of CPs in a explainable manner.

Chapter 4

Methodology

In the previous chapter, a literature review was conducted on charging sessions flexibility and how to quantify this flexibility. In addition, predictive models based on ML were identified used in current literature. Used data sets and features were identified that could be used to predict session duration, energy consumption and subsequently flexibility.

In this chapter, the methodology will be discussed, which is used to answer the research questions. This thesis will research how accurately the charging flexibility of individual charging sessions can be predicted from a direct control mechanism perspective. In addition, the objective is to provide a better understanding of the factors influencing EV charging behavior. This will be done by executing different experiments to predict the individual charging session flexibility. For this, the session duration and the energy consumption must first be predicted. Subsequently, in this section it will be described how, based on these predictions, the additional available charging time and the overall flexibility will be determined.

A ML model will be used to predict the session duration and energy consumption of a individual charging session. First, the philosophy of the ML models is presented and the choices that have been made are explained. In addition, a framework will be developed that illustrates the prediction process which can be used by aggregators. Subsequently, the model selection and the experimental setup and evaluation approaches will be explained. Thirdly, the data collection and the data preprocessing steps are discussed. Finally, the clustering method for the segmentation of data based on CPs criteria will be elaborated on.

4.1 Machine learning model philosophy

In this research, a ML approach is used to provide answers to the research questions and gain insight into individual charging session flexibility. Through an extensive review of background information and literature, a comprehensive understanding of the problem was attained. This section presents a detailed explanation of the selected ML approach.

Based on the literature review, a supervised ML approach was determined to be the appropriate method for predicting two target variables crucial to the prediction of charging session flexibility: session duration and energy consumption. As only one target variable can be predicted by a single model, two separate supervised ML models will be employed. Additionally, the use of supervised ML allows for the evaluation of the importance of all independent variables to be used in the models. This ML algorithm is labeled as "supervised" because it is trained using labeled examples that include both independent input variables and the corresponding dependent output variable, often referred to as the target variable. The supervised model is able to learn the relationship between the independent variables and the target variable through the labeled examples, which can then be applied to make predictions on new data [68].

In order to use the the energy consumption and session duration predictions, a supervised regression model was chosen over a classification model, as it enables quantification of charging session flexibility. A regression model predicts continuous numeric variables based on the independent variables [68]. Although some articles in Section3.4 use a classification model, it is preferred that the output for the energy consumption and session duration are continuous values. This allows the quantification of individual charging session flexibility.

In addition, the available data that can be used to train the ML model was identified. Only the data that is accessible at the start of the charging session for a centralized direct control mechanism approach will be utilized. This enables the CPO to determine their smart charging strategies with the predicted flexibility potential at the beginning of the charging session. Additionally, as explained in Section 1.3, there is currently no communication between the EV user and the CPO. If communication is established in the future, this approach allows the model to provide recommendations to the EV user regarding energy consumption and departure time. The different data sets will be explained in detail in Section 4.2.

Finally, in the next subsection, different units of generalization will be discussed that could be used for the ML model. The unit on generalization refers to the way in which data is collected, organized, and used to train and evaluate the ML models.

4.1.1 Unit of generalization

As mentioned before, an essential part of a successful ML model application is the data that is put into the model. Besides appropriate preprocessing steps, another condition is the availability of valuable data to train the algorithm. It would not be beneficial for the algorithm to identify a pattern that is not relevant for certain CPs or EV users. Therefore another part of designing an ML predictive framework is the chosen unit of generalization. The unit of generalization can be described as the level at which a sample or population is being analyzed [69]. For example, a EV user can have different charging behavior at specific CPs by default. In Figure 4.1, four different units of generalization approaches are developed and illustrated: Aggregated model, Charge point model, User model and Hyper personalized model. The different unit of generalization approaches have various advantages and disadvantages and will briefly be discussed.

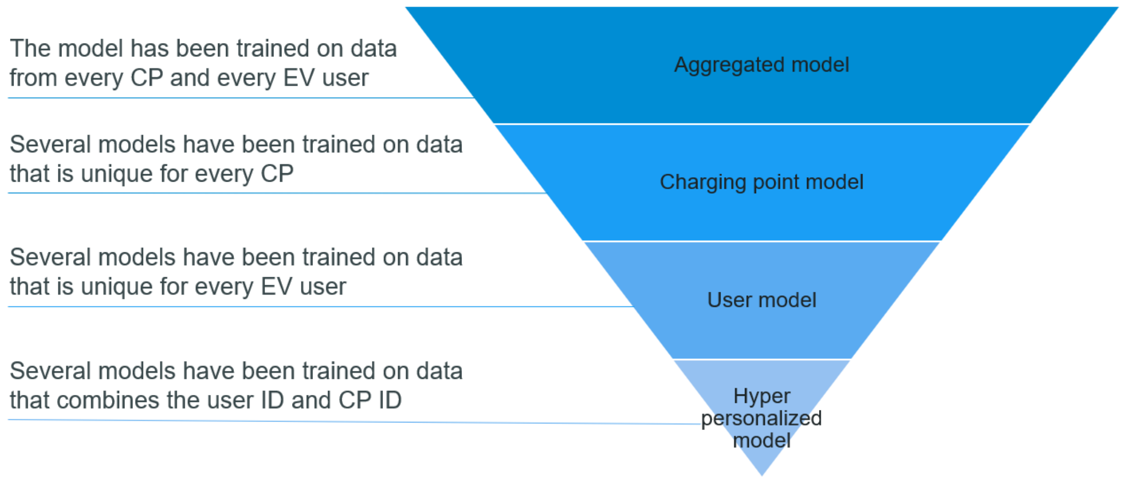

Figure 4.1: Different units of generalization

Aggregated model: Within this unit of generalization one model will be used where all the data for the unique charger CP ID's and user ID's are combined. All charging sessions are therefore used for training the model without making a distinction between charging station or user. The main advantage is the high generalization degree to different CPs and users. Another advantage is the large amount of data that is available for the ML model and the simplicity of training just one model. The disadvantage of this approach is that possible valuable patterns that individual users and charging stations have are not considered by the model, thus resulting in lower accuracy performance.

Charging point model: In this model the unit of generalization is from the CP. All charging sessions will be filtered for each CP. As a result, a unique model will be trained for each CP. From interviews with EV domain experts and data analysis it was identified that certain CP are used in a different way than other chargers. By training a separate model for each CP it has the advantage that the model is not trained on irrelevant data of other CP. A disadvantage could be that not enough data is available to train each model for each CP. There, no generalization can be made to different CPs. In addition, when training one model for each CP could be more computational intensive.

User model: In this model the unit of generalization approach is from the user ID. This has the same advantages and disadvantages as the charge point model related to data. However, since there are a significant amount more users than charging stations these disadvantages are more substantial. Both the charge station model and the user model could have the problem that not enough data is available to properly train the ML algorithm. One example could be a new user that has no or just a couple historical charging sessions. This problem is also known in literature as the 'cold start' problem. However, this problem will be rare in the future with the uptake of EVs. Another disadvantage could be the lack of generalization. When each user or charging station has their own trained model it would not make sense to use this model for another user of charge point with potentially different charging behavior patterns.

Hyper personalized model: This unit of generalization approach considers both the charge stations ID perspective and the anonymized user ID perspective. The data will be filtered for every user specific for each charging station. This approach has the disadvantage that it due to it's hyper specific nature, it is trained on a relatively small data set. Especially at public CPs this would be a problem with the low amount of sessions for each user and the large amount of CPs. It would be desirable to have the pattern of every user at every charging station. However, data research shows that this could only be applied to a small proportion of EV users and would not be applicable for new CPs or users.

In several studies, the CP unit of generalization has shown to be beneficial to the prediction of charging behavior [51, 20]. Another approach could be to cluster the charging stations based on similarities. Therefore, two different units of generalization were chosen for this research. The first unit of generalization is the Aggregated unit, where no distinction is made between the different CPs. This unit will serve as the base model for comparison with the second unit of generalization. The second unit of generalization is the CP Cluster unit. This is not a model per CP but the CPs are first aggregated in a cluster and that a model is developed for each cluster. Rather than training the ML on all the charging sessions, the CPs will be clustered based on their historical charging profile. In Section 4.6 the clustering technique that will be used within this research will be explained. A separate model will be trained, validated, and tested for each CP cluster.

4.2 Data

In this section, a overview of the collected data will be provided and the data collection process will be elaborated on. As described in the previous section, the data available at the start of the charging session from a direct control mechanism approach were identified. First, the data sets available to the CPO related to historical charging sessions are described. Subsequently, the other contextual data sources that could be useful for predicting charging session flexibility will be presented.

4.2.1 Historical charging sessions

The data set regarding the historical charging sessions from public EVSEs that are used for this research was obtained from CPO TotalEnergies. The data that relates to the EVSEs of the CPO is transferred from the energy service provider to the SQL database of TotalEnergies. This charging data set contains millions of parameters about historical charging sessions within the Netherlands. The time interval and important parameters of the data set are summarized in Table 4.1.

Table 4.1: Description of used dataset

Time interval	01/11/2021 - 01/11/2022
Amount of CPs	5,317
Amount of EVSEs	10,513
CDRs	2,481,403
Number of unique Auth ID’s	178,221
Total session duration (hours)	19,968,201
Total energy charged (kWh)	54,088,884

The locations of the CP’s belonging to TotalEnergies from the dataset are illustrated in Figure 4.2. As can be seen, the public AC CP’s are predominantly located in the north-west region of the Netherlands.

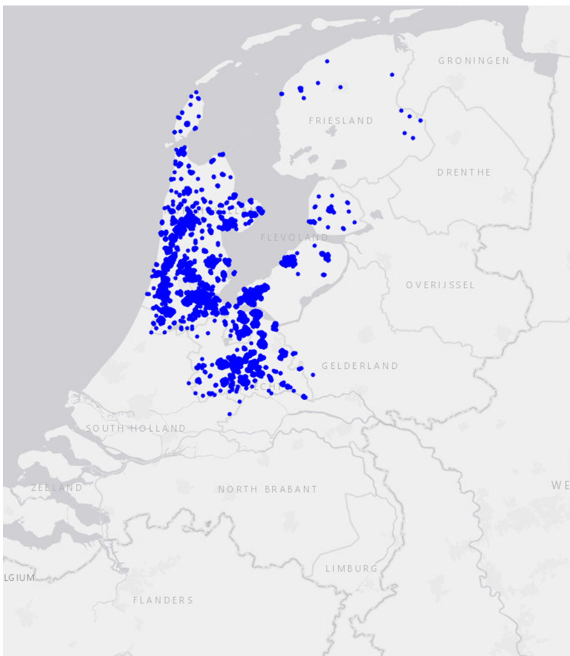

Figure 4.2: Geographical locations of all the charging stations within the used dataset.

The data will be sourced from the data platform of the TotalEnergies and will be accessed through Application Programming Interface (API) calls using file formats standardized by the Open Charge Point Interface (OCPI) protocol. The data is reasonably clean and anonymized to ensure user privacy. The data consists of different sub data sets and are summarized in Table 4.2

Table 4.2: Description of available data sets

Name data source	Description of the data set
Charge Detail Records (CDR)	Summarized charging session data. This data is formatted in a way that one row represents one separate charging session
SessionEvents	Contains in-session meter readings of kWh consumed since the last time step in a 15 minute time interval.
Locations	Information about the type and location, specific for each charging point.

Charge Detail Records (CDR) data set

The data present in the CDR data set is transactional, as it is generated at the end of each charging session by an EV user at an EVSE. The information about the charging session that can be found in the CDR data set is described in Table 4.3. The CDR data set contains a summary of every historical charging session at for every single EVSE and EV user. The data is used to bill the EV user but is also commonly used in analyzing and predicting EV charging behavior.

Table 4.3: Description CDR data

Name variable	Description of the variable
ID	Identification of the unique charging session
Start date time	Timestamp of the moment the charging session started
Stop date time	Timestamp of the moment the charging session ended
Auth ID	Indicates the unique and anonymized charge card ID
Location ID	Identification of the unique charging point
EVSE ID	Identification of the unique charging socket
Energy consumption	Energy consumption in kWh, target variable.
Session duration	Session length in hours, target variable

The CDR data set is important in the analysis and prediction of energy consumption and session duration in the research. This data set consists of a comprehensive record of all charging sessions conducted by each individual EVSE or EV user, allowing for granular analysis and prediction of charging behavior. Consequently, it serves as a primary source of information for the research objective of forecasting charging session flexibility.

SessionEvents dataset

The SessionEvents data set, described in Table 4.4, provides more granular information about the charging profile of each session. It contains a timeseries of data points for each charging session, with a fixed time interval of 15 minutes. The amount of kWh charged in the past time interval is stated in combination with the time that the EV is connected. In addition. a column is present that indicates the status of the charging session by means of started, active, parking or completed. Based on this information, the charging profile of an EV session can be derived. In this research, the SessionDetails database will be used to determine the maximum power (kW) that the EVSE can deliver or the maximum power (kW) that the EV user can receive. This information is important to have for determining the charging time from the energy consumption as can be seen in Equation 3.5.

Table 4.4: Description SessionEvents data

Name variable	**Description of the variable**
Session ID	Identification of the unique charging session
Status internal	Status of session in time period (Started, Active, Parking or Completed)
Charging kWh	Amount of kWh charged in time period
Charging time	Charging time within the time period
Idle time	Idle time within the time period
Event datetime	Date and time of the start time period
EVSE ID	Identification of the unique charging socket

Locations data set

The Locations data contains the geographical details of all the CPs. The data that will be used within this research is summarized in Table 4.5.

Table 4.5: Description Locations data

Name variable	**Description of the variable**
ID	Identification of the unique charging station
Name	Name of the charging station
Address	Address at which the charging station is located
City	City in which the charging station is located
Postal code	Postal code in which the charging station is located
Country	Country in which the charging station is located
Latitude	Latitude at which the charging station is located
Longitude	Longitude at which the charging station is located

Merging historical charging session data sets

The ID assigned to a charging session in the CDR data set and the SessionEvents data set are not consistent, rendering the direct linking of these data sets unfeasible. To address this issue, the present research proposes to establish a linkage between the two data sets based on the EVSE ID and the start time of the charging session. By employing this approach, the appropriate CDR session can be linked with the corresponding

SessionEvents session. In addition, the merged data set can be linked with the Locations data set by utilizing the Location ID in the CDR data set.

4.2.2 Contextual data

In addition to historical charging data, other data sources could potentially also provide information that can be used to predict charging behavior. Contextual data refers to information that helps to provide context to the charging session. Weather data, holidays data and neighborhood data will be used to provide more context to the individual charging session.

Weather data

The weather data that will be used within this research is collected from the Royal Netherlands Meteorological Institute (KNMI). The KNMI has several automatic weather stations within the Netherlands that record various weather attributes within a one hour time period [70]. Since most of the charging stations utilized within this research are located around the Schiphol area this weather station is chosen. A description of the weather data attributes that were selected can be found in Table 4.6.

Table 4.6: Description of available weather variables

Weather variable	**Description of the variable**
Wind speed	Mean wind speed (in 0.1 m/s) during the 10-minute period preceding the time of observation
Temperature	Temperature (in degrees Celsius) at 1.50 m at the time of observation
Sunshine	Sunshine duration (in 0.1 hour) during the hourly division
Radiation	Global radiation (in J/cm2) during the hourly division
Precipitation duration	Precipitation duration (in 0.1 hour) during the hourly division
Hourly precipitation	Hourly precipitation amount (in 0.1 mm)
Fog	Fog 0=no occurrence; 1=occurred during the preceding hour
Rainfall	Rainfall 0=no occurrence; 1=occurred during the preceding hour
Snow	Snow 0=no occurrence; 1=occurred during the preceding hour
Thunder	Thunder 0=no occurrence; 1=occurred during the preceding hour
Ice formation	Ice formation 0=no occurrence; 1=occurred during the preceding hour

National holiday data

The national holidays in the Netherlands will be included for the prediction of charging session flexibility. From previous research it was concluded that this could have impact on the charging behavior. The national holiday data was retrieved from the Holiday package that can be used in Python [71]. Both the national holidays of 2021 and 2022 were retrieved since the researched time period includes both years. The Dutch holidays with the dates are provided in Table C.

Neighborhood statistics

The Netherlands can be divided into provinces and these can be further subdivided into municipalities. The municipalities in the Netherlands are divided into districts and neighborhoods. Districts are sums of one or more contiguous neighborhoods. The data that will be used in this thesis relates to the lowest regional level, namely neighborhood data. The StatLine publication contain key figures for all districts and neighborhoods in the Netherlands [72]. The information that will be used is the urbanization degree at each neighborhood. The urbanization degree at each neighborhood is based on the surrounding address density and is be assigned to different classes. The approach for the class division can be found in Table 4.7.

Table 4.7: Description of urbanization degrees

Degree of urbanization	Surrounding address density
1. Very highly urbanized	Equal or more then 2,500 addresses per km²
2. Highly urbanized	1,500 - 2,500 addresses per km²
3. Moderately urban	1,000 - 1,500 addresses per km²
4. Little urban	500 - 1,000 addresses per km²
5. Non-urban	Less than 500 addresses per km²

Merging charging session data sets with contextual data

The weather data features can be merged with the historical charging sessions based on the day and the hour at which the charging session was started. In addition, the national holiday data can be merged based on the day at which the charging session was started. To conclude, the urbanization degree will be determined for each CP in the data set. Based on the Location data set the Longitude and Latitude is present for each Locations ID. Utilizing the geopandas package in Python each CP can be located at neighborhood level. Subsequently, the urbanization degree is examined for each neighborhood.

4.3 Model selection

There are many different supervised regression models that could be used for the prediction of charging behavior, each with its strengths and weaknesses. In the literature review different studies into the prediction of charging behavior were found. Based on this literature review, it was decided to use the supervised regression ML model XGBoost in this study.

XGboost is a type of gradient boosting algorithm, which means that it uses multiple decision trees to create a strong overall model. In this algorithm, the decision trees are constructed in a sequential manner, where each tree is built after the previous one. As a result, the errors made by the previous trees are taken into consideration, which frequently leads to superior performance. The equation for XGBoost is provided in Equation 4.1 [73]

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i), \quad f_k \in F \tag{4.1}$$

Here, $\hat{y}_i$ represents the predicted value for the i-th data point, K is the number of weak models being combined, f_k is the k-th weak model, and F is the set of all possible weak models. Each weak model is a decision tree that makes predictions based on the values of the input features [73].

The XGBoost model is then created by training each tree on a subset of the data, and then combining the trees in a way that minimizes the loss function associated with the model. In Figure 4.3 a visualisation of a simplification of the XGBoost model is illustrated.

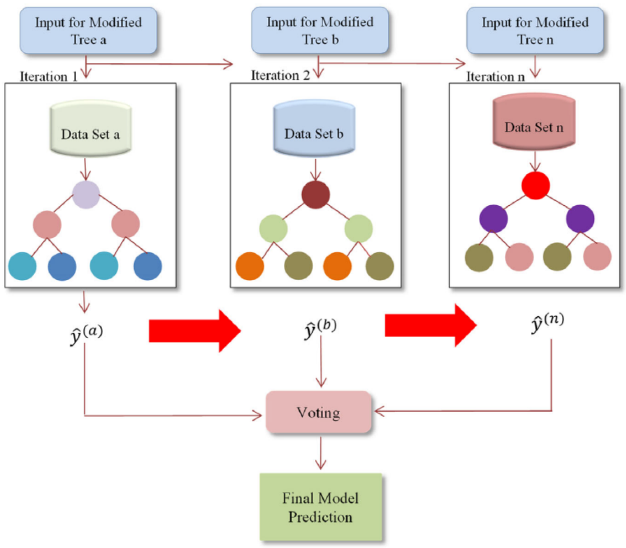

Figure 4.3: Illustration of XGboost [6]

One of the key advantages of XGBoost is that it is computationally efficient, which makes it well-suited for training and predicting on large data sets [73]. Additionally, it has a number of Hyperparameters that will be adjusted to improve the performance of the model, see Section 4.8, including the number of trees in the model and the depth of the trees. The XGBoost algorithm can be retrieved from the Scikit-learn library in Python.

4.4 Data preprocessing

The raw data sources that were collected in the previous chapter need to be prepared to be useful for data analysis and prediction purposes. This step in the process of a predictive modeling project is called data preparation. The following activities that are derived from Brownlee [74] will be conducted.

- Cleaning the Data
- Data Transformation
- Feature Engineering
- Feature Selection

The software that will be used is Python with the integrated development environment Pycharm.

4.4.1 Cleaning the Data

Data cleaning is an important step to prepare the data for effective learning by the ML algorithm. The cleaning process involves two stages: first, identifying and handling missing or zero values in the data, and second, detecting and managing outliers using statistical and visualization techniques such as boxplots. Extreme values in the data that are either faulty or unlikely to contribute to training the ML models will be identified and removed. Notably, the pricing of the kWh will not be considered in training the ML models. This decision is based on the fact that the pricing of charging sessions is determined through a tendering process that varies across different cities. Although [44] observed a positive correlation between pricing and connection duration at fast chargers, which are typically used for "stop and charge" events [43], this study will only focus on public AC chargers, and therefore pricing will not be included as a variable.

The raw data is first cleaned on incorrect data, such as a negative amount of energy charged and a maximum charging power that can not physically be achieved. The maximum charging power was set to 22 kW since this is the maximum power that the EVSE in this research theoretically can provide. After this, the data was filtered for maximum and minimum session durations and volumes. The minimum session duration was set at 15 minutes, which is derived from the time it takes when the first SessionEvents value is registered. The maximum session duration filter is set to 24 hours. Filtering out the long sessions is done since this could be errors and are not of interest for smart charging purposes. Smart charging policies are mostly applied within a 24 hour timeframe. The minimum energy consumption must be 2 kWh and the maximum is set at 120 kWh [75]. This is determined by the largest battery pack currently available for regular EVs. Charging sessions where the energy consumption exceeds this maximum can be seen as incorrect data or a regular EV does not conduct the session. To conclude, the data is also filtered for CPs that have completed less than 30 sessions within the dataset. However, this concerns a low number of CPs that have just been installed at the end of the time interval.

4.4.2 Data Transformation

Data transformation within predictive models is used to alter a dataset's distribution or type of variables. XGBoost is primarily designed to work with numerical data, but it can also handle categorical variables through a process called one-hot encoding [74].

First, the numerical transformations on the data set will be discussed. Each historical charging session is associated with a date and start time represented as a floating-point number. The start time values will be rounded to integer values to increase the number of instances in the dataset for each start time and auth ID or CP ID. In addition, the hour and week of the year are cyclical ordinal features and can be changed into Sin and Cos components. This was also done in current charging session behavior prediction literature [20, 51]. For example, the hour 23:00 is closer to 01:00 than 15:00. This transformation of features will result in two new features. This was done using the 'sin' and 'cos' packages from NumPy. NumPy is a Python library used for working with large, multi-dimensional arrays and matrices of numerical data. The Equations can be found in 4.2 and 4.3.

$$X_{sin} = sin\frac{2 * \pi * x}{max(x)} \tag{4.2}$$

$$X_{cos} = cos\frac{2 * \pi * x}{max(x)} \tag{4.3}$$

Secondly, the categorical features are transformed into numerical input by one-hot encoding. With one-hot encoding, each category is represented as a binary vector, with only one element of the vector being set to 1 while all other elements are set to 0. This indicates which category is present within the charging session. This was done for the urbanization degree of the neighborhood of the CP where the charging session occurred. In addition, the day of the week when the charging session took place is also one-hot encoded.

In this research, the choice was not to include the auth ID as a feature in the models due to a large number of unique values it would have created with one-hot encoding. One-hot encoding can lead to sparse data when dealing with many categories, such as the 180,000+ users in the used data set. This high-dimensional feature space can lead to overfitting and reduced ML model performance. Instead, other features were engineered that could capture relevant information about a user's charging behavior without leading to sparse data. This will be explained in more detail in the following subsection.

4.4.3 Feature Engineering

In this subsection, we explain the process of creating new features based on the original variables to enhance the ML model's performance. The goal of feature engineering is to extract relevant information from the raw data and represent it in a more meaningful way for the ML algorithm.

The first new feature created was a binary-encoded feature that distinguishes between weekdays and weekends. This feature takes the value 1 for weekend days and 0 for weekdays.

In addition, new features were created by calculating statistics related to the charging sessions. For instance, new features were created and added to represent the aggregated charging behavior of the CP where the charging session was conducted. This feature considers the mean session duration or mean energy consumption of all charging sessions at that unique CP. Moreover, features were created that provide information on a user's charging behavior over time, which can be used to capture patterns and trends that may be relevant for predicting future charging behavior. The choice was made to use the "rolling" or "moving" mean, max, min and standard deviation instead of the normal mean. This will prevent data leakage and ensure that the models only use information that is available at the time of connection. The statistical features that were added for each auth ID are summarized below were the moving mean, moving max, moving min, moving standard deviation and the moving count.

The addition of statistics related to specific CPs or auth IDs is also done in current predictive models for the prediction of charging behavior and turned out to be important features for both the prediction of session duration and energy consumption [76, 20, 22, 53]. For all the features included in the models see Table 4.8.

Table 4.8: Description of all the included features

Feature name	**Feature description**
Session duration	Total time connected to the EVSE (hours), Target variable
Energy consumption	Total amount of energy charged (kWh), Target variable
User_Moving_mean	Historical mean target variable, based on user ID
User_Moving_std	Historical std target variable, based on user ID
User_Moving_min	Historical minimum target variable, based on user ID
User_Moving_max	Historical maximum target variable, based on user ID
User_Moving_count	Historical count of overall sessions, based on user ID
User_CP_Moving_mean	Historical mean target variable, based on user ID and CP
User_CP_Moving_std	Historical std target variable, based on user ID and CP
User_CP_Moving_min	Historical minimum target variable, based on user ID and CP
User_CP_Moving_max	Historical maximum target variable, based on user ID and CP
User_CP_Moving_count	Historical count of overall sessions, based on user ID and CP
Time_mean	Historical mean session duration, based on CP ID
Energy_mean	Historical mean energy consumption, based on CP ID
Start_hour	Session start hour, rounded to integer values
Start_hour_x	Session start hour, cyclical encoded (sin)
Start_hour_y	Session start hour, cyclical encoded (cos)
Holiday	Indication of holiday, binary encoded
Day_of_the_week:	Day of the week, one-hot encoded
Urbanization degree	Urbanization degree where the CP is located, one-hot encoded
Day_of_year	Indication which day of the year
Week_of_year	Indicaiton which week of the year
Month_of_year	Indication which month of the year
Is_weekend	Binary indication if it is weekend
Wind speed	Mean wind speed (in 0.1 m/s)
Temperature	Temperature (in degrees Celsius)
Sunshine	Sunshine duration (in 0.1 hour) during the hourly division
Radiation	Global radiation (in J/cm2) during the hourly division
Hourly precipitation	Hourly precipitation amount (in 0.1 mm)
Fog	Fog, binary encoded
Rainfall	Rainfall, binary encoded
Snow	Snow, binary encoded
Thunder	Thunder, binary encoded
Ice formation	Ice formation, binary encoded

Note: The statistical features are determined for both the target variables Session duration and Energy consumption. The statistical feature is based on which target variable is predicted.

4.4.4 Feature Selection

Feature selection is a step in ML where the objective is to (automatically) identify and choose the features from a given dataset that possess a high degree of relevance or importance with respect to the target variable of interest. The primary aim of this process is to extract a subset of the most significant features that effectively captures the underlying patterns and relationships present within the data, thereby facilitating accurate and efficient prediction of the target variable [21]. Reducing the amount of features to only the most relevant subset will result in faster training times which could be beneficial if the charging flexibility needs to be predicted (near) real-time. Reducing the features also improves the explainability of the model by lowering the complexity. The existing feature selection methods can be broadly classified into filter, wrapper and embedded methods. Recently, in ML research, causality-based feature selection is investigated as causal features can improve the robustness and the interpretability of the predictive model across different settings. These approaches use independence tests to discover the causality between features from data [77].

In this research a causality-based feature selection approach will be used. The approach uses the training data to identify a causal structure between the features and the target variable. Subsequently, the approach identifies highly relevant features by learning the Markov Blanket (MB) on the obtained structure [77]. The MB is a term introduced in the Bayesian network theory to determine the structure and conditional independence relationships between variables in the network. It is formed by the parent nodes, children nodes, and the parents of the children nodes (excluding the parents of the target variable) in the network for a given target variable. This blanket of features captures all the direct causal relationships of the target variable in the network and plays a crucial role in efficient inference by reducing the number of variables to consider. Therefore from now on the approach will be called the MB approach.

4.5 Experimental setup

The historical charging sessions that are used within this study were provided by the CPO TotalEnergies, with available historical charging sessions from several years in the past. The time interval that is considered in this study is from November 2021 until November 2022. This time interval contains, after data preprocessing, over more than 2.4 million charging sessions. Which is in the current literature the largest amount of charging sessions used in literature on EV flexibility prediction studies. The charging sessions were conducted at public EVSE within the TotalEnergies network in the Netherlands. The choice to use this time interval has multiple reasons. First of all, the COVID-19 pandemic has made an impact on the charging behavior of EV users. Therefore, training the ML algorithm on older data can cause the model to train a faulty pattern and could therefore not generalize well on new data. Secondly, during this time period no COVID-19 'lockdowns' were implemented that could be harmful for the prediction abilities of the model.

The model needs to be trained, validated and tested to evaluate the performance and feature importance. This dividing of preprocessed data can be found in Figure 4.4, the data will be split into three subsets: training, validation and test data. The training data set is utilized to train the ML model, by fitting the model to this data and adjusting its parameters to minimize the prediction error on this data set. The validation data is used to tune the model's hyperparameters and to evaluate its performance during training. The tuning of the hyperparameters will be discussed in more detail in Section 4.8. It is an essential step in the development of any ML model, as it helps to ensure that the model is capable of generalizing to new data and is not overfitted to the training data. Finally, the testing data set is utilized to evaluate the performance of the final models.

The ratio of splitting the data into the three data sets training, validation and testing was set to 80/10/10. This splitting ratio is commonly used in literature. [20] [55] used 80% for training and 20% for evaluation. [54] used a 70/20/10 split, while [22] used three years of historical charging sessions, where the first year was used for training, the second year for validation and the third year for testing the model, which can be seen as a 33/33/33 split. However, there were more charging sessions in the most recent year.

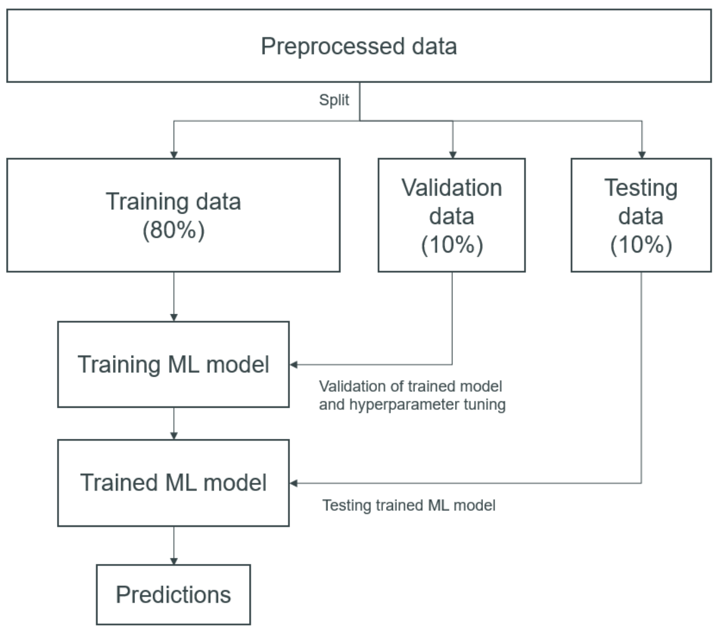

Figure 4.4: Framework training, validation and testing process

The choice has been made in this research to use a 80/10/10 split for dividing the data into training, validation and testing, since in practice the predictions must be made for future charging sessions. In the current literature regarding the prediction of charging behavior, the chronological splitting of data into training and evaluation sets is a common practice as it closely reflects the real-world scenario where models are trained on historical data and used to make predictions on new, unseen data points in the future. However, this approach is not immune to the possibility of selecting a biased sample, which may adversely affect the model's performance. To mitigate this risk, in this study also random splits are conducted and the results are compared to analyze possible biased training of the ML model.

While more random data splitting of the data can provide a greater conviction that the used data split is not biased, in this study this was not feasible due to computational resources and time constraints. To address this issue, in addition to testing several random splits, the hybrid approach was adopted where the model is both evaluated on the validation set and the testing set. In the next section the method to cluster the different public CPs will be discussed.

4.6 Clustering of charging points

After the data preprocessing steps are completed the CPs will be clustered based on their characteristics. This part will contribute to answer "RQ4: Does a segmentation through clustering CPs result in more accurate predictions for charging session flexibility?". From the literature review the Rule-based clustering approach of [7] was chosen. This approach was chosen due to the explainability of the identified pattern. This is a temporal approach that uses the historical charging sessions at each CP. A matrix is created for each CP based on their historical charging sessions. Each charging session that is conducted on the specific CP is placed in the matrix. The matrix is created based on the start hour of the session and on the duration of the session.

In Table 4.5, the two distinctions that are made within a charging session in this thesis are illustrated. The first one is a separation between short and long charging sessions. The sessions are defined as short when the connection duration is less than 6 hours and long if the connection duration is more than 6 hours. The other separation is based on the start/arrival time. The different intervals are 6 to 10, 11 to 13, 14 to 16 and 17 to 24. The categories are morning, noon, afternoon, and evening. These intervals are chosen based on a brainstorming session within the EV Development team of TotalEnergies.

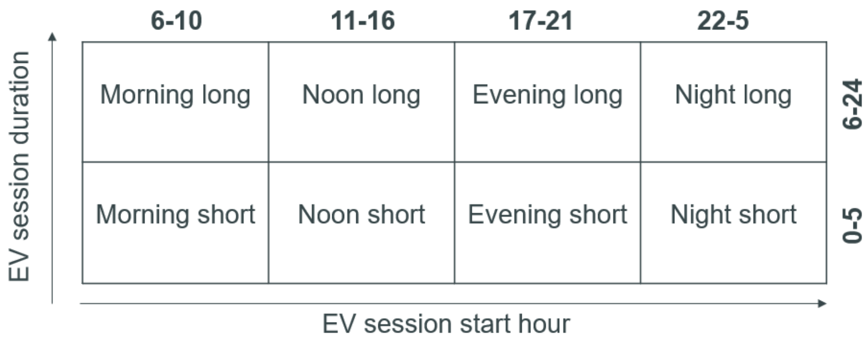

Figure 4.5: Partitioning of the charging matrix according to the start hour time and session duration time [7]

The method uses specific time intervals to divide the start time and session duration into sub-matrices. It then compares the sum of elements in each sub-matrix to a certain threshold (θ). Charging patterns are identified by the layout of sub-matrices with sums greater than the threshold value and charging stations are grouped based on their charging patterns. Within this research the threshold values 0.05, 0.06, 0.07, 0.08 and 0.09 will be tested and evaluated on the best clustering results.

Based on these two dividing strategies, a charging pattern can be recognized for each CP. Since the splitting of the CPs is done in 8 submatrices, the maximum number of clusters that can be obtained is $2^8 = 256$. The 10 largest clusters will be analyzed and used for the prediction of charging session behavior and evaluation on their flexibility potential.

4.7 EV Expert interviews and survey on feature importance

During the research process, semi-structured interviews were conducted with EV experts to gain insight into the opinions of EV experts on smart charging and the possibilities of predicting charging behavior which is part of RQ2. The selected participants worked in the EV domain, both research and commercial organizations. The interviews focused on the possible predictive features for charging behavior and how these features can be implemented in a predictive model. A list of interviewees and their respective organizations can be found in Table 4.9. The questions asked during the qualitative interviews can be found in Appendix B.

Interviewee positition	**Organization**
Project manager charging infrastucture	MRA elektrisch
Data scientist	TotalEnergies
EV researcher	Amsterdam University of Applied Sciences (HVA)
Data scientist	ElaadNL
Phd candidate smart charging	University of Twente
Postdoctoral Researcher energy systems	Empa

Table 4.9: List of interviewees and the organization

In addition to the interviews, an online survey was sent to the same EV experts and other EV experts within TotalEnergies. In the survey, the EV experts were asked to give their opinion on the feature importance for predicting session duration and energy consumption on the selected features. This was done to verify the findings from the interviews and to obtain additional information on the perception that EV experts have on features that influence session duration and energy consumption. The online survey included a list of features, which can be found in the Appendix B. This included the features that were identified as important in previous studies for predicting session duration and energy consumption, as well as other features mentioned by the experts during the interviews.

The experts were asked to rate each feature on a scale of 1 to 10, with 1 indicating that they expect the feature to affect session duration or energy consumption and 10 indicating that the feature has a significant impact. Finally, there was also an open question in which the EV experts were given the opportunity to fill in which variables they were missing that they expect will have an impact. The survey results were analyzed to identify critical variables that EV experts believe influence session duration and energy consumption. These findings are compared to the ML feature importance results to see similarities and understand differences. Additional variables may also be added based on the interviews or survey.

4.8 Training parameter tuning

Within ML, two types of parameters are set to improve the performance of the algorithm. The first type is the learning parameters determined by the algorithm which will dependent on training the data. Within XGBoost, these parameters include the value of the leaf weights, the value of the regularization parameters and the split points in the trees. These values are learned by the algorithm itself from the data by minimizing a loss function such as the MAE.

The second type of parameter are the hyperparameters, which are set before the training process and can not be learned from the data during the training process. The process of determining these hyperparameters for a model is called hyperparameter tuning. Hyperparameters that can be adjusted within XGBoost include the maximum depth of the tree, the number of samples on a leaf and the number of trees [78].

In this research, a grid search will be used for hyperparameter tuning on the validation dataset for each model. This means that this hyperparameter tuning is also performed separately for each cluster. In Appendix F, the different hyperparameter options are presented that are tested for each model on the validation data set.

4.9 Evaluation of feature importance

The feature importance of the ML models will be evaluated to understand the model, not only to increase the model's accuracy but also to improve the explainability of the model. First of all, interviews were conducted with EV experts about feature importance within charging behavior prediction. The interview questions can be found in Appendix A. In addition to this interview, a survey was also sent after the interview was conducted.

Besides this qualitative approach, several quantitative data approaches were conducted as well. The SHapley Additive exPlanations (SHAP) method will be used. SHAP is a method for interpreting the output of ML models by determining the contribution of each feature to the prediction for a specific instance [79]. This method is based on the concept of Shapley values from cooperative game theory, which provide a way to fairly distribute a value among a group of individuals based on their contributions. The contribution of each feature is determined by calculating the difference between the predicted values with and without the addition of each feature for all possible combinations, and taking the average of the results. This allows to understand which features have a significant influence on the predictions. The Shapley value is the average marginal contribution of each permutation. There are different SHAP explainers available depending on which type of ML algorithm that is being used. In this thesis the SHAP tree explainer will be used since the XGBoost algorithm consists of decision tree. The formula for the SHAP value can be found in Equation 4.4.

$$SHAP(i,y) = (S)(|S|+1)!(|F|-|S|-1)! * (f(SUi) - f(S))/|F|! \tag{4.4}$$

Where S is a subset of the set of features F, such that S $\subseteq$ F. The cardinality of the subset S is denoted by |S|, while the cardinality of the full set of features F is denoted by |F|. f(SUi) is the output of the model f for the data point y with the feature i being set to its reference value. f(S) is the output of the model f for the data point y with the features in subset S set to their values in y.

Finally,the MB feature selection approach also serves as a way to demonstrate the feature importance of a predictive model. Only the relevant features are selected for which a causal relationship has been found.

4.10 Maximum power

The P_{max} will be used to determine the individual charging session flexibility from the predicted session duration and energy consumption using Equation 4.5. The P_{max} of a charging session is determined by the combination of the EVSE and the EV. During a charging session, the maximum charging speed will depend on the lowest P_{max} of the two. If an EVSE can supply 11 kW but the EV only has charging capabilities of 5 kW, charging will be occur with a P_{max} of 5kW.

It is important to mention that an EV is not always charged with the P_{max} during a charging session. In most cases the charging power will be higher at the start of a charging session when the battery has a lower SOC and will decrease as the battery approaches maximum SOC. This difference in charging power is due to several factors, such as the temperature of the battery, the EV's battery management system and the number of EV's connected to a CP. When multiple EVs are connected to a single CP, the total amount of power that can be delivered to the EVs will be shared among them [80]. This is called load balancing and is done to ensure that the electrical current that is drawn from the grid does not the exceed the P_{max} of the CP. This means that the P_{max} of the vehicle could be lower then the P_{max} of the CP. This could cause that the charging power available to each individual EV will be lower than the maximum power output of the EVSE.

In the SessionEvents dataset all the historical charging sessions with a 15 minute time interval are present. As described in Section , the CDR dataset and the Metervalues can be merged together. From the SessionEvents, the power supplied by the EVSE for each CDR at every timestep can be determined by dividing the consumed energy (kWh) by the timeperiod (h). This results in a P for every timestep. The Pmax is then derived by applying a MAX function to all these P values for each individual historical session. The P_{max} is then filtered by finding the maximum value for each EVSE and user in the training data. Subsequently, by a statistical method, the P_{max} of future sessions is predicted at the start of the session using Equation (4.5.

$$P_{max} = min\{EVSE - P_{max}, USER - P_{max}\} \tag{4.5}$$

Here $EVSE - P_{max}$ is the maximum power that the EVSE can deliver and $USER - P_{max}$ is the maximum power that the EV can absorb based on historical sessions. Finally, the minimum of the two is used to determine the P_{max} that can be delivered in a charging session.

4.11 Determining individual charging session flexibility

In the previous sections the methods to predicting the session duration, energy consumption, and the maximum charging power for an charging session were described. In this section the method on how to transform these variables into flexibility potential by employing Equation 3.4 will be further eleborated on. To illustrate the quantification of charging session flexibility, the same example as depicted in Figure 3.1 will be employed.

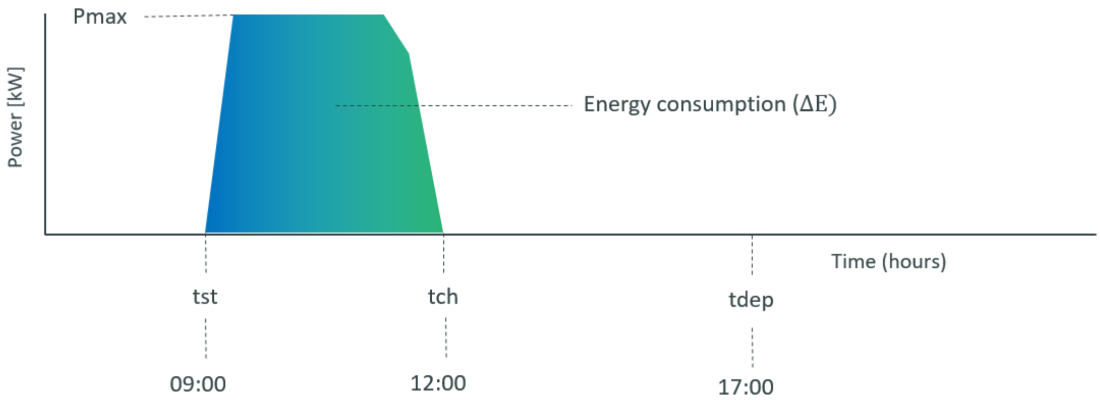

Figure 4.6: Example of a individual EV charging session

In the example, the start time of the charging session is 9:00 AM, and the predicted or actual P_{max} is 12 kW. Additionally, the predicted or actual energy consumption and departure time is 36 kWh and 17:00 respectively.

For determining the time flexibility Δt_{flex} from the session duration, the same method as found in the literature review will be used [36, 22, 40]. From the literature review the following equation for was derived for the time flexibility: Δt$_{flex}$ = t_s - t_{ch}. The session duration (t_s) is predicted using the ML approach. The charging duration (t_{ch}) can be determined with Equation 3.5, by taking the predicted energy consumption and dividing this with the P_{max} that the CP can provide to the EV. This equation assumes that the maximum power is present throughout the whole charging session.

When the example of Figure 4.6 is used, this creates to the following charging duration. Charging duration (Δt$_{ch}$) is ($\frac{36kWh}{12kW}$) = 3 hours. Which indicates that the charging, within a unsteered charging session, would end at 12:00. Therefore the Δt$_{flex}$ is (8 hours - 3 hours) = 5 hours.

The t_{flex} can not take on a value that is negative, since this would suggests that the charging duration is longer than the session duration the t_{flex}. Therefore when the determined charging time is longer then the predicted session duration, the time flexibility takes the value of zero. This is indicated in Equation 4.6.

$$\Delta t_{flex} = max\{t_s - t_{ch}, 0\} \tag{4.6}$$

From this equation, the time flexibility in the example can be calculated. Since the predicted time flexibility in the example is not a negative value, the time flexibility is set to be 5 hours. To conclude, the total individual charging flexibility in the example from Figure 4.6 would be 36 kWh * 5 hours = 180 kwh^2. In addition to the example, it is beneficial for aggregators such as a CPO to have an operating framework for using the described methodology in practice. Therefore, an operating framework for aggregators was developed and can be found in Figure 4.7. This framework serves as a blueprint and visually represents the different steps involved in the methodology and their interconnectedness, which can help ensure that the methodology is implemented correctly.

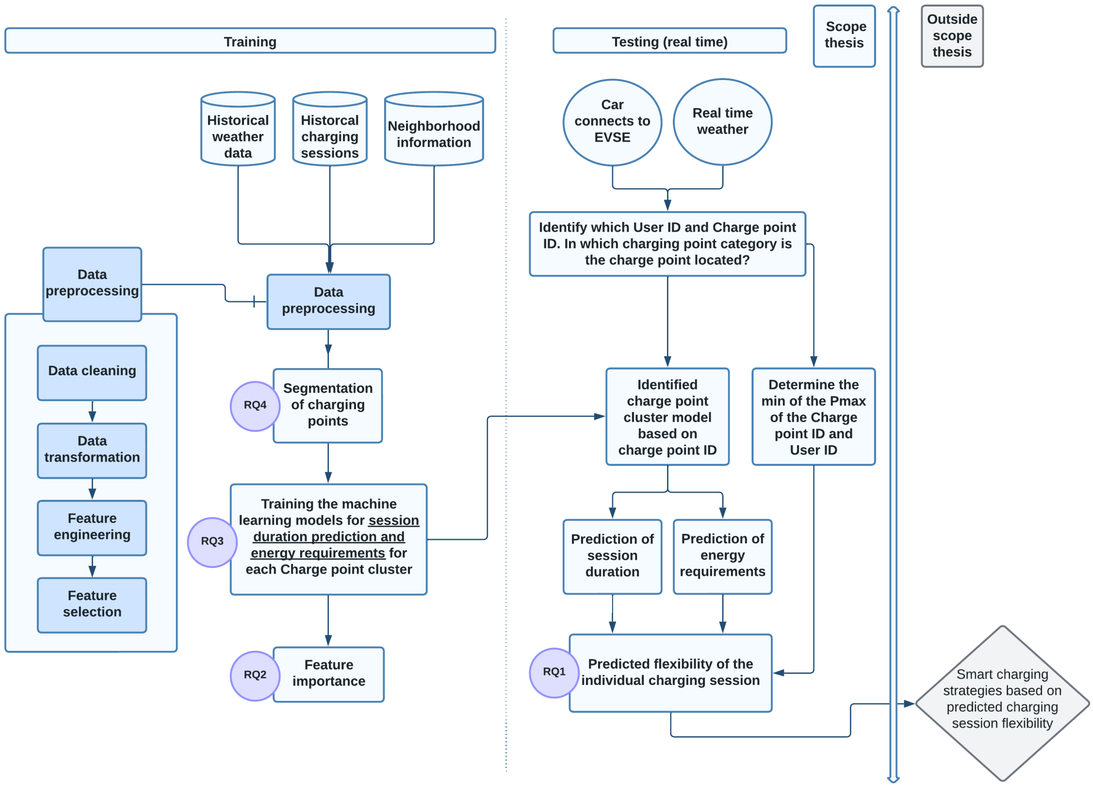

Figure 4.7: Operational flow diagram EV charging flexibility prediction

4.12 Evaluation of the predictive models

The performance of the XGBoost regressor models and the statistical P_{max} prediction will be evaluated using a number of metrics, including MAE, Mean Squared Error (MSE) and Symmetric Mean Absolute Percentage Error (SMAPE). Each of these metrics provides a different perspective on the quality of the model's predictions. The smaller the MAE, MSE or SMAPE, the better the performance of the predictive model. All three metrics will be used in this thesis for model performance evaluation

The MAE measures the average of the absolute difference between the predicted values and the actual values. It is a interpretable metric that gives an idea of the magnitude of the error. However, the MAE does not indicate the direction of the error. The model could for example always make a overestimation compared to the actual value. In addition to this metric, a histogram plot will therefore be made of all predictions errors to visualize the direction. The formula for MAE can be found in Equation 4.7.

$$MAE = (\frac{1}{n})\sum_{i=1}^{n}|y_i - x_i| \tag{4.7}$$

Here n is the number of observations in the dataset, y_i indicates the actual value, x_i indicates the predicted value and $(\frac{1}{n})$ is used to create the mean for the errors by dividing the sum of the errors by the total amount of predicted data points.

The MSE measures the average of the squared differences between the predicted and actual values of the target variable. Because it uses the squared of the error, significant errors are punished more severely. The formula for MSE can be found in Equation 4.8.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)^2 \tag{4.8}$$

Here n is the number of observations in the dataset, y_i indicates the actual value, x_i indicates the predicted value and $(\frac{1}{n})$ is used to create the mean for the errors by dividing the sum of the squared errors by the total amount of predicted data points.

SMAPE is a percentage-based metric that measures the symmetric mean of the absolute percentage differences between the predicted and actual values of the target variable. The formula for SMAPE can be found in Equation 4.9.

$$SMAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_i - x_i|}{(|y_i| - |x_i|)/2} * 100\% \tag{4.9}$$

Here n is the number of observations in the dataset, y_i is the actual value of the target variable and x_i is the predicted value of the target variable.

Another common way to evaluate a prediction model is by looking at the bench mark model that is the state-of-the-art for the specific task. However, at the moment there is no open access benchmark model in place that can be used with the same data. One study [22] has been identified from the literature study that predicts the energy consumption, session duration and subsequently the flexibility for a large set of public EVSE. This study could be used to compare the performance of the model.

4.13 Chapter summary

In this chapter, the methodology of this thesis was outlined, which is used to obtain answers to the research questions. First, the philosophy behind the ML model was explained and the choices that were made were elleborated on. Various units of generalization have also been developed and explained. Ultimately, it was decided to research two different units, namely the Aggregated model and the CP cluster models. Subsequently, the different data sets, data preprocessing steps and the different features that will be used for training the XGBoost model were explained. It is also illustrated how the maximum charging power in a charging session will be determined and how the charging session flexibility can then be derived. The chapter concludes by expounding on the Hyperparameters, the methods employed for evaluating the ML models, and the features used.

In the next chapter first, a summary of the data set used in this research will be provided. This will be followed by evaluating the results obtained from the ML models and the various units of generalization.

Chapter 5

Data Exploration

Chapter 4 explained the methodology used to answer the research questions. This chapter will examine the data set that was collected from TotalEnergies and prepared for analysis. The purpose of this exploration is to gain a better understanding of the structure and characteristics of the data and to generate insights that will guide our subsequent analysis. First the data set will be evaluated. Subsequently the target variables will be discussed and the used independent variables will be explored.

5.1 Data set evaluation

Figure 5.1 illustrates the total amount of charging sessions that occur at each day of the week within the dataset. From the illustration, it can be seen that the utilization of the public EVSEs in the dataset occurs consistently throughout the week. There are some variations in the number of sessions with a slightly higher frequency on Fridays and a slightly lower frequency on Sundays, but this difference is not significant.

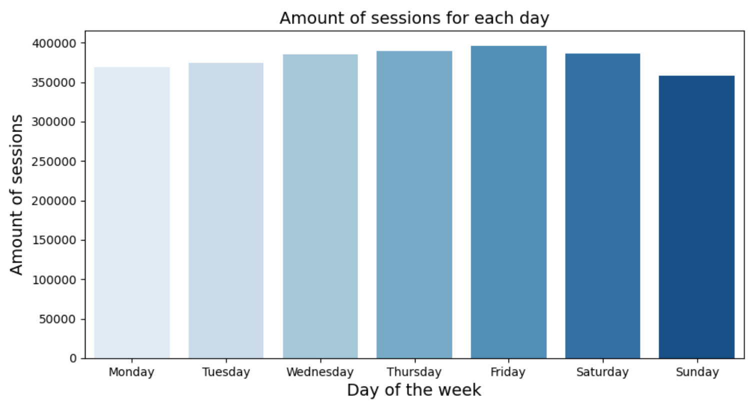

Figure 5.1: Countplot for number of sessions recorded for each day of the week.

In Figure 5.2, the distribution of charging sessions across months is depicted. As demonstrated by the figure, a higher number of sessions occurred in the months of September and October compared to November and December. This increase in charging sessions can be explained by the time interval of the used dataset. As more charging stations were added over time, the total number of charging sessions increased as well. Nevertheless, upon examining the total number of sessions for each month, the difference is not substantial enough to affect the outcome of the research.

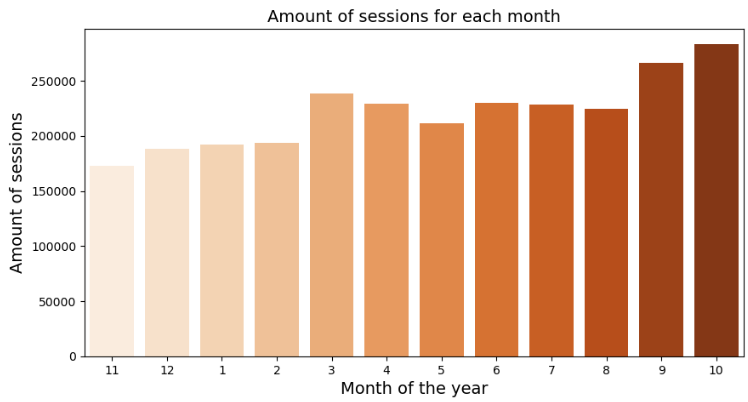

Figure 5.2: Countplot for number of sessions recorded for each month of the year.

Each unique user ID in the dataset has on average conducted a charging session on 2.6 different CPs. The distribution of the number of CP per user is shown in Figure 5.3. This shows that on average a user typically only use a small amount of different CPs.

In addition, on average, each authentication ID has around 14 unique sessions within the dataset. However, further analysis of the data reveals that it follows the Pareto Principle, which suggests that roughly 80% of the effects come from 20% of the causes [81]. In the context of our dataset, the top 20% of most

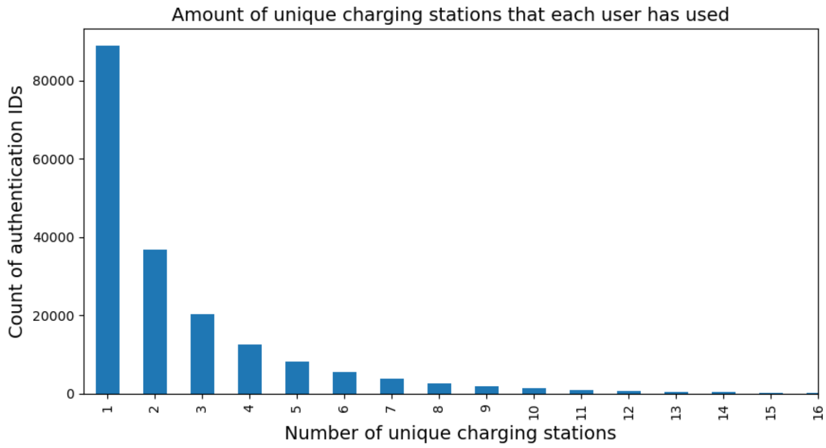

Figure 5.3: Histogram for the number of unique charging stations that each user has used.

active users account for 82.2% of all charging sessions. Figure 5.4 shows a density plot of the distribution of the number of unique sessions per authentication ID. The x-axis represents the number of unique sessions per authentication ID, while the y-axis represents the density of each value. The red dashed line indicates the threshold for the 80th percentile of authentication IDs, which corresponds to the number of sessions required to account for the top 20% of most active authentication IDs.

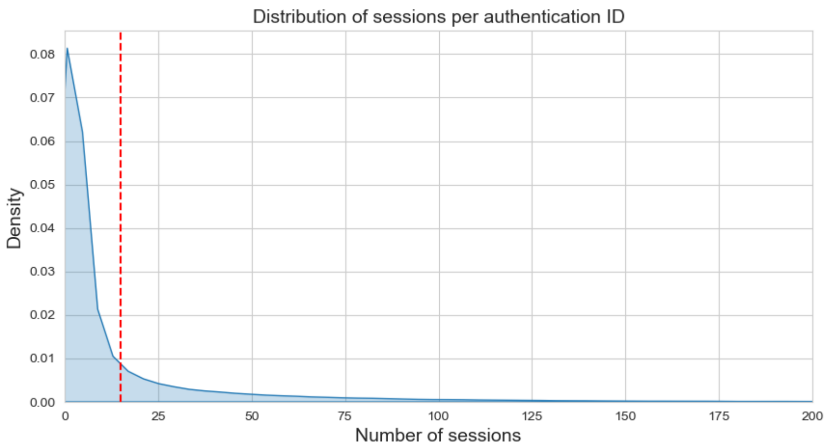

Figure 5.4: Density plot for the number of unique charging sessions that each user done.

The density plot shows that the distribution of the number of unique sessions per authentication ID is skewed to the left, with a long tail of high values to the right. Overall the density plot reveals a tilted distribution of sessions across authentication IDs, characterized by a minority of IDs that contribute to the majority of sessions, alongside a large number of users who engage in only a few sessions.

To ensure that the low-frequency users were not simply new additions to the dataset at the end of the time interval a check was conducted. To accomplish this, the start date of each authentication ID's first session was examined. It was found that the low-frequency users had start dates spread throughout the dataset period, indicating that they were not solely recent additions. Authentication ID's with less than 15 sessions in total were identified as low-frequency users.

5.1.1 Descriptive statistics

The target variables from the dataset and used in this research with their descriptive statistics are shown in Table 5.1.

Table 5.1: Descriptive statistics of the target variables

Variable	N	Mean	s.t.d.	Minimum	Maximum
Session duration (hours)	2,481,403	8.05	6.05	0.25	23.99
Energy consumption (kWh)	2,481,403	21.80	16.90	2.00	118.86
Max power (kW)	2,481,403	7.51	3.60	0.13	21.99
t_{flex} (hours)	2,481,403	5.13	5.45	0	23.64
Flexibility (kWh^2)	2,481,403	122.34	176.62	0	1627.48

The descriptive statistics presented in the table reveal that a charging session's average duration is 8.05 hours, with a standard deviation of 6.05 hours. The range of session durations is limited by preprocessing steps, which require a minimum duration of 15 minutes and a maximum of 24 hours for smart charging purposes. The energy consumption during the historical charging sessions has a mean of 21.80 kWh and a relatively large standard deviation of 16.90 kWh, indicating a wide range of energy consumption, with some sessions exhibiting considerably higher consumption than the mean. Similarly, the t_{flex} statistic displays a standard deviation higher than the mean, suggesting that some sessions have t_{flex} values substantially larger than average. This observation is consistent with Equation 4.6, which specifies that sessions with no idle time during the charging session are assigned a t_{flex} value of zero. The same applies to the flexibility statistic derived from t_{flex} and energy consumption using Equation 3.4. The correlation matrix between the target variables can be found in Figure 5.5.

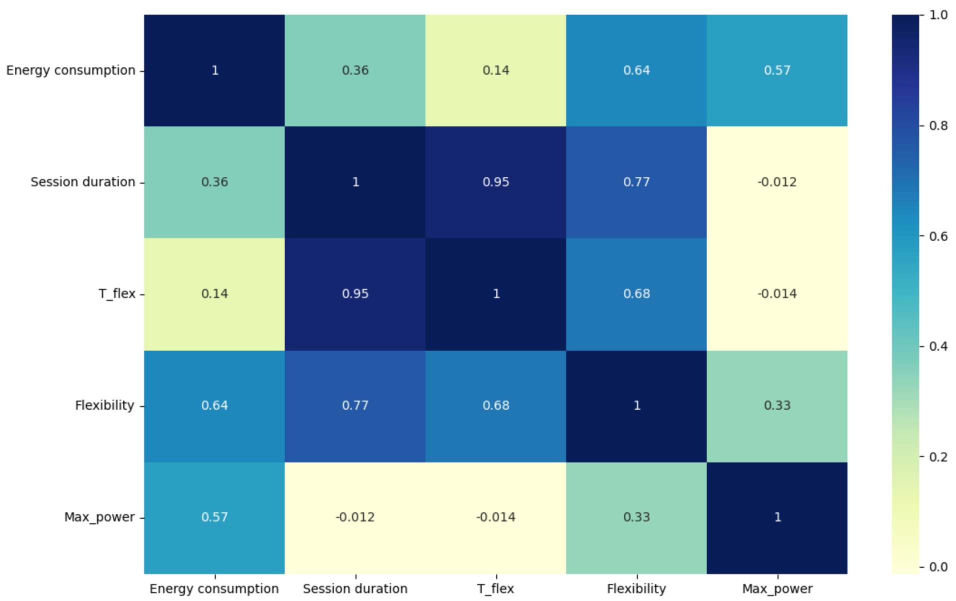

Figure 5.5: Correlation plot between target variables

5.1.2 Session duration

In Figure 5.6 the data distribution of the session duration is illustrated. It showcases the frequency of records for all the session durations, providing insights into the typical duration of charging sessions for EV users in the dataset. As can be seen in the figure, there is a peak in sessions that last between one and five hours. Approximately 53% of all sessions are observed to last longer than five hours.

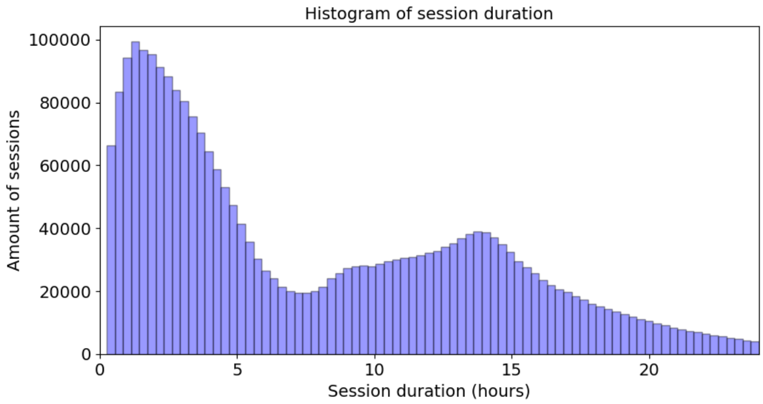

Figure 5.6: Histogram for total session duration.

The session duration per day of the week is depicted in a box plot (Figure 5.7). The plot provides a visual representation of the median and quartiles of the session durations for each day of the week. The median session duration for Friday and Saturday is observed to be lower compared to the other days of the week, but not significant lower.

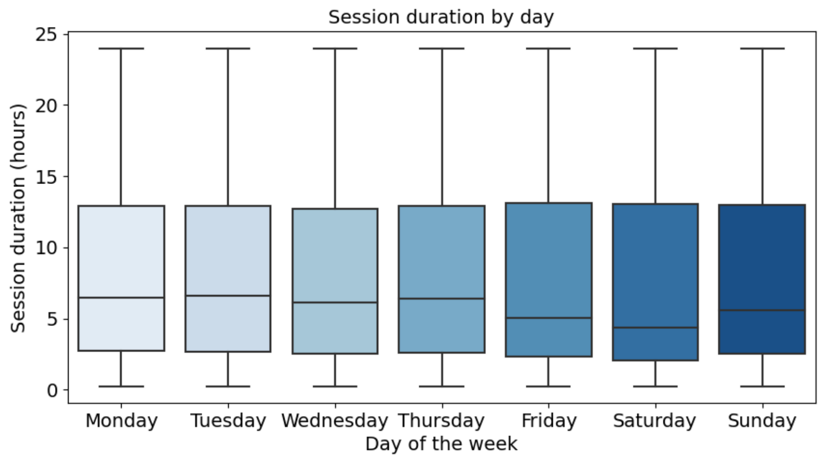

Figure 5.7: Boxplots for every day of the week indicating the session duration

With a longer session duration for a sessions, the charging often takes place overnight, resulting in a different start and stop day of the week. The days depicted in the box plot are determined based on the start time and hence the start day of the week. To analyze the charging patterns better for each day of the week, density plots for the start time and stop time are presented in Figures 5.8 and Figure 5.9, respectively. As depicted in Figures 5.8, fewer sessions start between 6:00 and 10:00 on weekends, with a shift to a later time between 10:00 and 15:00.

The stop time of the sessions on weekends, as shown in Figure 5.9, also demonstrates differences compared to weekdays. The sessions tend to end later in comparison to weekdays, which could explain the

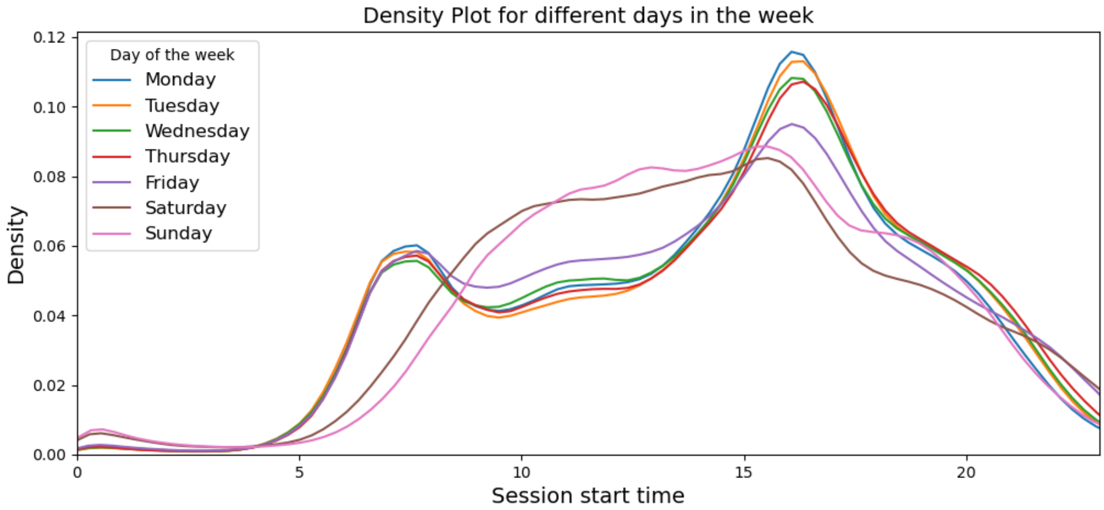

Figure 5.8: Density plot of the session start time for each day of the week

lack of difference in the boxplots from Figure 5.7. Both the deviations between the weekend and weekdays can be attributed to the absence of work patterns and commute. The difference between weekdays and weekend could be a relevant predictive feature in the XGBoost model. In addition, the observed pattern of stop times on Tuesday and Thursday, which are more aligned with typical working hours than other weekdays, suggests that these days are preferred for office attendance by the majority of the EV users in the dataset.

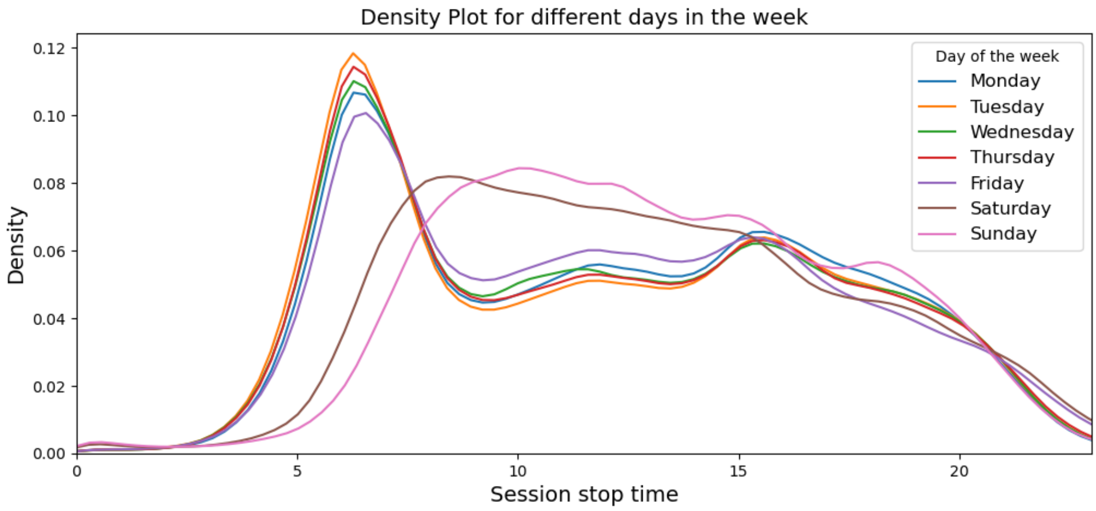

Figure 5.9: Density plot of the session stop time for each day of the week

5.1.3 Energy consumption

Figure 5.10 depicts the data distribution of the energy consumption within charging sessions. A notable peak is evident, indicating a high concentration of charging sessions that fall within the range of 5-15 kWh. Furthermore, analysis of the data reveals that 58.2% of the charging sessions has a energy consumption of less than 20 kWh. The upper limit of energy consumption was specified to be 120 kWh during the pre-processing steps, taking into consideration the maximum battery capacity of available EVs. However, as demonstrated by Figure 5.10, instances of high energy consumption within a single charging session are scarce, with only 3.1% of the sessions recording energy consumption values exceeding 60 kWh. This observation can be attributed to the common practice among EV users of connecting to a EVSE with residual energy remaining in their EV.

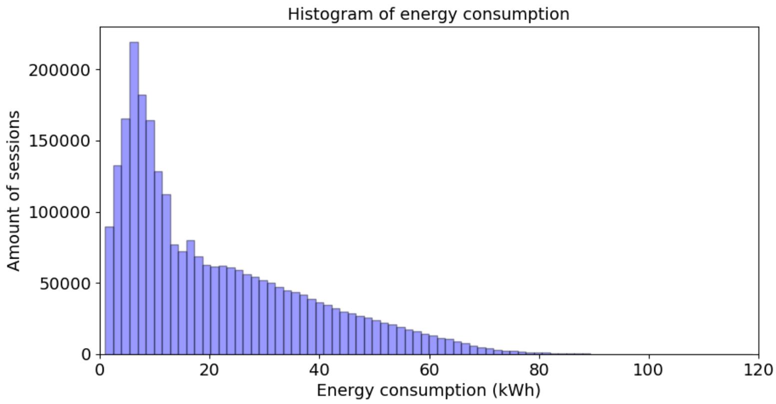

Figure 5.10: Histogram for total energy consumption

In Figure 5.11 the energy consumption is illustrated in a boxplot for every month. No clear difference per month could be obtained from the illustration. However, a small reduction in the median and quartiles in the summer months June, July and August can be observed.

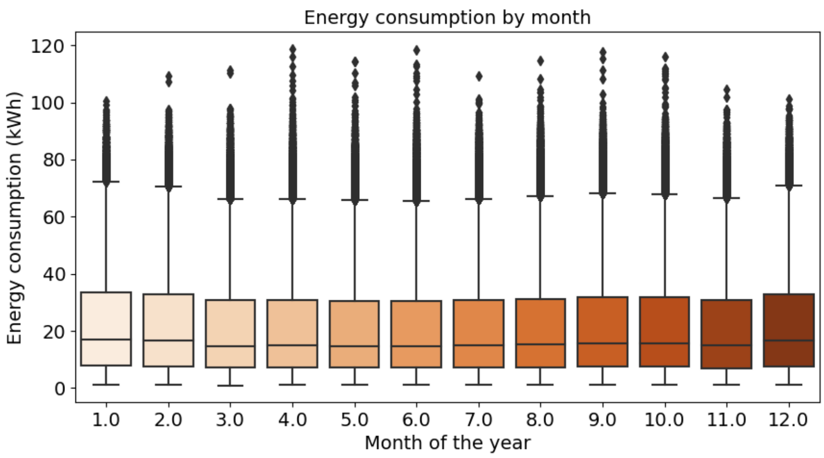

Figure 5.11: Boxplots for month of the year indicating the energy consumption

5.1.4 Maximum power data distribution

To determine the flexibility of a charging session, it is necessary to determine the maximum charging speed. With the maximum power it is possible to ascertain the time required for an EV to complete charging to the desired energy level. This was accomplished by analyzing the SessionEvents data to determine the maximum power for each charging session. Subsequently, the maximum power per EVSE or EV was determined by grouping the charging sessions per EVSE or EV user. Figure 5.12 displays the distribution of the maximum power per EVSE on historical data.

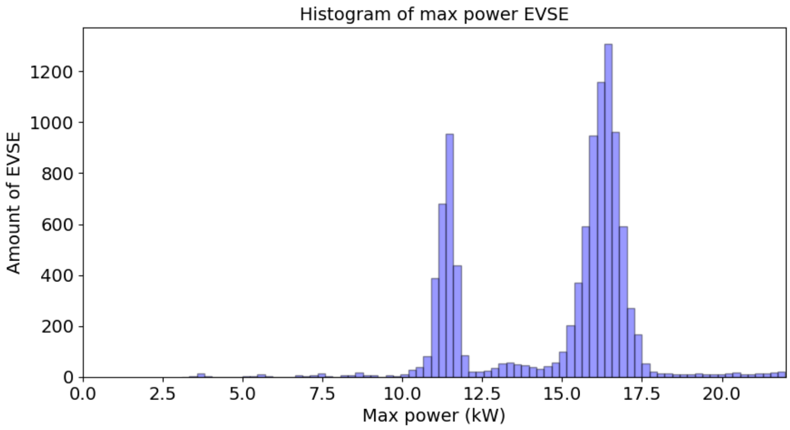

Figure 5.12: Maximum power for EVSE based on historical sessions training data set

The data distribution in Figure 5.12 reveals two distinct EVSE groups, which can be reasoned by different CP models within TotalEnergies' public AC Charging Pool. The CP can supply either 16 or 25 Ampere. The EVSE that can supply a maximum of 11 kW and 16.5 kW was identified, with some deviations that could be attributed to load balancing.

The maximum power grouped by each authentication ID was analyzed based on a minimum of 3 charging sessions in the training set. Figure 1 displays a histogram representing the maximum power per authentication ID from the training data set.

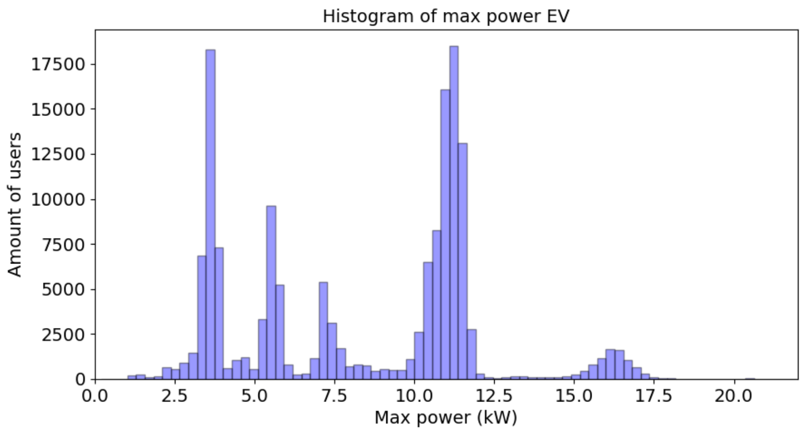

Figure 5.13: Maximum power for EV based on historical sessions training data set

The data distribution in Figure 5.13 indicates several distinct user groups. For instance, EV users with lower maximum charging speeds are likely using a 1-phase charger, while EV users charging at a rate between 10 and 12.5 kW are likely using a three-phase charger. Additionally, a small peak was observed between 15 and 17.5 kW, which is probably due to EV users with vehicles that support higher kW charging sessions, such as a Tesla Model S or X [82].

By analyzing both figures, it can be seen that the P_{max} around 16.5 kW for a large amount of EVSEs from Figure 5.13 can be attributed to a small group of EV users from Figure 5.13. As a result, the EV user's P_{max} probably has a more critical role than the P_{max} of the EVSE in Equation 4.5.

5.1.5 Flexibility quantification

When applying Equation 3.4 for determining the flexibility to the historical data set, Figure 5.14 was developed. In the figure the average flexibility for a charging session that is started for each start hour during the day in kWh^2 is plotted. A red dotted line was drawn to indicate the maximum average flexibility during the day. It can be observed that charging sessions that start around 19:00 have the highest average flexibility. This high average flexibility can be explained since these sessions have a high probability of being connected to the EVSE throughout the night and therefore have a larger t_{flex}.

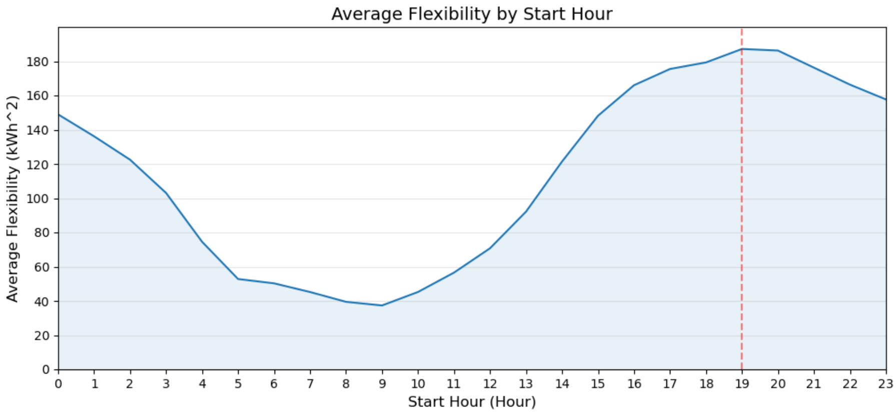

Figure 5.14: Average flexibility for each charging sessions for each start hour

In addition to the average also the aggregated flexibility, sorted by start hour, for the whole Charging Pool was plotted and can be found in Figure 5.15.

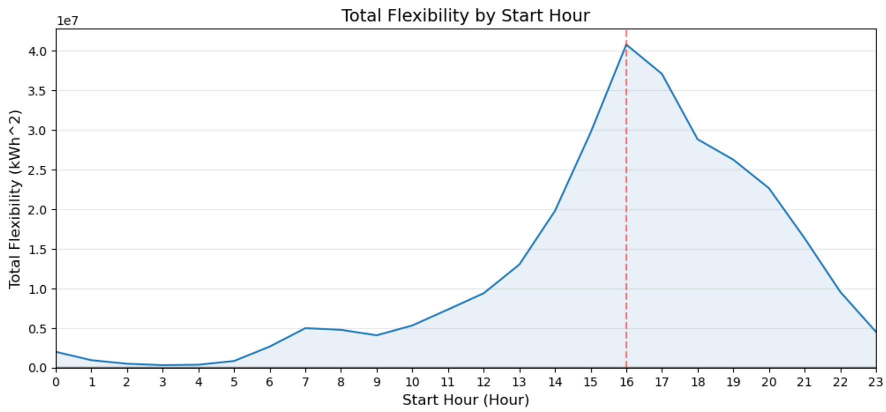

Figure 5.15: Aggregated flexibility for charging sessions in the dataset for each start hour

Figure 5.15 shows that the highest aggregated flexibility within the whole CP portfolio can be found with charging session that start around 16:00 PM. This difference in average and aggregated flexibility can be attributed to the average charging pattern at the CPs. As you can see in Figure 5.8 most sessions start around 16:00 PM. While flexibility is high for sessions starting between 19:00 PM and 1:00 AM, the aggregated flexibility is lower given the number of charging sessions that are started in this time period.

5.1.6 Heatmap of all the charging sessions

In this research, all the data comes from public EVSE. However, by analyzing historical charging sessions and plotting a heatmap of the connection time versus connection duration, it was possible to identify three distinct subgroups of historical charging sessions. Public chargers are also used as work or home charging because of the unavailability of private chargers. Figure 5.16 illustrates these subgroups, which are referred to as groups. The same charging session groups that were identified in [51, 56] will be used.

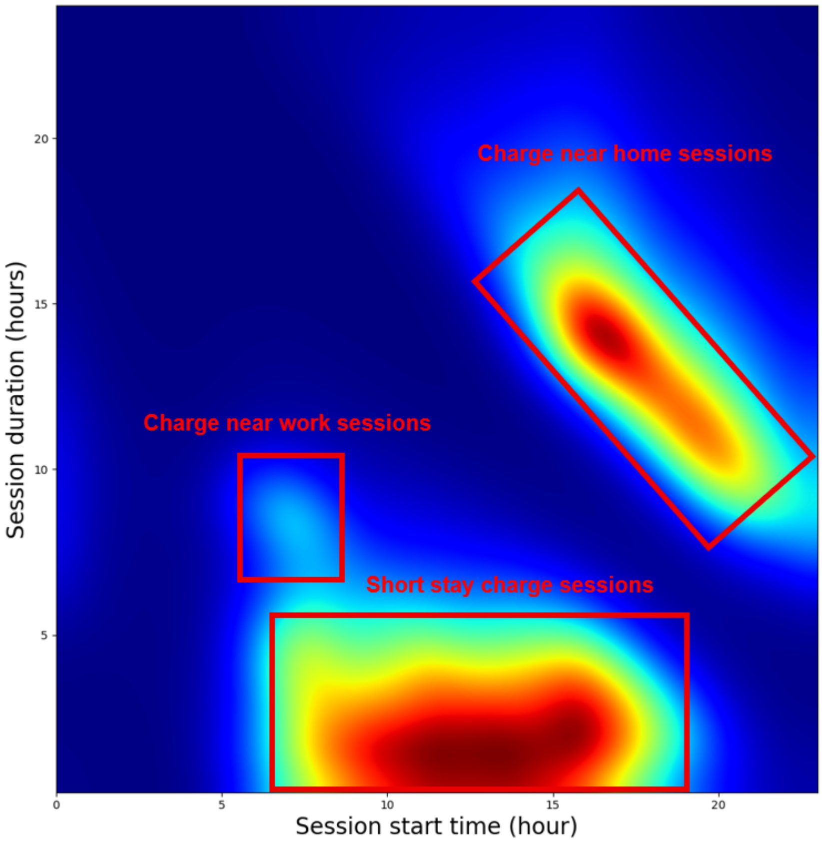

Figure 5.16: Heatmap for all the sessions in the dataset for the session start time and session duration

The first group, referred to as "short stay charge sessions," represents relatively short charging sessions (typically lasting less than 5 hours) initiated throughout the day. The second group of charging sessions, called "charge near work sessions," is characterized by sessions that begin in the morning between 6 am and 9 am and last for approximately 7 to 10 hours. Finally, the third group of charging sessions, known as the "charge near home sessions" group, describes charging sessions that begin in the late afternoon (around 4 pm) and last approximately 10 to 15 hours, typically conducted overnight.

5.1.7 Holidays

To assess whether there are any disparities in charging behavior when there is a national holiday, an analysis was conducted on historical sessions filtered on national holiday or not. As depicted in Figure 5.17, violin plots were generated to analyze the session duration and energy consumption for both non-holidays, represented by 0.0, and holidays, represented by 1.0.

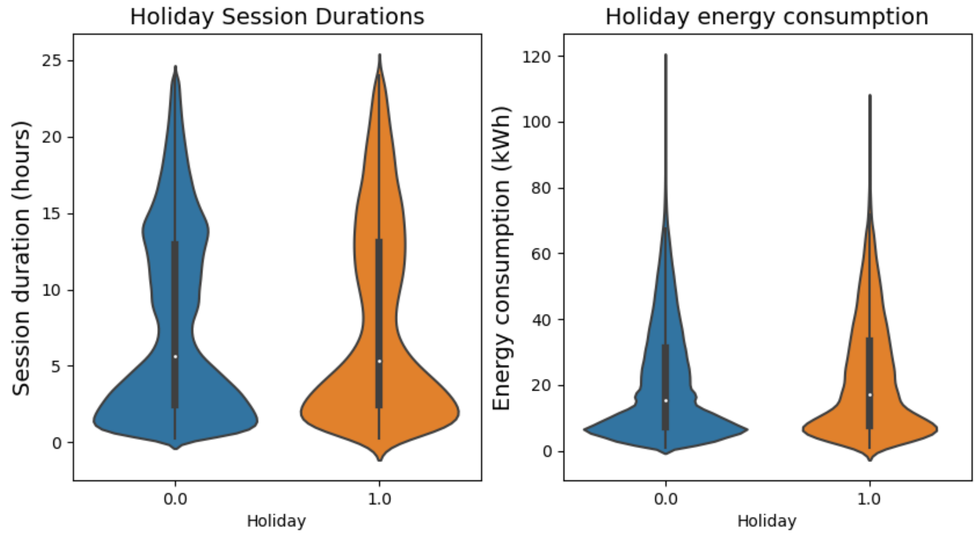

Figure 5.17: Violin plot that indicates if it is a holiday or not for the (a) sessions duration and (b) energy consumption

These violin plots show that the charging behavior shows little difference between national holidays and non-holidays. In addition, a plot has been generated to visualize the variation between the average session duration for the connection hour of the day, as illustrated in Figure 5.18. However, no significant variance can be observed from the plot.

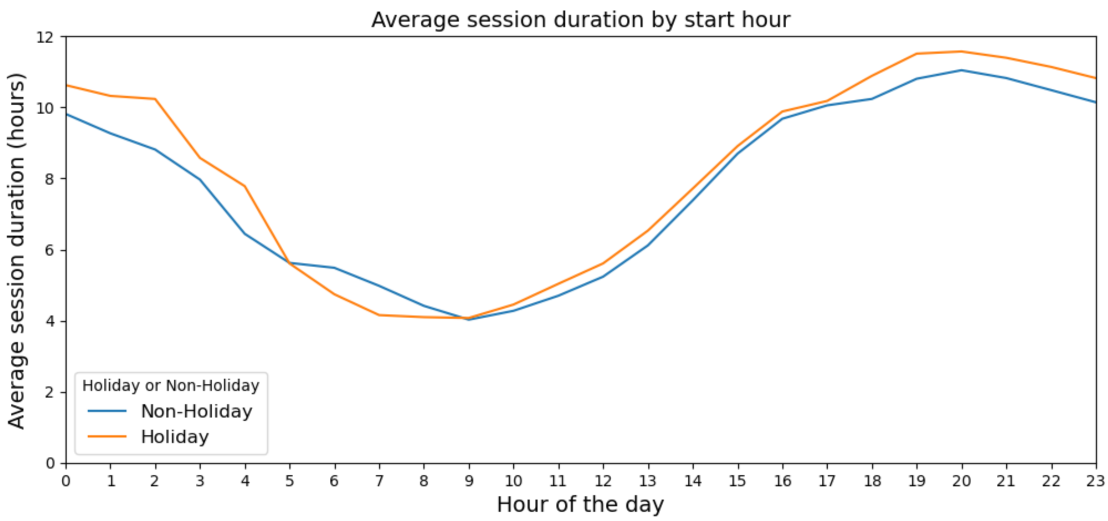

Figure 5.18: Average session duration for hour of the day separated for Non-Holiday and Holiday

5.1.8 Urbanization degree

Figure 5.19 depicts the distribution of the number of CPs across different levels of urbanization. The results reveal that the majority of CPs are concentrated in areas classified as having an urbanization degree of 2. However, for certain neighbourhoods in the Netherlands, information on urbanization degree was unavailable, and hence, represented as NaN. It is noteworthy that the neighbourhoods with an urbanization degree of 5 exhibit the least number of CPs. The geographic locations of CPs with their respective urbanization degrees are provided in Appendix D.

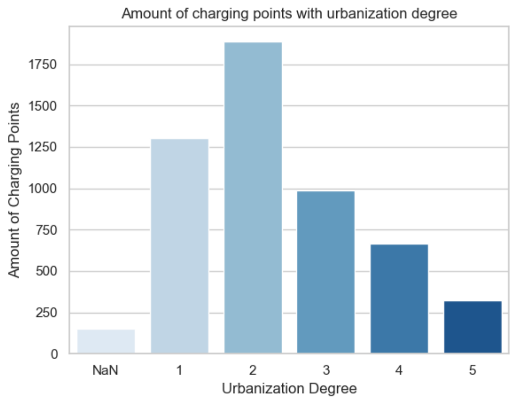

Figure 5.19: Countplot for the amount of charging points for each urbanization levels

Figure 5.20 presents box plots for session duration and energy consumption categorized by urbanization degree. Notably, an observable deviation is observed for degree 5, wherein the box plot for session duration displays lower quartiles and median. Furthermore, the box plot for energy consumption indicates that urbanization degree 1 exhibits lower energy consumption in comparison to other degrees.

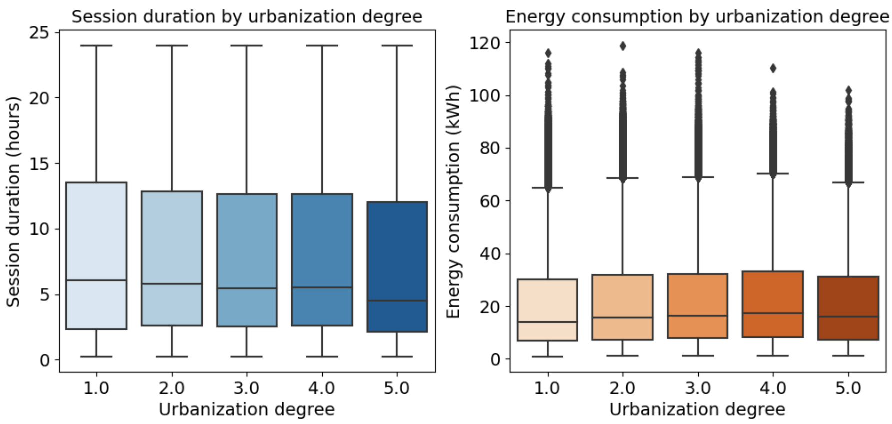

Figure 5.20: Boxplots for (a) session duration and (b) energy consumption for each urbanization degree

In order to obtain a comprehensive understanding of the charging patterns for charging stations across various levels of urbanization, density plots were constructed for each start and stop time, similar to those generated for different days of the week. These plots are provided in Appendix D. Closely examining the plots reveals that only urbanization degree 5 exhibits a discernible deviation from the other degrees. Nevertheless, the observed difference is relatively insignificant.

Chapter 6

Results

In Chapter 5 a data exploration was done on the used data set. This chapter will discuss the results for predicting the target variable's session duration and energy consumption on the explored dataset using XGBoost. This will be done by comparing the two units of generalization, namely Aggregated and CP cluster models and applying the MB feature selection approach. In addition, also the statistical method for determining the maximum charging power within a charging session will be presented. Subsequently, the variables session duration, energy consumption and maximum power will be used to predict the individual charging session flexibility. The feature importance will also be analyzed based on the interviews and survey with the EV experts and the mathematical approaches discussed in the methodology.

6.1 Clustering the charging points

The CPs were grouped according to a Rule-based clustering approach, as detailed in the methodology. Various threshold values, ranging from 0.6 to 0.9, were examined, and the outcomes of the various threshold values and the ten largest clusters are provided in Appendix E. Based on a brainstorming session with multiple EV experts within TotalEnergies, a threshold value of 0.08 was selected to achieve a proportionally balanced distribution across clusters. In total, 92 unique cluster patterns were identified from a possible 256 within the Charging Pool of TotalEnergies. The top ten clusters, containing 4555 CPs, accounted for 85.67% of all CPs in the dataset and were selected for further analysis based on their charging pattern. The top 10 cluster patterns generated using the Rule-based approach can be found in Appendix E.

Figure 6.1 presents the charging patterns of the ten most substantial clusters, as determined by the start and stop times of the charging sessions. Using density plots, it is possible to discern distinct subgroups of public chargers. In this research the proposition is made to name the subgroups the following: Hybrid, Home, Work, and Short Stay clusters.

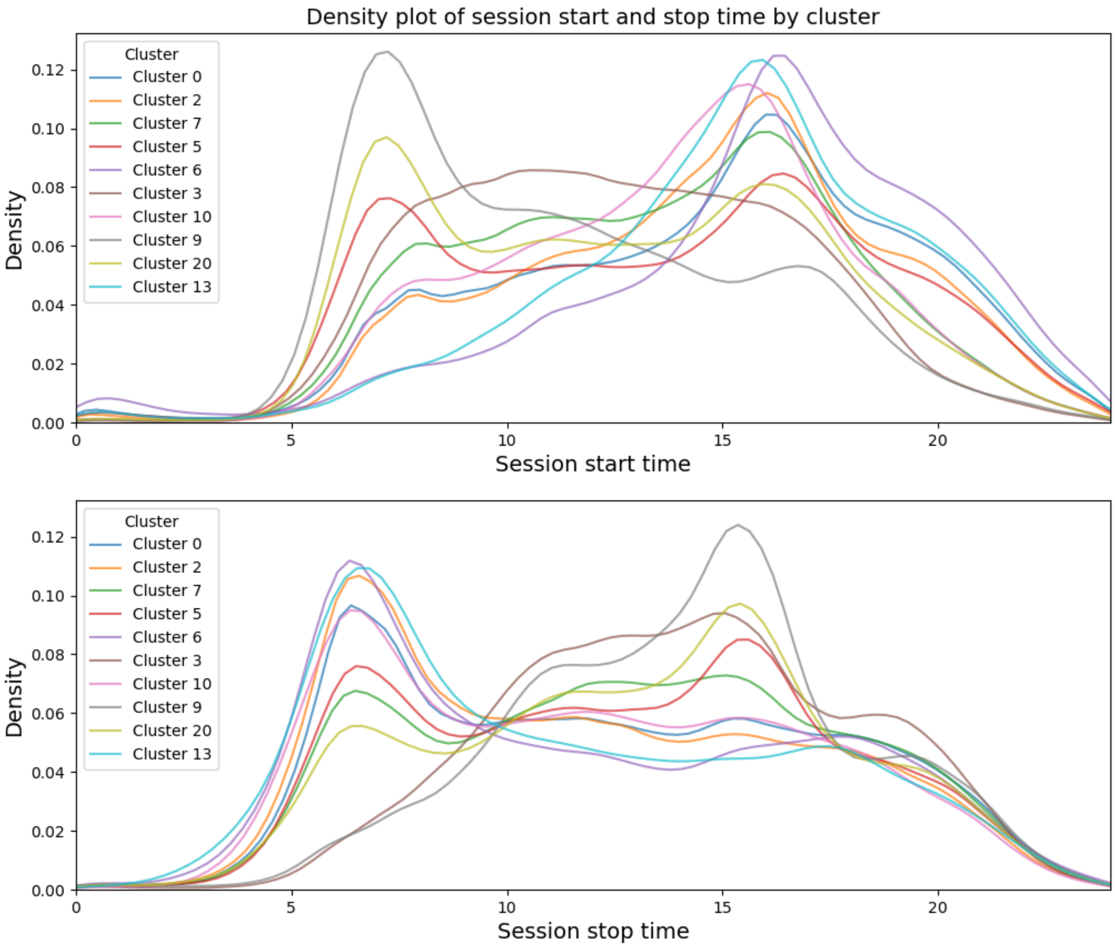

Figure 6.1: Density plot of the (a) start time and (b) stop time for each cluster

Hybrid public chargers are utilized for diverse charging requirements, encompassing prolonged overnight home charging sessions, work sessions and short charging sessions during the day. The Home subgroup predominantly has extended charging sessions that commence later in the evening. In contrast, the Work subgroup mainly comprises charging sessions initiated in the morning and are aligned with the conventional 9-5 working pattern. The Short Stay chargers are primarily used for short charging sessions and may be situated in locations like shopping centers.

A heat plot, similar to the one generated for all charging sessions (Figure 5.16), has been produced for each cluster by grouping all the charging sessions within each cluster. The heat plots, located in Appendix E, demonstrate distinct variations among the different clusters.

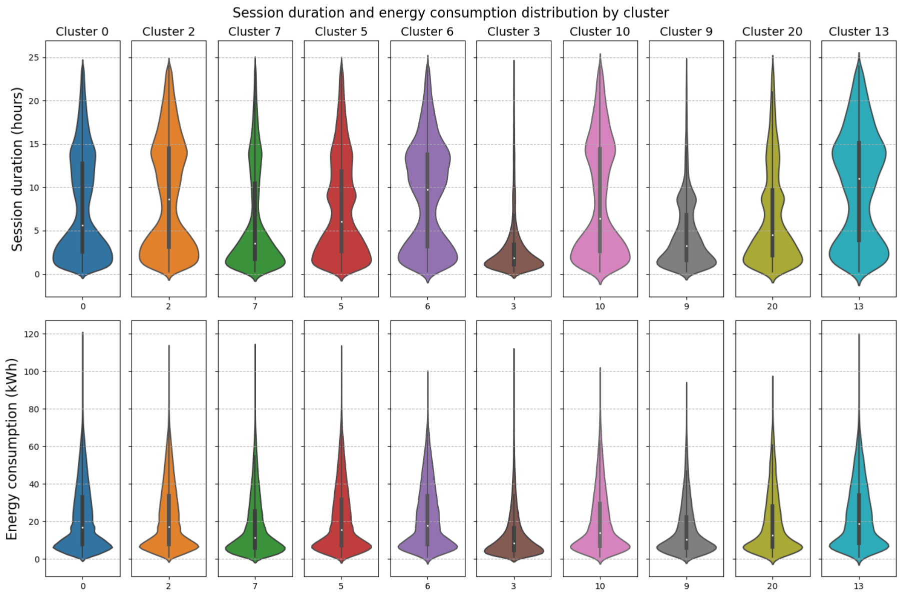

Figure 6.2: Violin plots for the session duration and energy consumption for each cluster

Table 6.1 presents the descriptive variables for the different Clusters. The data reveals that the Hybrid subgroup represents the largest share of the CPs within TotalEnergies' Charging Pool. Additionally, Cluster 3 exhibits a comparatively lower mean session duration and energy consumption.

Table 6.1: Description of the different charging point clusters

Cluster	Amount CPs	Amount CDRs	Mean session duration	Mean energy consumption	Subgroup
0	2283	1,098,625	7.99	22.71	Hybrid
2	824	445,370	9.31	22.95	Hybrid
7	307	131,885	6.43	18.76	Hybrid
5	288	172,093	7.80	21.95	Hybrid
6	232	78,579	9.31	22.93	Home
3	160	82.518	3.39	14.10	Short stay
10	147	63,542	8.86	20.62	Hybrid
9	111	47,244	4.77	16.73	Work
20	107	51,028	6.73	20.02	Work
13	95	34,736	10,40	23.41	Home

6.2 Prediction of session duration

Table 6.2 displays the evaluation metrics for the session duration prediction using the aggregated model without the MB feature selection approach. In Table 6.3 the evaluation metrics obtained using the MB feature selection approach with the aggregated model are presented.

Table 6.2: Aggregated Session duration model **without MB** results

Metric	Validation	Test
MAE (hours)	3.275	3.324
MSE (hours)	21.254	21.741
SMAPE (%)	47.9	50.37
Training time	1714 seconds	
Evaluation time	0.265 seconds	

Table 6.3: Aggregated Session duration model **with MB** results

Metric	Validation	Test
MAE (hours)	3.282	3.313
MSE (hours)	20.817	21.100
SMAPE (%)	49.6	50.0
Training time	553 seconds	
Evaluation time	0.094 seconds	

From these results it can be seen that the evaluation metrics are not substantially improved with the MB feature selection approach. Utilizing the MB feature selection approach or otherwise, the MAE, MSE and SMAPE show similar results. The metrics for the test data set are highly equivalent to the validation metrics, indicating that the model does not demonstrate overfitting tendencies. This means that the model generates comparable predictions for data not explicitly fitted for the hyperparameters that can be found in Appendix F.

However, the training time is reduced significantly by 67.7% with the MB approach. Repeating the model training process in the short term is unnecessary, but it may offer benefits in terms of complexity reduction. As the metrics presented in the tables above provide limited information about the direction of the errors, a histogram plot was created to further analyze the errors. Figure 6.3 displays the aforementioned plot.

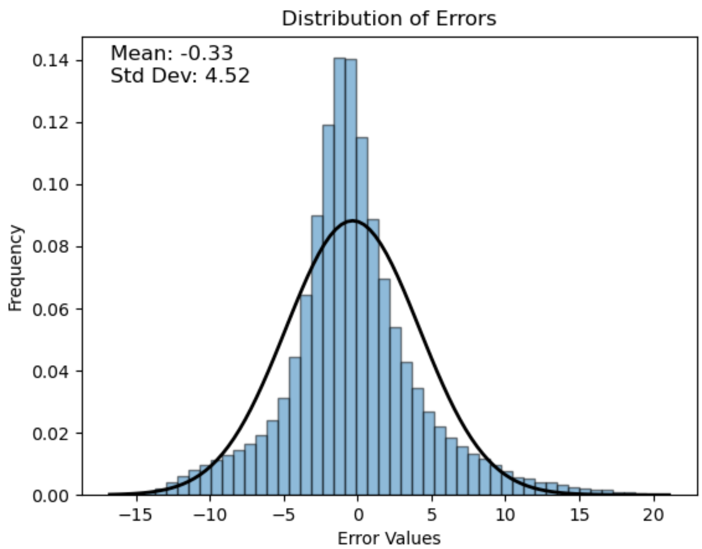

Figure 6.3: Histogram of the distribution of errors for prediction the session the duration using the aggregated model with MB

To calculate the errors, the predicted value was subtracted from the actual value for each charging session. The resulting errors exhibit a normal distribution, demonstrated in a normal plot where the mean and standard deviation are indicated.

The normal distribution of the errors suggests that the model tends to both underestimate and overestimate session duration proportionally. In addition it indicates that most errors are concentrated around the mean of the errors, with fewer errors further away from the mean. This could suggest that the model generally performs well but occasionally makes significant mistakes. The hyperparameters that were selected during the hyperparameter fitting with the validation data can be found in Appendix F. Notably, for the session duration predictions, experiments were also done with several random splits, which resulted in similar evaluation metrics, underscoring the robustness of the proposed training, validating, testing approach.

6.2.1 Session duration feature importance aggregated approach

The feature importance without the MB feature selection approach using the SHAP package in Python is depicted in Figure 6.4.

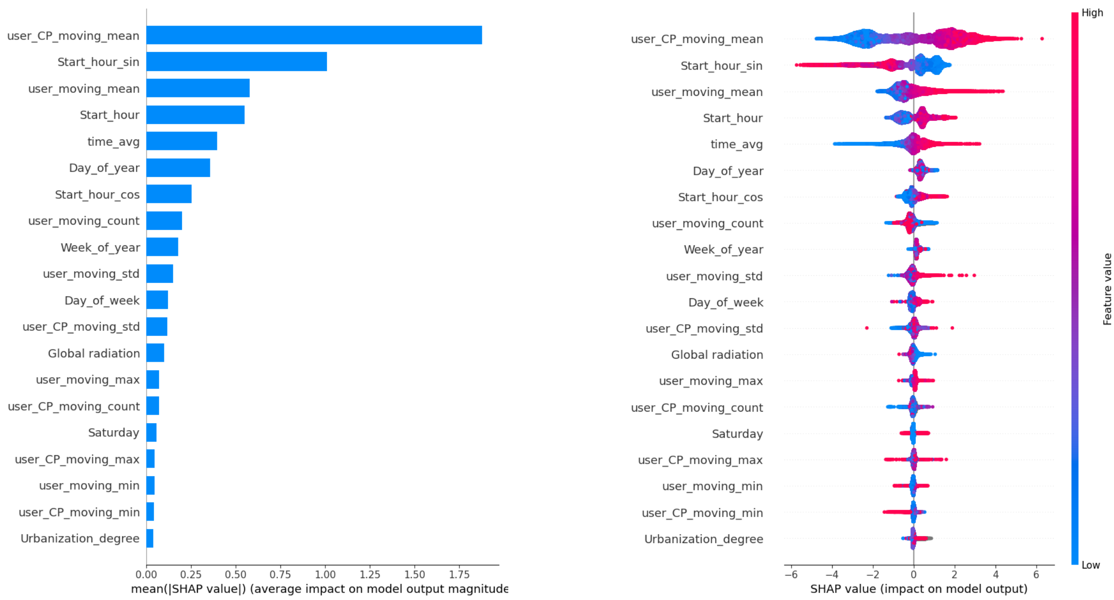

Figure 6.4: Feature importance for the aggregated session duration prediction model

Figure 6.4 shows that mainly the historical sessions of the user on a specific CP are important in combination with the start time. On the right side of the figure is a plot called the Beeswarm SHAP plot. From this, it can be deduced what a larger feature value (i.e. higher feature values are red) does for the prediction. It can be seen that, logically a higher historical mean yields a higher prediction. It can also be seen that a higher moving count yields a lower prediction. This is could be explained by the fact that a EV user often does a shorter sessions.

The features that the MB approach has selected for the aggregated session duration model and their importance can be found in Figure 6.5.

Figure 6.5 shows that the MB approach has selected three features: the historical duration of the user ID in combination with the CP ID, the start time of the session and the historical session duration of the user ID. These features are also the most relevant ones according to Figure 6.4. The same accuracy can be achieved with only three features compared to using all the features that were selected in the methodology. As seen in the Beeswarm plot on the right, the higher the start hour of the session, the higher the predicted

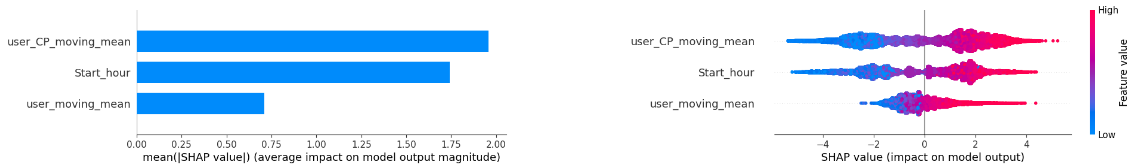

Figure 6.5: Feature importances for the aggregated session duration prediction model with MB

session duration. This can be linked to overnight sessions that start in the evening. Given the reduction of training time and complexity, the MB approach model will be used for the Cluster approach.

6.2.2 Session duration prediction for each Cluster

In Section 6.1, several clusters were identified, each with their unique charging patterns. A distinct model was trained and assessed for each cluster by segmentation of the data for all the CPs that are present in the top ten clusters. In addition, the MB feature selection approach was used for each cluster separately. The predictions of these models were then compared to those of the aggregate model based on the test data. The results of the comparison between generalization approaches can be found in Table 6.4.

Table 6.4: Results of two approaches for session duration prediction with 10 Clusters on test data

Cluster	**Aggregated model**			**Cluster approach models**		
	MAE	**MSE**	**SMAPE (%)**	**MAE**	**MSE**	**SMAPE (%)**
0	3.363	21.311	48.72	3.320	21.181	50.06
2	3.812	26.476	48.17	3.806	25.992	50.12
7	2.933	17.511	50.18	2.809	17.101	51.47
5	3.119	18.466	46.25	3.100	18.618	48.27
6	3.602	23.228	47.03	3.641	23.685	49.22
3	2.088	8.663	58.82	1.572	7.255	46.51
10	3.826	27.224	51.00	3.789	26.389	52.92
9	2.340	9.977	51.49	2.074	9.508	48.68
20	3.017	18.099	48.60	2.869	17.670	49.44
13	4.117	29.489	47.75	4.119	28.549	49.95
Overall	3.382	21.654	48.86	3.305	21.212	49.89

Table 6.4 demonstrates significant prediction disparities among various clusters within the Aggregate approach as well as the Cluster approach. Notably, Cluster 13, belonging to the subgroup of Home chargers, exhibits the largest MAE deviation of 4.117 hours. Conversely, Cluster 3, comprising of Short Stay chargers, displays a considerable better prediction compared to the other clusters, presenting an MAE of 2.088 hours with the aggregated approach. This can explained by the mean session duration of Cluster 3, which is notably lower in comparison to the remaining clusters, as presented in Table 6.1.

The segmentation of data for each cluster further enhances the predictive capabilities, leading to a improvement in MAE, particularly in Cluster 3 and 9, exhibiting improvements of 24.7% and 7.4%, respectively. The overall improvement between the Aggregated approach and the Cluster approach is negligible, as the MAE shows a modest improvement, from 3.382 to 3.305. This modest improvement can be traced back to the large number of CPs in the subgroups Hybrid and Home, with little to no improvement in the prediction accuracy. Conversely, the overall SMAPE demonstrates an small increase from 48.86% to 49.89%, indicating an small increase in the mean deviation from the predictions.

Similar to the Aggregate approach illustrated in Figure 6.3, histograms with the corresponding errors were generated for each cluster. These histograms and the hyperparameters chosen for each cluster can be found in the Appendix G. The same normal distribution of the errors can be observed for the Cluster approach.

In addition, the MB feature selection approach was employed for each cluster model, with the selected features and their feature importance specified in Appendix G. Notably, distinctive features were occasionally chosen for each cluster to supplement those of the aggregate model. For instance, Cluster 3 and Cluster 9 encompassed the inclusion of the user's historical maximum session duration value. In Cluster 13 and Cluster 20, the features denoting the weekend or Saturday were observed to impact the prediction.

A density curve of the predicted and actual session duration values was constructed to obtain a more comprehensible understanding of the predicted session duration values, as shown in Figure 6.6.

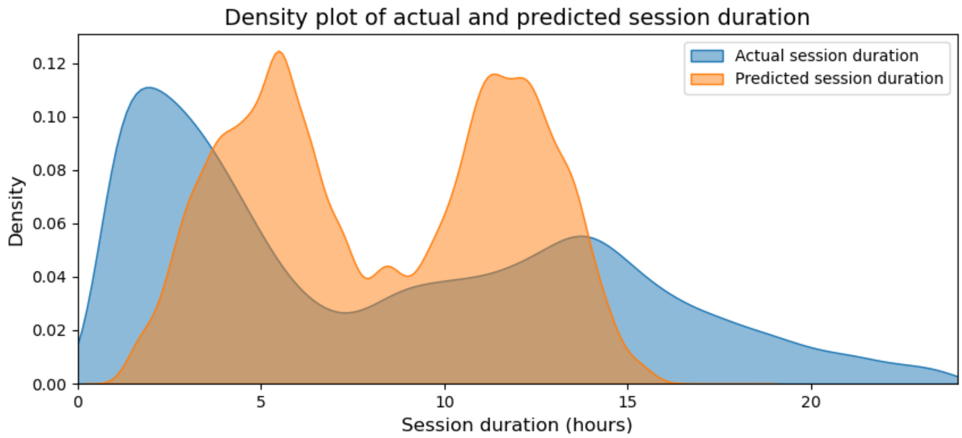

Figure 6.6: Density curve for the session duration on the test data

The XGBoost model appears to under predict the long charging sessions (more than 15 hours), while shorter charging sessions (less than 5 hours) are predicted to take a longer time. Notably, there is no prediction made where charging sessions lasting approximately more than 15.5 hours, which could be due to such sessions being classified as outliers, and the model's goal of minimizing the average deviation.

6.3 Prediction of energy consumption

The evaluation metrics results of the energy consumption prediction with the Aggregated approach without and with the MB feature selection approach are presented in Table 6.5 and Table 6.6. For both models, there seems to be a reasonably high deviation between predicted and actual energy consumption. With an MAE of around 7.2 kWh and a mean energy consumption of 21.80, this is reasonably high. It is notable that the test data set yields better results than the validation data set. However, this improvement is too small to be significant. Both the aggregated model with and without the MB approach show comparable results. Similar to the results regarding session duration prediction, there is a significant improvement in training time. For the energy consumption predictions, experiments were also trained, validated and tested with several random splits, which resulted in similar evaluation metrics.

Table 6.5: Aggregated energy consumption model **without MB** results

Metric	Validation	Test
MAE (kWh)	7.248	7.234
MSE (kWh)	111.847	111.048
SMAPE (%)	35.0	35.2
Training time	1628 seconds	
Evaluation time	0.285 seconds	

Table 6.6: Aggregated Energy consumption model **with MB** results

Metric	Validation	Test
MAE (kWh)	7.281	7.224
MSE (kWh)	112.455	112.762
SMAPE (%)	35.5	35.3
Training time	563 seconds	
Evaluation time	0.108 seconds	

Similar to the session duration prediction there is limited insight offered by the metrics presented in the preceding tables regarding the error's direction. A histogram plot was generated to provide insight into the direction of the errors. This plot is depicted in Figure 6.7

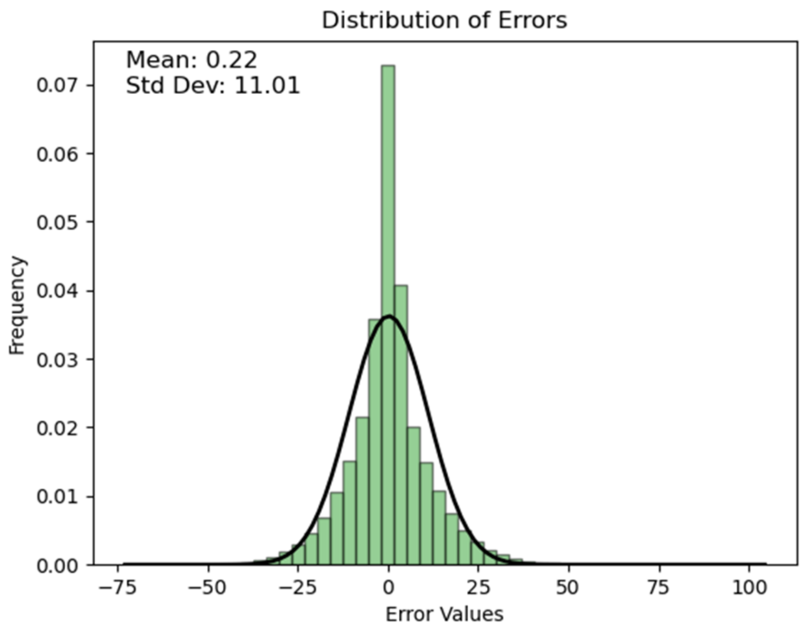

Figure 6.7: Histogram of the distribution of errors for prediciton the session the duration using the aggregated model with MB

6.3.1 Energy consumption feature importance aggregated model

The feature importance without the MB approach for the energy consumption using the SHAP package in Python is presented in Figure 6.8. The features are ranked based on their relative importance for the prediction of the energy consumption at the start of the charging session. This ranking is determined by the mean SHAP value which is the average contribution of a feature across all possible coalitions of features in a model.

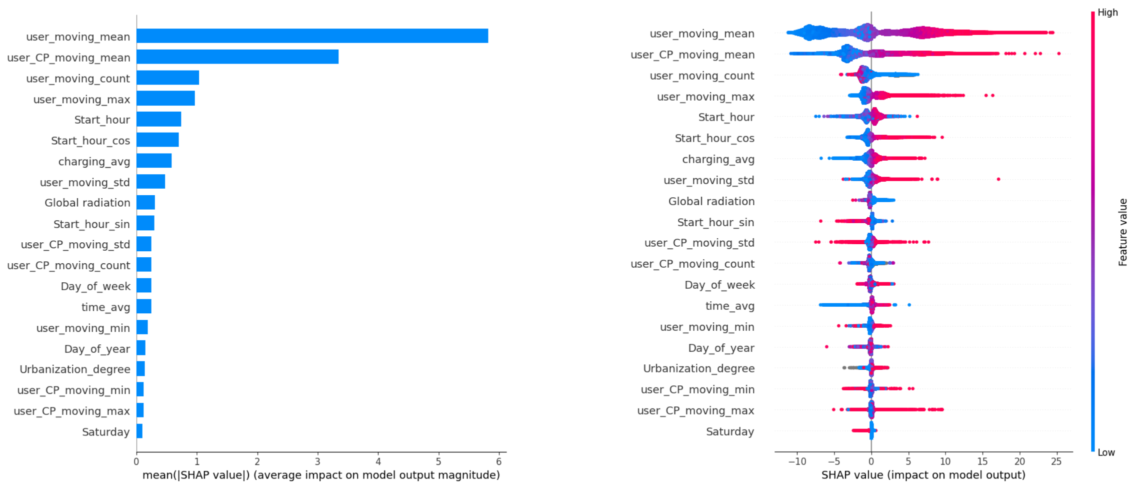

Figure 6.8: Feature importance for the aggregated energy consumption prediction model

Figure 6.8 shows that the historical mean energy consumption of the EV user is by far the most important feature, followed by the historical average energy consumption for the user ID on the specific CP. In addition, the count of the historical sessions and the maximum energy consumption are also important features. It is notable that the degree of urbanization where the CP is located or one of the weather variables do not appear to have a impact on the prediction.

Figure 6.9 illustrates the selected features and their respective importance for the Aggregated approach session duration using the MB feature selection approach.

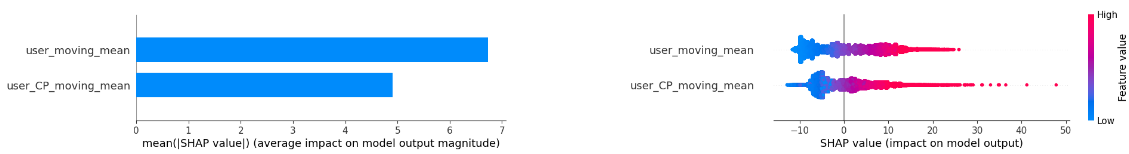

Figure 6.9: Feature importance for the aggregated energy consumption prediction model with the MB approach

The MB feature selection approach only selected the user_moving_mean and user_CP_moving_mean for training the XGBoost model. This suggests that the MB approach did not detected a causal relationship between the remaining features in the Aggregated approach. Among the features, the average energy consumption of the EV user, coupled with that of a particular CP, was found to be important in contrast to other features. This observation is explainable, given that it provide insight into to the EV's battery capacity. Given the reduction of training time and complexity, the MB feature selection approach was chosen.

6.3.2 Energy consumption prediction for each Cluster

As with the session duration is prediction, the unit of generalization of the CP cluster is also used for the prediction of energy consumption. The results per cluster for the Aggregated approach and the CP Cluster approach can be found in Table 1. Again, the MB feature selection approach and hyperparameter tuning have been applied for each model separately.

Table 6.7: Results of two approaches for energy consumption prediction with 10 Clusters on test data

Cluster	Aggregated model			Cluster approach models		
	MAE	MSE	SMAPE (%)	MAE	MSE	SMAPE (%)
0	7.282	113.309	32.60	7.057	106.688	31.76
2	7.348	115.159	32.37	7.184	110.170	31.61
7	6.879	101.786	35.47	6.493	97.393	31.99
5	7.187	112.542	32.47	7.120	112.560	30.94
6	7.390	115.725	32.76	7.286	114.937	31.75
3	6.470	87.378	43.82	4.532	57.379	29.62
10	6.884	102.459	33.76	6.740	100.852	32.53
9	6.424	91.524	37.24	5.536	80.268	28.72
20	6.920	109.889	34.73	6.403	100.437	30.76
13	7.756	123.854	34.11	7.801	127.399	34.13
Overall	7.217	111.628	33.26	7.001	106.625	31.65

Table 6.7 showcases the same results between the clusters as the session duration predictions among the various clusters. A disparity between the clusters is present in the Aggregated approach and the CP Cluster approach. The worst score on all evaluation metrics is also achieved in Cluster 13, which is categorized as the Home CP cluster. Furthermore, the best scores are achieved in Cluster 3 and 9, which are the Short Stay and Work chargers. The segmentation and training of separate models also seem to yield the most benefit for these latter clusters. The MSE for Cluster 3 and Cluster 9 is improved with 34.42% and 12.29%, respectively. The overall improvement between the Aggregated approach and the Cluster approach is more prominent in the energy consumption than the session duration. All the evaluation metrics show improvements, whereas the MAE shows an improvement from 7,217 kWh to 7,001 kWh. Still, the improvement varies a lot per cluster.

Similar to the Aggregated approach illustrated in Figure 6.3, histograms with the corresponding errors were generated for each cluster. Appendix H shows these histograms and the hyperparameters chosen for each cluster. The same normal distribution of the errors can be observed for the Cluster approach.

In addition, the MB feature selection approach was employed for each cluster model, with the selected features and their feature importance specified in Appendix H. Notably, distinctive features were occasionally chosen for each cluster to supplement those of the aggregate model. It is striking that for each cluster to the historical user moving mean for energy consumption and the user and CP combination also, the start hour is selected within all the clusters. This is different from the aggregated model, where only the first two mentioned were selected.

A density curve of the predicted and actual energy consumption values was constructed to obtain a more comprehensible understanding of the predicted energy consumption values, as shown in Figure 6.10. The density curve shows that the sessions with high kWh energy consumption are not correctly predicted.

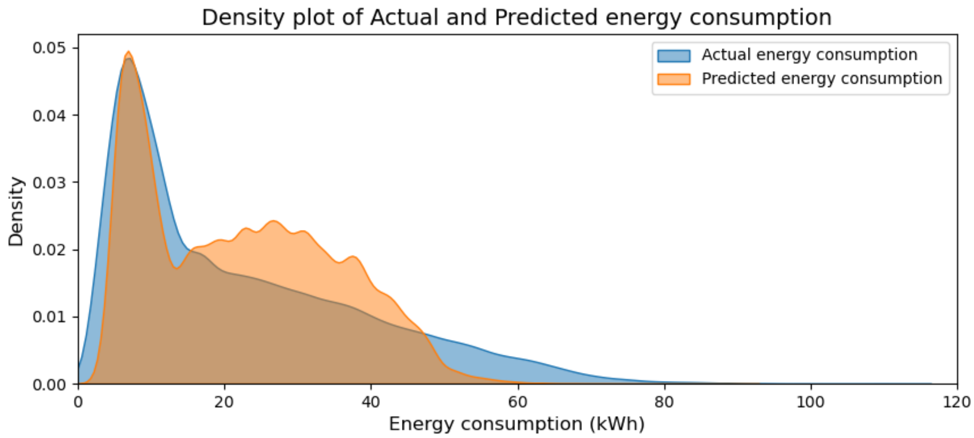

Figure 6.10: Density plot of the distribution of the actual and predicted energy consumption using the aggregated model with MB

6.4 Feature importance survey results

This subsection will discuss the results of the survey sent to the EV experts about their view on feature importance for session duration and energy consumption. The background of the respondents can be found in Appendix J. To obtain a comprehensive understanding of the survey results the average score was calculated based on the responses. The findings related to the session duration are presented in Figure 6.11.

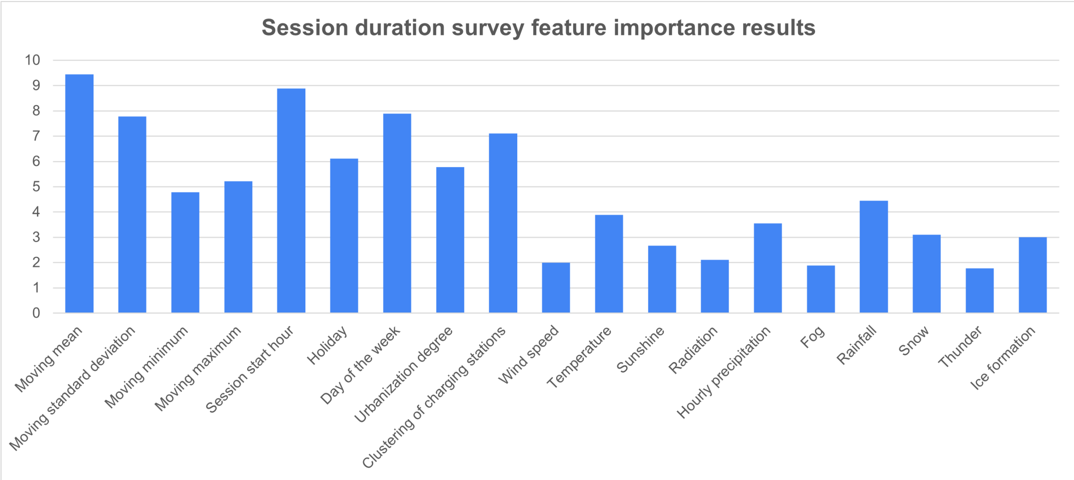

Figure 6.11: Histogram of the average feature importance for the session duration indicated by the EV experts

Figure 6.11 shows that the EV experts expect the moving mean, session start hour and the day of the week to be the most important features for session duration. It is also noteworthy that the correspondents expect that the weather variables will not be important independent variables. The estimates of the EV experts are very similar to the outcomes of the feature importance from the ML model, which can be found in Section 6.2.1. In addition, the MB approach has selected the EV user's historical mean, the EV with the CP user's historical mean and the start hour.

The findings related to the energy consumption survey are presented in Figure 6.12.

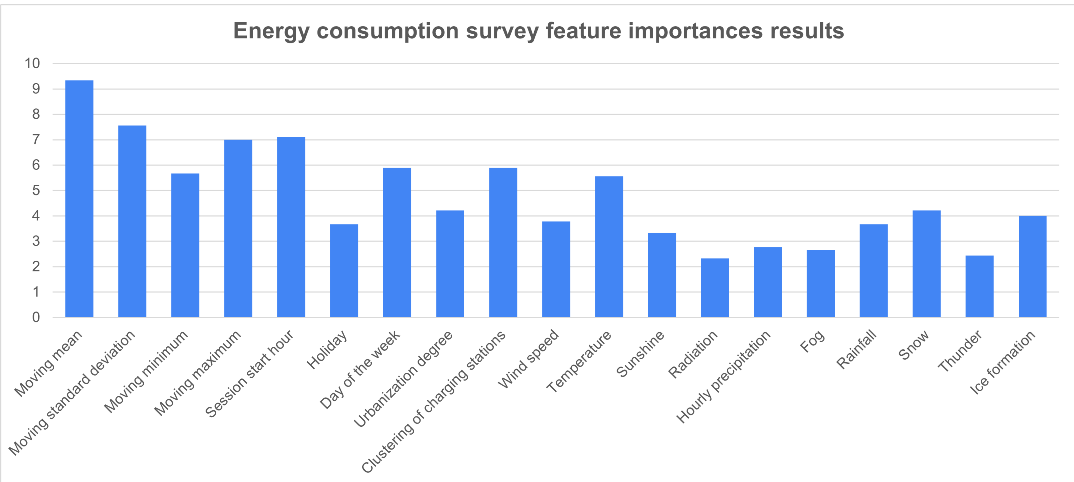

Figure 6.12: Histogram of the average feature importance for the energy consumption indicated by the EV experts

As shown in Figure 6.12, the EV experts' expectations for the feature importance of energy consumption are very similar to those of session duration. However, some differences stand out and are worth mentioning. For example, the EV experts estimate the moving minimum and the moving maximum of the EV user to be higher. This was also reflected in the interviews and can be explained because this information can say something about the size of the battery in the EV. The EV experts also see the temperature as more important in the energy consumption prediction than in the session duration prediction. This can be explained by the fact that the charging speed is lower at lower temperatures. The EV experts expect that the start hour of the session will have less influence on the energy consumption than the session duration. This is also the same conclusion that comes back in Section 6.3.1. Here, the start hour of the session is less relevant for the energy consumption within an individual charging session. These are also the same features that the MB approach has selected. This shows that the EV experts have good insights into independent variables that could be important for predicting energy consumption.

To conclude the survey the EV experts could submit any information or features they thought are essential to consider when predicting session duration or energy consumption with information available at the start of the charging session as indicated in the methodology. This resulted in the following suggestions:

- Is there a feature that you would add which was not mentioned? Why do you think this feature could be important?
  - Average session time on charging pole
  - Entropy of charging pole
  - Entropy of charging time duration
  - Neighborhood Income
  - Electricity Price
  - Price per kWh at specific charging station/price difference other charging stations
  - Distance to other charging stations with different pricing
  - Connection tariffs
  - Smart charging benefits for end-users
  - Amount of jobs and facilities in the neighbourhood where the charging station is located
  - Flexibility

The first suggestion with the average session time on the specific charging pole was adopted within the ML model with the addition of the feature called User_CP_Moving_mean. In this feature the historical mean of the session duration or energy consumption was calculated based on the user ID and CP ID. The other suggestions could be taken into account in future research.

6.5 Prediction of Pmax

The results for predicting the maximum charging rate at the start of a charging session based on historical sessions can be found in Table 6.8.

Table 6.8: Predicting Pmax results

Metric	Validation	Test
MAE (kW)	0.98	1.00
MSE (kW)	5.24	5.25
SMAPE (%)	12.64	12.87

Based on the evaluation metrics, it can be seen that the maximum power can be predicted reasonably well. With a MAE of 0.98 in the validation set and a 1.00 in the test set. An MSE of 5.24 and 5.25 and a SMAPE of 12.64% and 12.87% also indicate no major deviations in the actual Pmax and predicted Pmax.

Figure 2 also shows that the maximum power charged during a charging session can be accurately predicted using Equation . The Figure shows a density plot of the actual max power (blue) and the predited max power (orange).

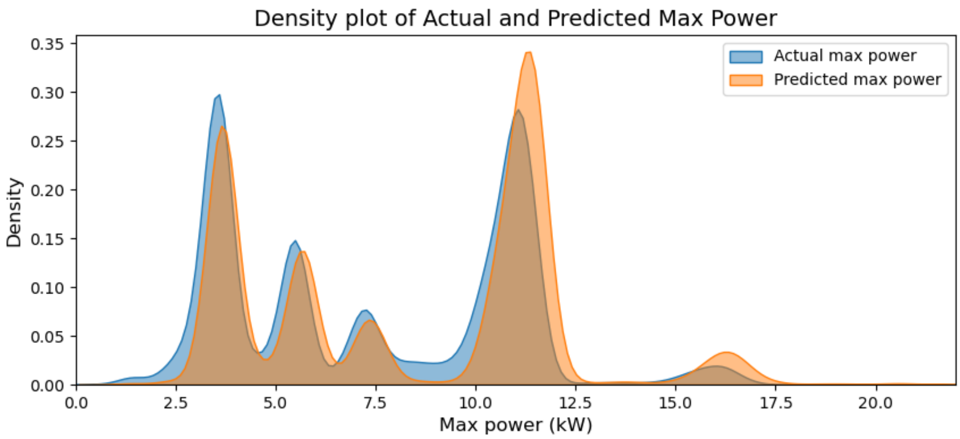

Figure 6.13: Density plot for the actual and predicted max power within a charging session

When analyzing the figure, it can be seen that the maximum power is reasonably accurately predicted. It can be seen that when the maximum power is not predicted correctly, it almost always overestimates the maximum power rate. This can be explained by load balancing between the EVSEs at a CP.

6.6 Determining the individual charging session flexibility

The variables session duration, energy consumption and maximum charging power are predicted, as seen in the previous sections. In this subsection, the charging duration will first be determined for the validation and test data based on the predicted variables energy consumption, the maximum charging power and Equation 3.5. Subsequently using Equation 4.6 the time flexibility will be determined. The results for the prediction of time flexibility can be found in Table 6.9. Once the time flexibility has been established, the flexibility of each charging session for an individual is derived by multiplying the energy consumption by the time flexibility. Both the predicted and actual values are subjected to this calculation. The evaluation metrics that indicate the results can be found in Table 6.10.

Table 6.9: Determining t_{flex} results

Metric	Validation	Test
MAE (hours)	3.123	3.152
MSE (hours)	18.556	18.905
SMAPE (%)	85.50	85.65

Table 6.10: Determining flexibility results

Metric	Validation	Test
MAE (kWh^2)	82.106	83.324
MSE (kWh^2)	18,245	18,711
SMAPE (%)	90.86	91.24

It is worth noting that the evaluation metrics for time flexibility are better than the prediction of the session duration. Figure 6.14 shows the density plot for actual and predicted time flexibility values for the test data. This is similar to the session duration prediction, where all when all the charging sessions are aggregated a low time flexibility is overestimated and a high time flexibility is underestimated.

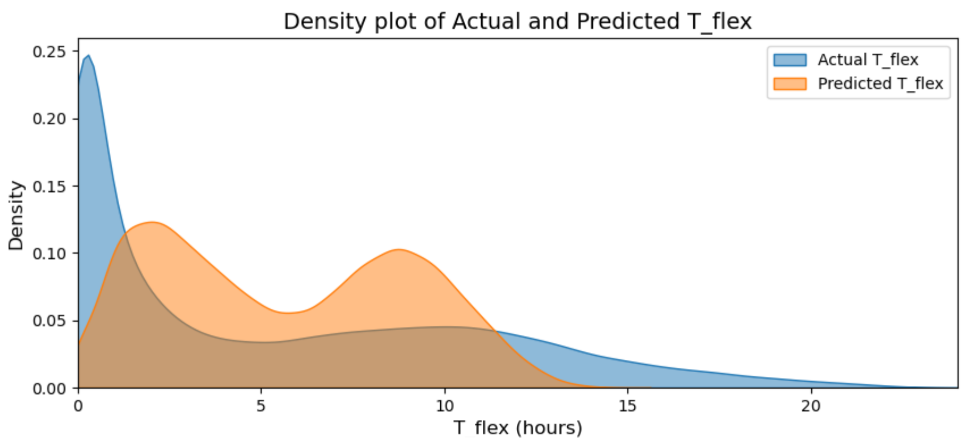

Figure 6.14: Density curve for the time flexibility on the test data

In conjunction with the evaluation metrics for the flexibility prediction, a histogram was generated to represent the distribution of errors. This plot can be found in Appendix I. As depicted in the figure, the model exhibits a tendency to both overestimate and underestimate the flexibility of the individual charging sessions. This suggests that the model may be biased towards certain types of charging sessions or that some underlying factors are not accounted for in the model.

Figure 6.15 displays a density plot depicting all charging sessions collectively. The plot suggests that the model's predictions for flexibility are improved significantly when aggregated.

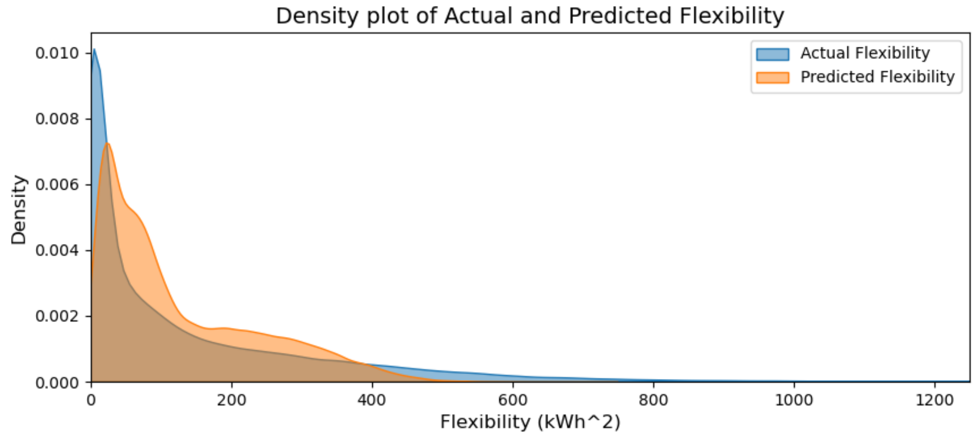

Figure 6.15: Density curve for the flexibility on the test set

This has been further investigated and it appears that due to the normal distribution of the errors, the aggregated flexibility during the day can be predicted well. This can also be shown when plotting the aggregated flexibility, grouped for each hour of the day using the test set (Figure 6.16). Here the blue line represents the actual flexibility and the orange line the predicted flexibility for each hour of the day. In this figure it is interesting to see that the errors within individual sessions cancel each other out in the aggregated flexibility throughout the test set. This is relevant information for the system operator who would like to know the aggregated flexibility. Nevertheless, when it comes to managing individual charging sessions from a centralized outlook, it does not hold much practical value.

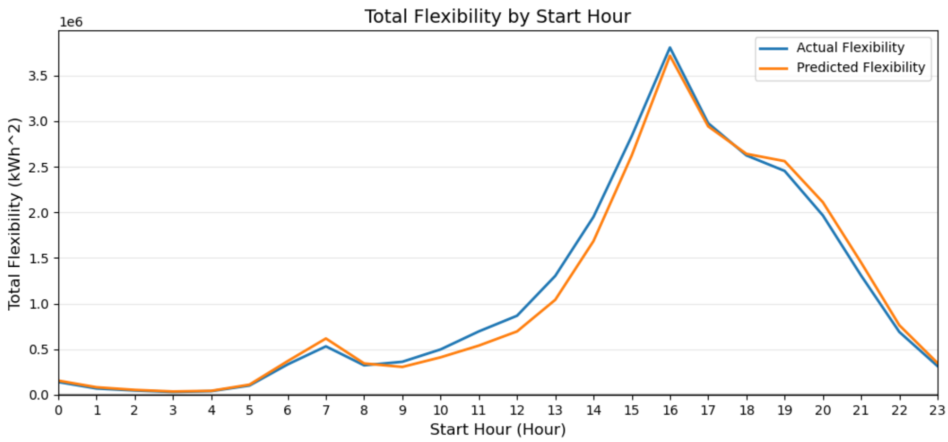

Figure 6.16: Line plot for the actual and predicted aggregated flexibility on the test data set

6.7 Chapter summary

In this chapter the CPs were grouped based on their charging profile and put into subgroups, the session duration was predicted, the energy consumption was predicted, the maximum charging power was predicted, the generalization units were compared, and the flexibility within charging sessions was quantified. In the next chapter, the results will be discussed and compared to the current literature, the limitations will be presented, and recommendations will be made.

Chapter 7

Discussion

In the previous chapter, the results of the described methodology were presented. In this chapter, the significance and implications of the obtained results will be discussed. First, the results will be compared to the current literature for predicting session duration, energy consumption and charging session flexibility. Subsequently, the research's limitations will be discussed and recommendations will be made for future academic research and for practical implications.

7.1 Discussion of the results

7.1.1 Charging duration

First the results on the session duration prediction will be compared to the current literature. In the paper from Shahriar et al. [20], an MAE of 66.5 minutes was obtained which is around 1.1 hours. This significantly lower than the overall MAE of around 3.3 hours for the session duration predictions in this thesis. The explanation for this difference is that the authors in [20] incorporated the ML model on only one CP which is located at a University. Therefore this EVSE is mainly used for "work" charging sessions which can be concluded since there are zero to no sessions recorded in the weekend. Work chargers are generally less complex to predict since there are not a lot of overnight sessions, which result in smaller errors. In this thesis, a considerable number of public EVSE were utilized in the data set. It presents a challenge to differentiate between overnight charging, short charging sessions, and work sessions when all of these charging sessions take place with these public EVSE. When considering specific clusters of CPs from this thesis, such as Cluster 3 or 9, which are classified as Short Stay and Work CPs, the degree of deviation is notably lower (around 1.5 hours). Nevertheless, it is still realistic that EV owners could leave their vehicles plugged in overnight at these CPs.

Chung et al [54] obtained an MED of 1.16 hours for the session duration prediction. This is a median of the absolute errors instead of the mean, which reduces the presence of large outliers in the evaluation metric. In addition, from the paper it can be found that the average duration of a charging session is 3 hours, with no charging sessions over 6 hours. Therefore the study from [54] does not provide a good comparison with our results.

De Witte [22] obtained an MAE around 3.3 hours for the prediction of session duration of a large amount of public CPs. This is in line with the results obtained by the aggregated model that was used during this research. However, it remains difficult to compare different charging session data sets.

7.1.2 Energy consumption

Although compared to the current literature, this study's aggregated energy consumption prediction also appears to be underperforming, this can logically be explained. In the study from Almaghrebi [53] an MAE of 4.57 kWh was obtained compared to around 7 kwh in this thesis. This lower evaluation metric can be attributed to the mean energy consumption that is much higher in the data set used in this thesis. Because more recent data has been used in this study, there is a higher mean energy consumption throughout charging sessions. This can be explained by the fact that more and more EVs are entering the market with larger batteries. This higher mean energy consumption can cause a more significant prediction deviation.

7.1.3 Clustering

The clustering of CPs can be compared to the paper of Straka et al. [7]. A substantial portion of the CPs in our data set can be found in the top 10 clusters (85.67%). This is comparable with the paper from Straka et al., where around 75% of all the CPs were present in the top 10 CP clusters. Concerning predicting charging behavior using a separate ML model for each cluster, there is no comparison to be made with current literature since this is a novelty. For the prediction the overall improvement with the Cluster approach to the Aggregated approach is neglectable since a lot of Hybrid subgroups were identified. However, in certain clusters that are defined by subgroups Work and Short Stay chargers the improvement is significant.

7.1.4 Feature importance

The results of this thesis demonstrate that the historical mean for the user ID and the user ID for a specific CP are the most important features in combination with the start hour of the sessions for predicting session duration and energy consumption. This is in line with the current literature regarding charging behavior [22, 44, 45, 53]. Including the different IDs of the users in the prediction proves helpful. The min, max, and average kWh of previous sessions say something about the battery capacity of the users.

Furthermore, none of the weather variables investigated in this study appear to be relevant for the prediction of charging behavior. This outcome is consistent with the findings of de Witte [22], but is in contrast of the findings of Shahriar et al. [20]. A possible explanation for this discrepancy could be attributed to the geographical location of the CP investigated by Shahriar et al. in California, in contrast to the data sets examined in the current study and that of de Witte, which were obtained from the Netherlands. Since the Netherlands is not a large country it could be that in larger countries this would these features would be more significant. The survey that was send to the EV experts and the interviews confirm this outcome. The majority of EV experts had indicated not to expect any of the weather variable to be important for the prediction. It was mentioned in an interview that the temperature can play a role in the number of charging sessions, but not so much in the session duration.

A novel data source and feature that was used in this thesis was the urbanization degree of the neighborhood where the CP is located. It had already become clear from the data exploration that the charging profiles at the various urbanization degrees are nearly identical to each other. The feature selection approach and the SHAP feature importance method support this finding and show that the new feature does not substantially contribute to the prediction of charging behavior variables. This can be possibly be explained by the fact that the urbanization degree is too high level, being the neighborhood level.

7.2 Limitations

In this thesis, some assumptions are made to predict charging session flexibility. First, an assumption is made for determining the charging duration by using the maximum charging power in a session. In practice, the charging power during a charging session will be higher at the start and will decrease as the battery approaches maximum SOC. This difference in charging power is due to several factors, such as the battery's temperature, the EV's battery management system and the number of EV's connected to a CP.

Secondly, not all CPs were included in the ten largest clusters with the Rule-Based clustering approach. In future research, other clustering approaches, such as the K-means or DBSCAN method, can be explored to cover all the CPs within a Charging Pool.

Thirdly, it is important to mention that the MB approach search speed depends on the number of CPU cores present in the computer running the feature selection approach, as it is a paralleled process. In this research, there was access to a maximum of 4 cores. When more CPU cores are available, the MB feature selection process could be much faster since the number of parallel processes can be increased. However, the difference in the training time with and without MB is evident and there is also a slight improvement in the total MAE when selecting the relevant features.

To conclude, a limitation concerning the data splitting procedure can be found in this study. Only a single data split was conducted in this thesis, and the robustness of this split was subsequently evaluated via multiple random data splits on the data set. Therefore, it is assumed that the obtained results may not deviate considerably with a different data split, particularly given the magnitude of the data set. Nonetheless, from a statistical standpoint, future research would benefit from performing more random splits on the data to prevent a biased trained ML model.

7.3 Academic Recommendations

In this thesis, it was decided to apply an aggregated approach and a CP cluster approach as the unit of generalization. In addition, the charging behavior of individuals and CPs was incorporated by adding a statistical variable such as the historical mean, maximum, minimum and standard deviation. Another approach could be to use a different panel structure such as training a model for each individual user. This was not chosen in this study given the large number of gaps in the data, which amount to charging sessions that are not available to a CPO. Different panel structures can be researched in the future literature to see if this yields more accurate predictions. It could also be investigated if the clustering of EV users in combination with clustering CPs could provide interesting results.

During the survey with EV experts, several independent variables were identified by the experts that could be used to further investigate the factors influencing the use and adoption of electric vehicle charging stations. These variables include:

- Entropy of CPs: The entropy of CPs could refer to the amount of other CPs in a given area. The entropy could be used as an additional variable to research charging flexibility.
- Neighborhood income: The income level of the surrounding neighborhood can influence the use and adoption of CPs.
- Electricity price at specific CP and the difference with other CPs: The price of electricity at a specific CP, as well as the price difference with other CPs in the area, can influence the usage pattern.
- Smart charging benefits for end-users: Smart charging features, such as the ability to schedule charging during off-peak hours or receive notifications when charging is complete, can influence the charging behavior of EV users.

- Amount of jobs and facilities in the neighborhood where the CP is located:The availability of nearby facilities, such as shops, restaurants and other services, can affect charging behavior.
- The maximum charging power: In this thesis the maximum charging power was derived by taking the maximum of historical charging sessions of both the EV user and the EVSE. In future research the maximum charging power can also be derived from the first data point that is received from the CP.

By considering these independent variables, future research could provide a more comprehensive understanding of the factors that influence charging behavior

To conclude, although the focus of this thesis was on data that is available at the beginning of the starting session, future research could include the updating of the prediction during the charging session with new data.

7.4 Practical recommendations

On a practical or commercial level, the quantification and prediction of charging session flexibility can be used to manage public EV charging sessions. The ML framework developed in this thesis can be utilized to predict the most efficient charging schedule for CPOs based on their objectives. When predicting the flexibility for individual charging sessions, EVs with low flexibility can be prioritized by not reducing the charging power. The predictions can also be used to indicate the potential availability of charging points. The potential challenge faced by CPOs is the possibility of not fully charging all the kWh due to an excessively delayed charging session. The proposed ML approach predicts the maximum time the charging within a charging session can be delayed before the CP needs to charge at maximum charging power. However, in practice, different smart charging strategies could also be used where the charging rate is not reduced to zero but from 11 kW to 6 kW, for example. This ensures that sufficient kWh is charged in a charging session, even if the prediction is incorrect. It is recommended to investigate which smart charging strategies would be most relevant for each subgroup of CPs. It would, for example, be a good idea not to reduce the charging rate as much at the subgroup Short Stay chargers.

Furthermore, there are some recommendations to be made about data availability. In this thesis, the data used came from public CPs in the Netherlands and the prediction was made from a direct control mechanism perspective. One limitation of the data is that not all the charging sessions that the EV has conducted are available to a CPO. The data analysis showed that a large part of the authentication IDs had completed a small number of sessions on the TotalEnergies CPs within the time interval of one year. Research from Quiros Tortes [83] showed that 70% of EV users charge their EV daily. This indicates the large gap of unseen charging sessions that are conducted at private chargers, work chargers or other public chargers that TotalEnergies do not operates. While a time series model was also considered, specifically designed to make predictions on ordered time data, it was found to be less suitable for predicting individual charging sessions from a CPO perspective due to the need for continuously shared data from the EV. Time series ML models are specifically designed to make predictions on data that is ordered in time. This has a high degree of temporal dependence, meaning that the value of a particular data point is highly correlated with the values of nearby data points in time. For example, the temperature at 11:00 PM is highly correlated with the temperature at 12:00 PM. This time series approach could also be applicable to the prediction of charging behavior. The approach is already used to predict aggregated charging demand of EV charging sessions. However, there are disadvantages to such a model for the prediction of individual charging sessions from a CPO perspective that will be discussed briefly. The time series approach could be suitable when data is continuously shared from the EV. This means that all data regarding the driving and charging behavior of an EV user is available. For example, the time between the last charging session and the amount of kWh charged could be valuable information. However, a CPO in the Netherlands only has information available about their own CPs. This means that there are blind spots in the data when an EV uses other EVSE that is not operated by the CPO, such as private residential chargers or (semi) public chargers that another CPO operates. With these blind spots, data about, for example, the number of kilometers driven, last charging session and SOC are not available. Therefore the recommendation is made for more data sharing between CPOs to enable better use of the flexibility of the charging session.

As also mentioned in the introduction, it could also be an option to ask the EV user directly about their departure time and energy requirements by means of an app. The predictive framework that was established in this thesis with the MB feature selection approach provides a fast and easy prediction of individual charging session flexibility. This can be a solution for the identified problem that EV users are potentially not interested in entering their departure time and energy consumption each time. With the combination of the prediction and an app the EV user could have the option to change the prediction made by the ML algorithm and even provide more information. This could help with a large number of outliers that are present in the predictions. The normalized curve in the distribution of errors with the ML models indicate that there may be some underlying factors that are not accounted for in the model.

In addition to the prediction of individual charging session flexibility, the observed high accuracy for the prediction of aggregated flexibility could be a very relevant input for system's operator.

Chapter 8

Conclusions

This thesis focused on developing predictive models using the XGboost algorithm to predict session duration and energy consumption for public EV charging infrastructure at the individual level. The public CPs were successfully clustered into subgroups based on their charging profile, including Hybrid, Work, Short Stay, and Home, within the Charging Pool of TotalEnergies. Furthermore, a statistical approach was used to predict the maximum power a given EV and EVSE can charge. Ultimately, by integrating these target variables, the time flexibility of each session was derived. With this information, the flexibility within an individual charging session with data present at the start of the session could be predicted. This chapter contains the key points and main conclusions. First, the main findings of the research will be presented by addressing the four research sub-questions. Following this, the overall conclusion of the thesis is presented.

How can charging session flexibility be quantified and which data are available at public charging stations at time of connection?

Based on the literature review conducted in this thesis, the following definition for DER flexibility was adopted in the context of EV charging session flexibility: *A device has flexibility if it is capable of shifting its production or consumption of energy in time within the boundaries of end-user comfort requirements and without changing its total energy production or consumption.*[41]. In addition, based on this definition, the following quantification approach was used throughout the thesis [5]. The flexibility can be quantified by multiplying the time flexibility with the energy consumption within a charging session. The formula for this quantification can be found in Equation 8.1.

$$\Delta f = \Delta E \cdot t_{flex} \tag{8.1}$$

The time flexibility (t_{flex}) is the time that the EV is connected to the CP without charging and the energy consumption (ΔE) is the energy charged within a session. This makes it necessary to know the charging behavior of the EV user, which is defined from the CPO perspective as the session duration and energy consumption. In addition, the maximum charging rate that the EV can charge is required to determine the charging duration in this approach.

The data that is considered in this research is data from a direct control mechanism approach, whereby the EV user is excluded from the control loop. Consequently, information about the SOC or (intended) departure time is not available. In this thesis historical charging sessions data of the EV user and CPs were used. In addition, contextual data such as weather data, holidays data and the urbanization degree of the neighbourhood where the CPs are located were used.

What are the most important independent variables that influence the individual charging session flexibility?

The results found that the historical mean of both the EV user and EV for a given CP, in terms of both session duration and energy consumption, represent the most important features. In addition, the start hour at which the charging session is initiated was important for predicting both variables. The feature selection approach did not select any of the other (contextual) features extracted from the available data. It is concluded that the contextual data, such as the weather variables, holiday indication or urbanization degree, are not relevant for the prediction of session duration or energy consumption and, therefore, flexibility. These are the same conclusions found from analyzing the surveys sent to the EV experts.

What machine learning model can be applied for the prediction of individual charging session flexibility?

From the performed literature review several machine learning models were identified that could be applied for the prediction of individual charging session flexibility. The choice was made to use the XGBoost regressor given the good accuracy results obtained in previous research. Although the XGBoost interpretability is low, the causality based MB feature selection approach was used to improve the model interpretability. In addition, the XGBoost algorithm is computationally efficient which makes it suitable for training and predicting on large data sets such as the one used in this thesis.

Does segmentation of the data through clustering charging points result in more accurate predictions for charging session flexibility?

This study successfully clustered public charging stations based on their charging profiles into subgroups, which were labeled as Hybrid, Home, Short Stay, or Work chargers. Moreover, the thesis compared two units for generalization: the Aggregated unit and the CP Cluster unit for predicting charging behavior. The CP Cluster unit was based on data segmentation of all the charging sessions within a cluster of CPs. The results showed significant prediction disparities among various clusters within the Charging Pool of TotalEnergies for both the Aggregated unit and the CP Cluster Unit, emphasizing notable differences in predictability between them. The segmentation of data resulted in significantly more accurate predictions for charging session flexibility in the Short Stay and Work subgroups. The research found that the CPs in the Short Stay and Work subgroups were predicted more accurate since they typically have fewer overnight charging sessions. However, due to the large number of Hybrid and Home chargers present in the used Charging Pool, the overall improvement in accuracy was not significant. These findings offer valuable insights into the clustering of public charging stations and highlight the importance of considering different units for improving prediction accuracy.

To conclude, the main research question of this research is: **How accurately can individual EV charging session flexibility be predicted, at public charging stations, with information available at time of connection?**

This thesis highlights the potential for determining the flexibility of an individual EV charging session based on the conditions outlined in the main research question. While it remains a challenge to accurately predict flexibility for such a large amount of public CPs with the available data at the time of connection, the study reveals valuable insights through clustering the CPs based on their historical charging behavior. Notably, this research identifies significant improvements in predicting session duration and energy consumption for the Short Stay and Work subgroups. However, for public CPs labeled in the subgroup as a Hybrid or Home charger, it was concluded that it remains challenging to determine the EV user's charging behavior in advance. Erratic behavior, such as very short or long sessions, makes it difficult to accurately predict individual charging session flexibility with the available information.

From the normalized error distribution found for both the session duration and energy consumption prediction, it was concluded that more information might be required to enhance the prediction accuracy further. With the available data, it is challenging to predict very short or long sessions without the presence of more information that could indicate this. The prediction is expected to improve significantly if the EV user history is available, which will likely happen soon. However, with certain smart strategies, it is possible to consider predictive errors through risk-aware optimization approaches.

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Appendix A

Charging profiles

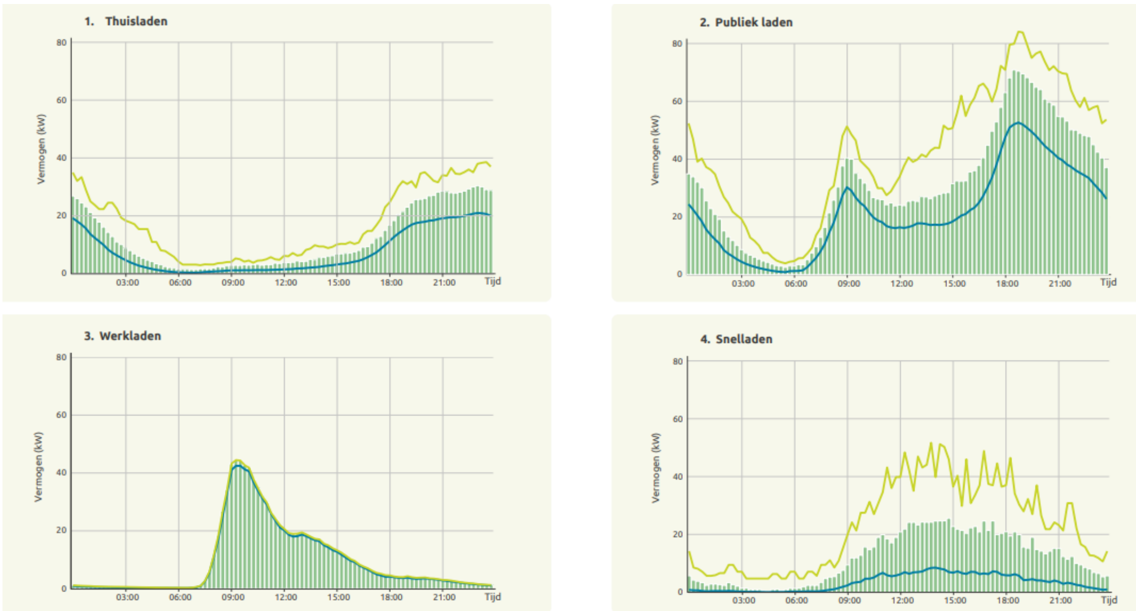


Figure A.1: Regular charging profiles for 100 EVs [8]

Appendix B

Interview questions

Questions for semi-structured interviews EV experts about predicting charging behavior.

First a summary of the research will be provided. This includes defining how charging behavior and charging session flexibility is defined in this research.

- 1. Can you tell me about your background?
- 2. What do you think about predicting the charging behavior of electric vehicles? Do you think this would be beneficial for e.g. smart charging purposes?
- 3. What do you think are the most important variables to consider when predicting the charging behavior of electric vehicles?
- 4. How do you think about the role of external factors, such as weather variables such as rain and temperature, in predicting charging behavior?
- 5. What do you think about the importance of what 'type' of charging station someone plugs into for the predicting of charging behavior?
- 6. Do you think it could be beneficial to segment the charging stations based on historical charging behavior at that specific charging station?
- 7. How do you think the EV charging infrastructure will develop in the coming years and how will this affect the prediction of the charging behavior of EV users?

Table 1: Description of all the included features

Feature name	**Feature description**
Session duration	Total time connected to the charging point (hours), Target variable
Energy consumption	Total amount of energy charged in the charging session (kWh), Target variable
Moving_mean	Historical mean session duration, based on user ID
Moving_std	Historical standard deviation session duration, based on user ID
Moving_min	Historical minimum session duration, based on user ID
Moving_max	Historical maximum session duration, based on user ID
Start_hour	Session start hour, cyclical encoded
Holiday	Indication of holiday, binary encoded
Day_of_the_week:	Day of the week, one-hot encoded
Urbanization degree	Urbanization degree of neighborhood where the charging station is located
Cluster	Clustering of charging stations based on historical sessions
Wind speed	Mean wind speed (in 0.1 m/s)
Temperature	Temperature (in degrees Celsius)
Sunshine	Sunshine duration (in 0.1 hour) during the hourly division
Radiation	Global radiation (in J/cm2) during the hourly division
Hourly precipitation	Hourly precipitation amount (in 0.1 mm)
Fog	Fog, binary encoded
Rainfall	Rainfall, binary encoded
Snow	Snow, binary encoded
Thunder	Thunder, binary encoded
Ice formation	Ice formation, binary encoded

Figure B.1: Features included in the survey

Appendix C

National Holidays

Table C.1: Dutch holidays with related dates

Holiday	**Date**
New Year's Day	(2021,01,01), (2022,01,01)
Good Friday	(2021,04,02), (2022,04,15)
Easter Sunday	(2021,04,04), (2022,04,17)
Easter Monday	(2021,04,05), (2022,04,18)
King's Day	(2021,04,27), (2022,04,27)
Ascension Day	(2021,05,13), (2022,05,26)
White Sunday	(2021,05,23), (2022,06,05)
Whit Monday	(2021,05,24), (2022,06,06)
Christmas Day	(2021,12,25), (2022,12,25)
Boxing Day	(2021,12,26), (2022,12,26)

Appendix D

Urbanization degrees

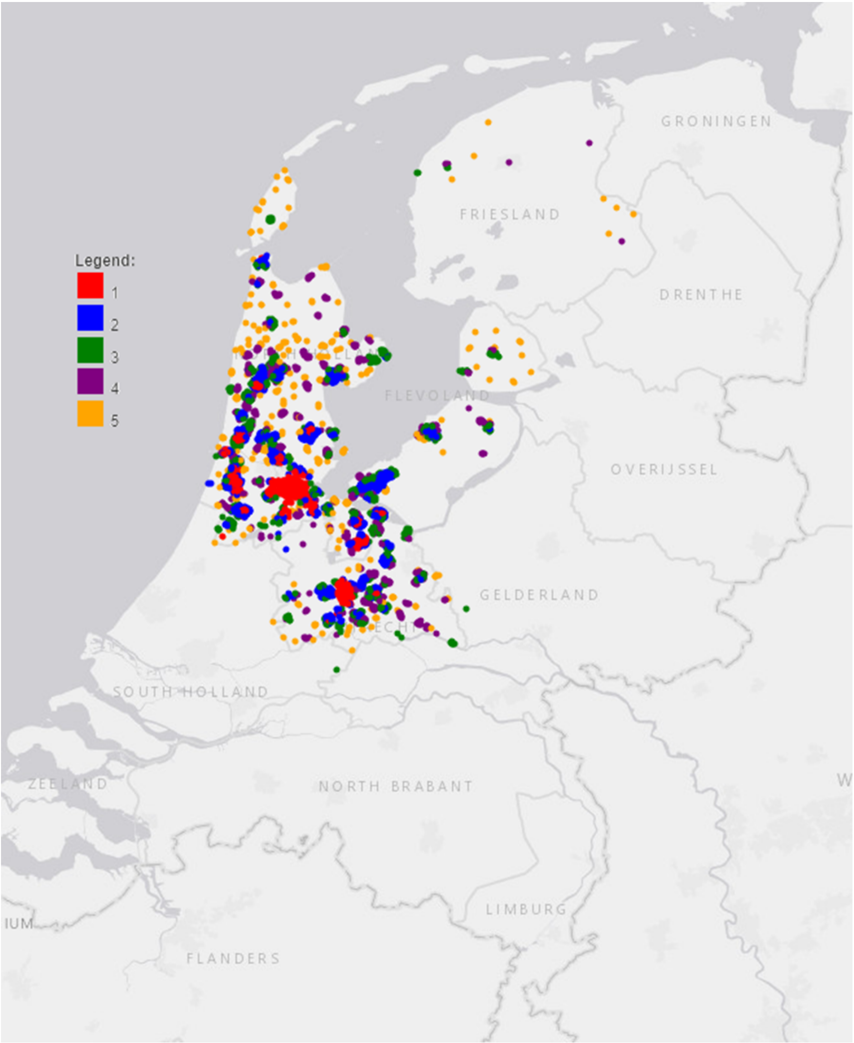


Figure D.1: Geographical locations of the charging stations with urbanization degrees

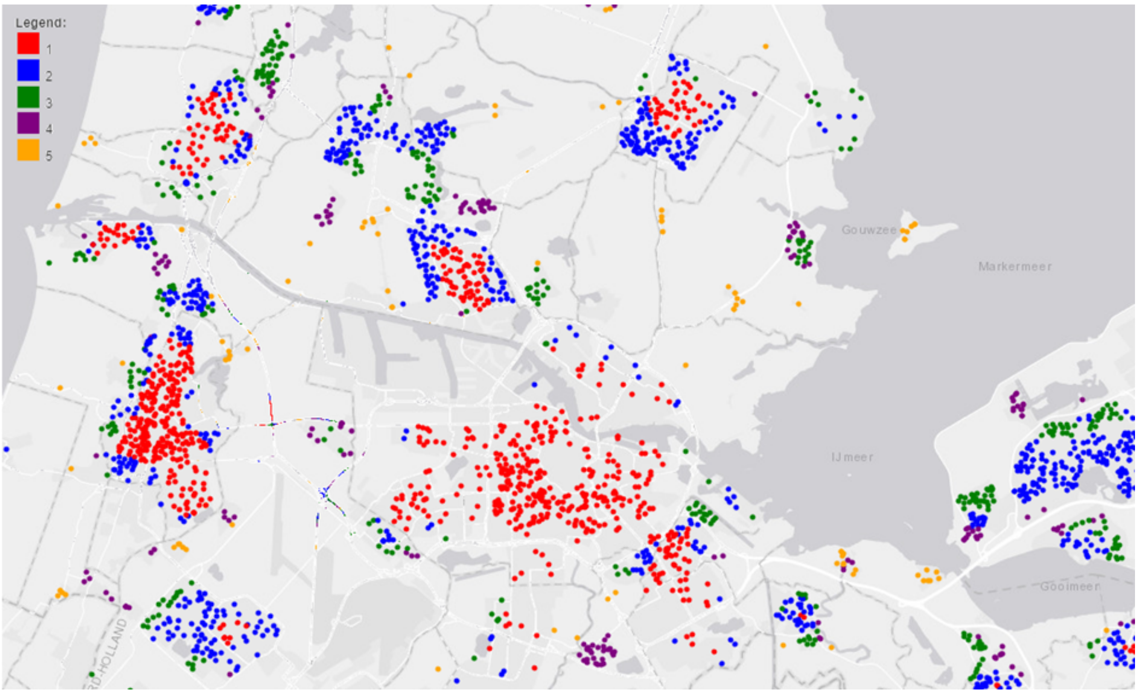


Figure D.2: Zoomed in geographical locations urbanization degrees Amsterdam area

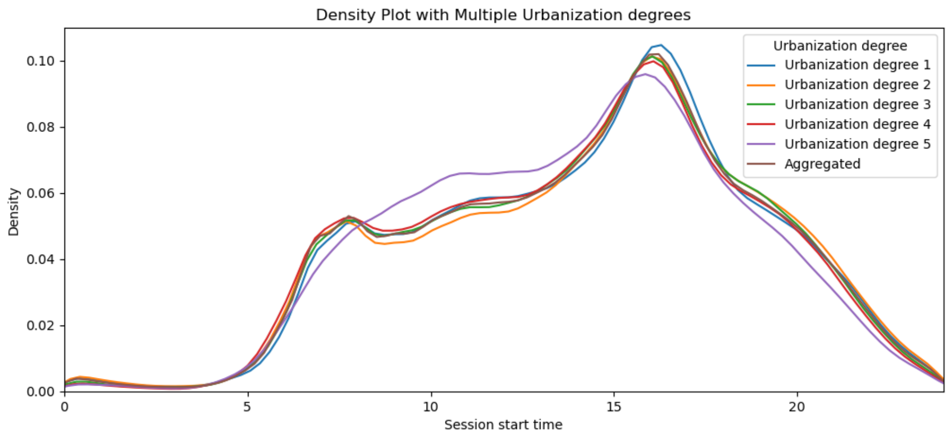


Figure D.3: Density plot for session start time for each urbanization degree

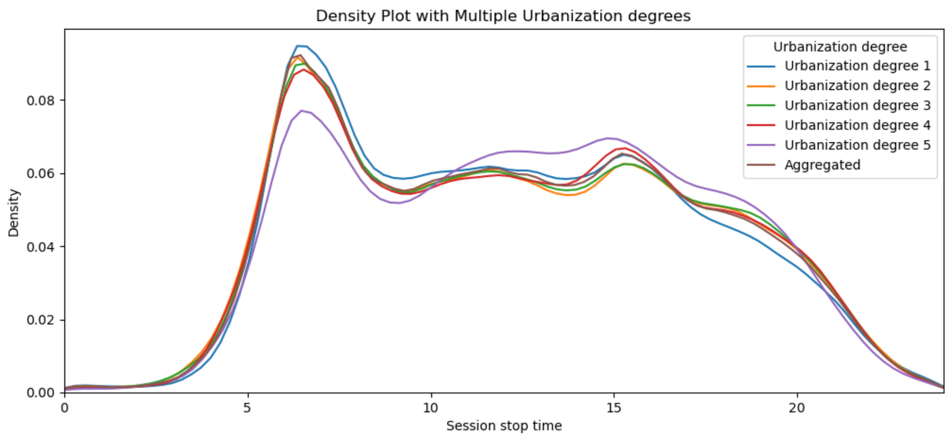


Figure D.4: Density plot for session stop time for each urbanization degree

Appendix E

Clusters

Table E.1: Threshold values and corresponding values

Threshold value	Largest ten clusters sizes	Sum of largest ten clusters
0.05	1926, 1074, 931, 487, 107, 99, 70, 57, 56, 54	4861
0.06	1678, 1630, 478, 447, 116, 115, 83, 82, 77, 69	4775
0.07	2057, 1308, 381, 201, 192, 126, 117, 113, 105, 104	4704
0.08	2284, 824, 307, 288, 232, 160, 147, 111, 107, 95	4555
0.09	2217, 496, 437, 360, 193, 184, 139, 117, 115, 102	4360

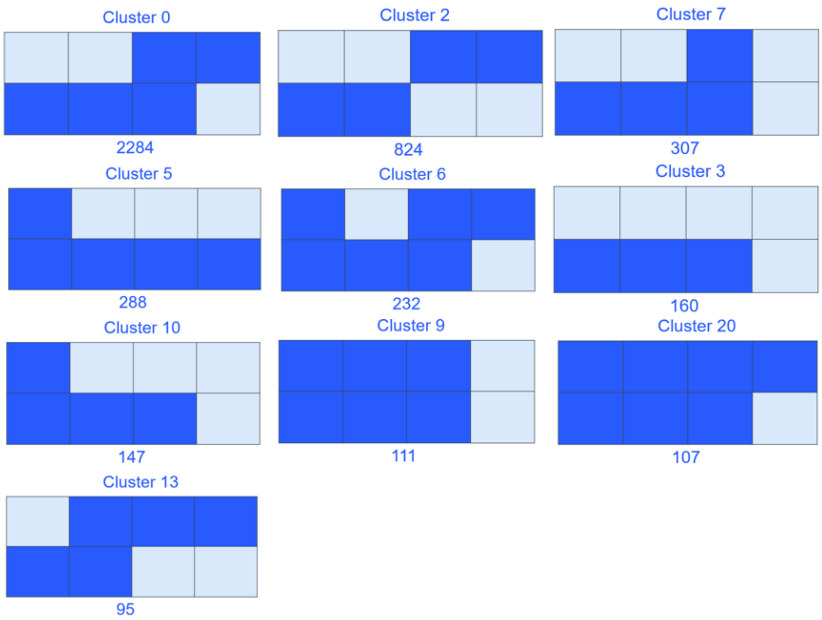


Figure E.1: Top ten cluster patterns

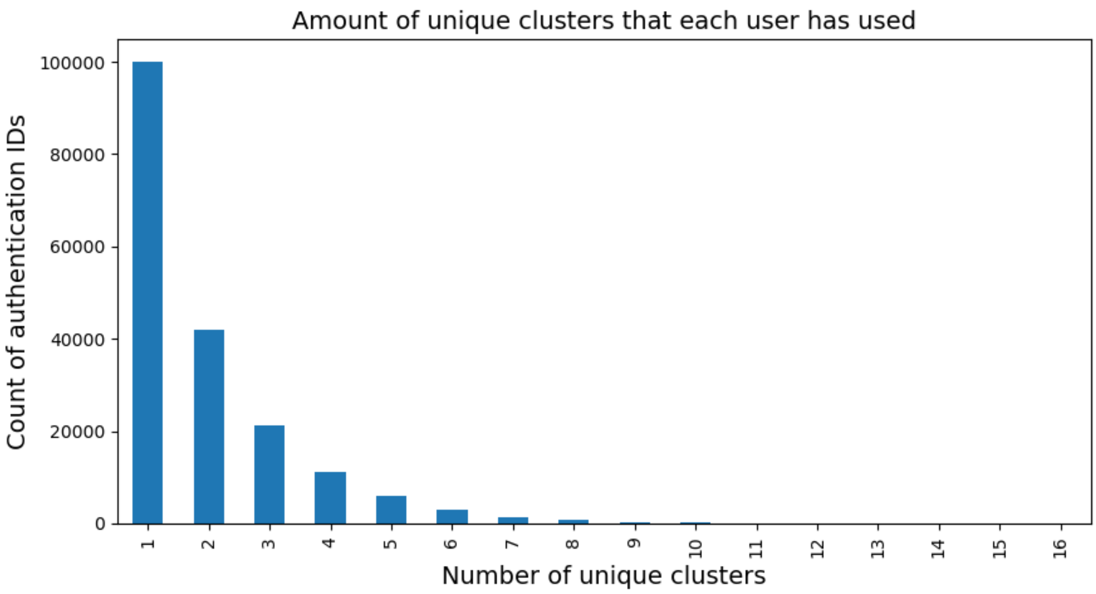


Figure E.2: Amount of unique cluster that each authentication ID has used in the dataset

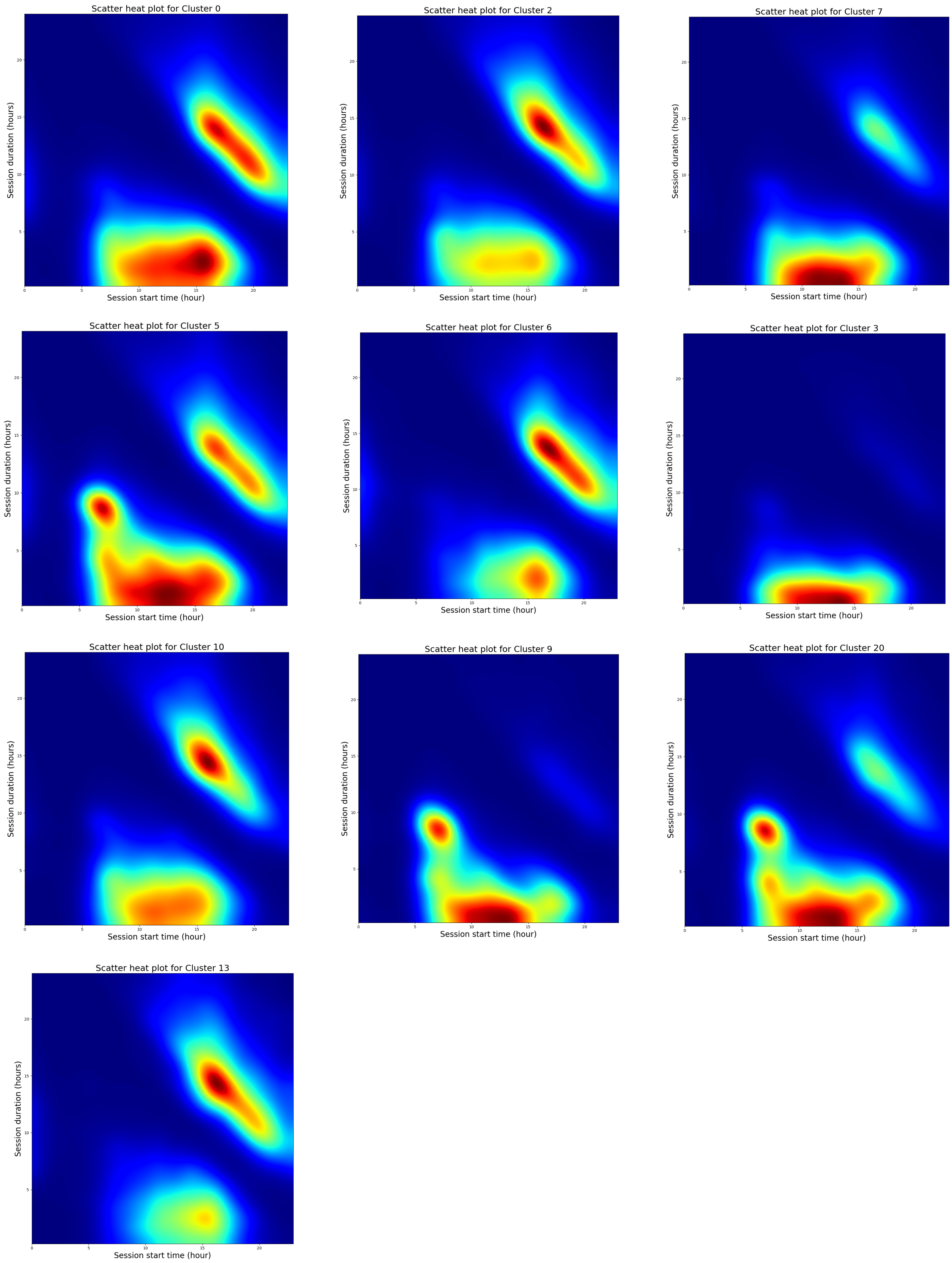


Figure E.3: Heatmap vizualization of all the session for the top 10 clusters 0, 2, 7, 5, 6, 3, 10, 9, 20, 13.

Appendix F

Hyperparameters

Table F.1: Hyperparameters used for the grid search

Parameter	Default setting	Grid Ranges
Max depth	6	[4,5,6]
N estimators	100	[100, 500, 1000]
Min child weight	1	[1.0, 2.0, 3.0]
Colsample bytree	1	[1.0, 2.0]

72 fits for every model

Table F.2: Aggregated model Hyperparameters Results

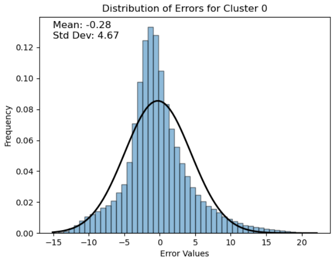
Model	Best Hyperparameters
Session duration	{'colsample_bytree': 1.0, 'max_depth': 4, 'min_child_weight': 2.0, 'n_estimators': 100}
Energy consumption	{'colsample_bytree': 1.0, 'max_depth': 5, 'min_child_weight': 3.0, 'n_estimators': 100}

Appendix G

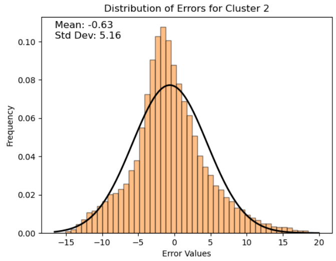
Session duration cluster results

Table G.1: Session Duration model hyperparameters results by Cluster

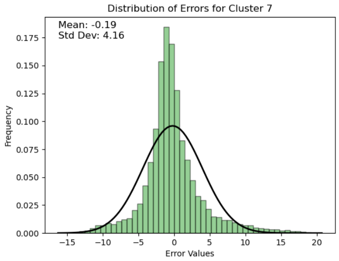
Cluster	Best Hyperparameters
0	{'colsample_bytree': 1.0, 'max_depth': 4, 'min_child_weight': 2.0, 'n_estimators': 100}
2	{'colsample_bytree': 1.0, 'max_depth': 4, 'min_child_weight': 1.0, 'n_estimators': 100}
7	{'colsample_bytree': 1.0, 'max_depth': 4, 'min_child_weight': 2.0, 'n_estimators': 100}
5	{'colsample_bytree': 1.0, 'max_depth': 5, 'min_child_weight': 3.0, 'n_estimators': 100}
6	{'colsample_bytree': 1.0, 'max_depth': 4, 'min_child_weight': 2.0, 'n_estimators': 100}
3	{'colsample_bytree': 1.0, 'max_depth': 4, 'min_child_weight': 1.0, 'n_estimators': 100}
10	{'colsample_bytree': 1.0, 'max_depth': 4, 'min_child_weight': 2.0, 'n_estimators': 100}
9	{'colsample_bytree': 1.0, 'max_depth': 4, 'min_child_weight': 2.0, 'n_estimators': 100}
20	{'colsample_bytree': 1.0, 'max_depth': 4, 'min_child_weight': 3.0, 'n_estimators': 100}
13	{'colsample_bytree': 1.0, 'max_depth': 5, 'min_child_weight': 3.0, 'n_estimators': 100}



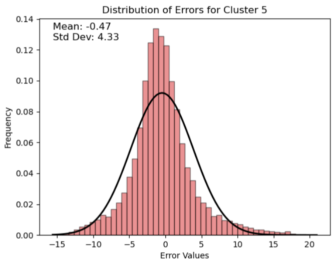
(a) Cluster 0



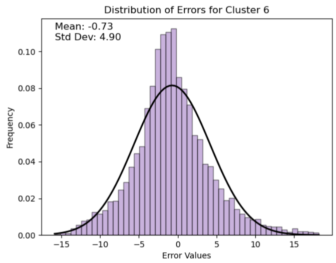
(b) Cluster 2



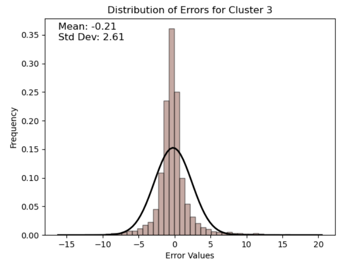
(c) Cluster 7



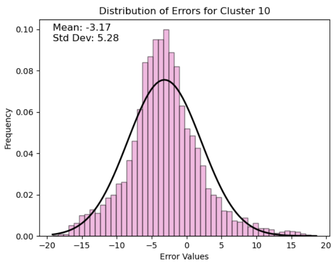
(d) Cluster 5



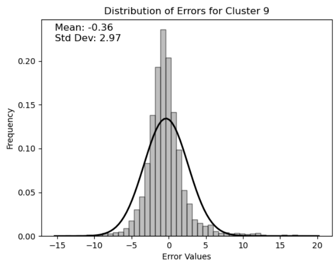
(e) Cluster 6



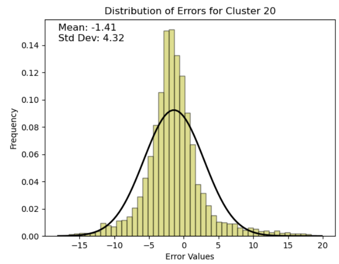
(f) Cluster 3



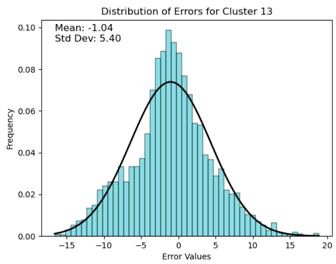
(g) Cluster 10



(h) Cluster 9

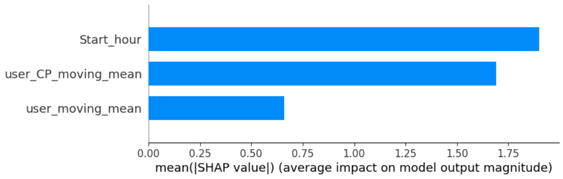


(i) Cluster 20

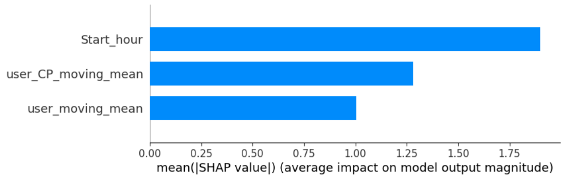


(j) Cluster 13

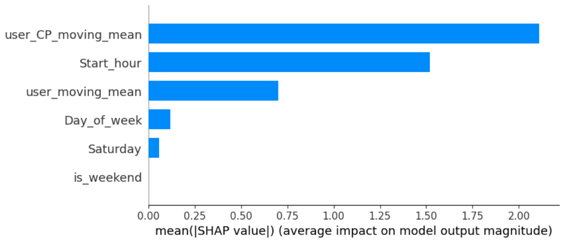
Figure G.1: Histogram of errors with CP cluster models for session duration prediction



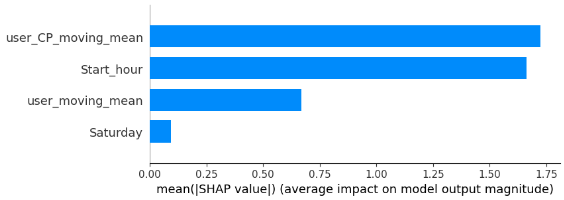
(a) Cluster 0



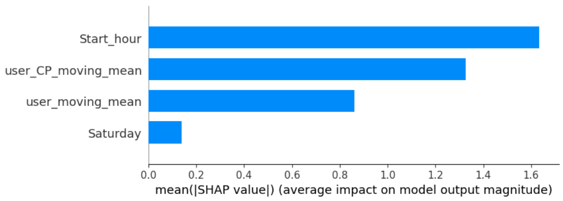
(b) Cluster 2



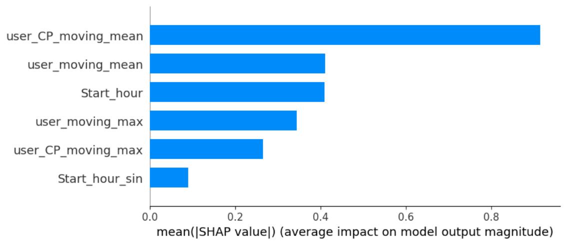
(c) Cluster 7



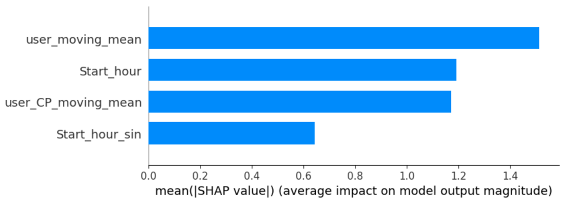
(d) Cluster 5



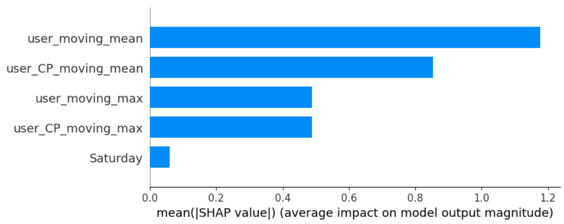
(e) Cluster 6



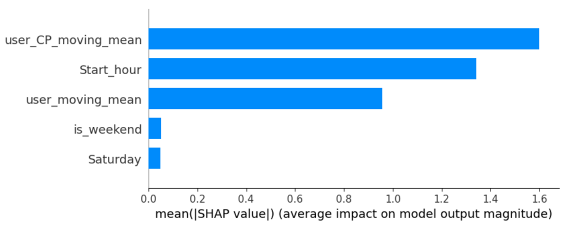
(f) Cluster 3



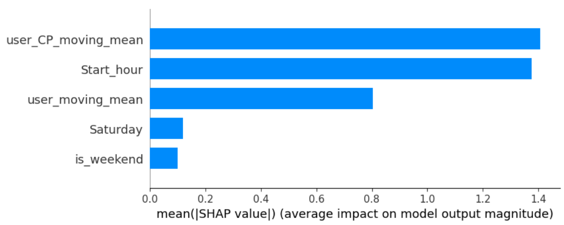
(g) Cluster 10



(h) Cluster 9



(i) Cluster 20



(j) Cluster 13

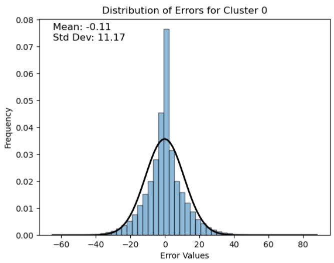
Figure G.2: Features importance with CP cluster models for session duration prediction

Appendix H

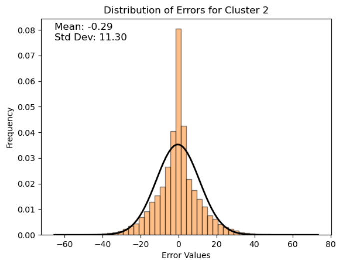
Energy consumption clusters

Table H.1: Energy Consumption model hyperparameters results by cluster

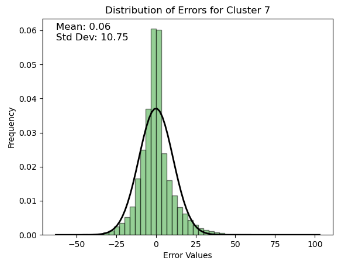
Cluster	Best Hyperparameters
0	{'colsample_bytree': 1.0, 'max_depth': 4, 'min_child_weight': 2.0, 'n_estimators': 100}
2	{'colsample_bytree': 1.0, 'max_depth': 4, 'min_child_weight': 1.0, 'n_estimators': 100}
7	{'colsample_bytree': 1.0, 'max_depth': 5, 'min_child_weight': 2.0, 'n_estimators': 100}
5	{'colsample_bytree': 1.0, 'max_depth': 4, 'min_child_weight': 3.0, 'n_estimators': 100}
6	{'colsample_bytree': 1.0, 'max_depth': 4, 'min_child_weight': 1.0, 'n_estimators': 100}
3	{'colsample_bytree': 1.0, 'max_depth': 4, 'min_child_weight': 3.0, 'n_estimators': 100}
10	{'colsample_bytree': 1.0, 'max_depth': 4, 'min_child_weight': 2.0, 'n_estimators': 100}
9	{'colsample_bytree': 1.0, 'max_depth': 4, 'min_child_weight': 1.0, 'n_estimators': 100}
20	{'colsample_bytree': 1.0, 'max_depth': 4, 'min_child_weight': 3.0, 'n_estimators': 100}
13	{'colsample_bytree': 1.0, 'max_depth': 5, 'min_child_weight': 3.0, 'n_estimators': 100}



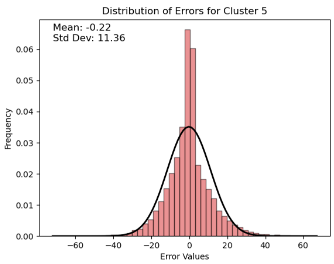
(a) Cluster 0



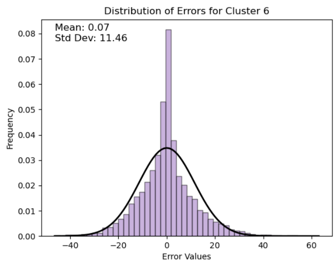
(b) Cluster 2



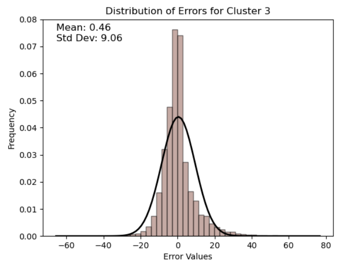
(c) Cluster 7



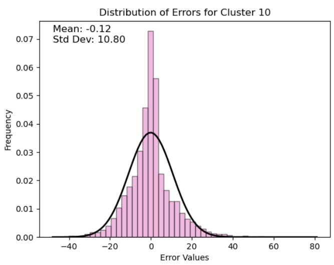
(d) Cluster 5



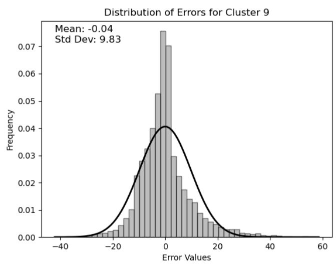
(e) Cluster 6



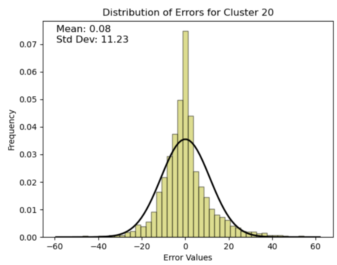
(f) Cluster 3



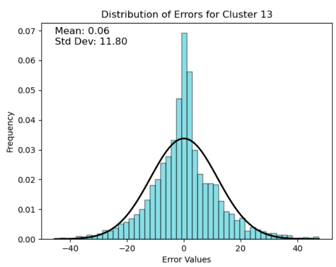
(g) Cluster 10



(h) Cluster 9

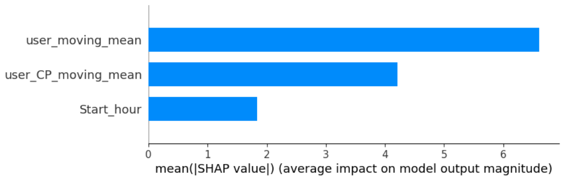


(i) Cluster 20

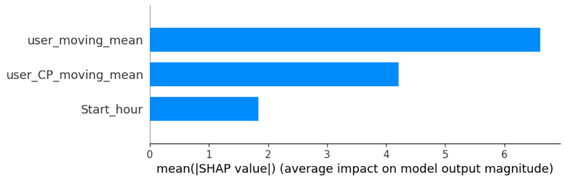


(j) Cluster 13

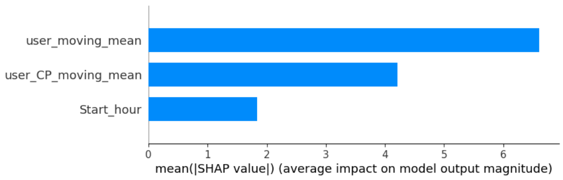
Figure H.1: Histogram of errors with CP cluster models for energy consumption prediction



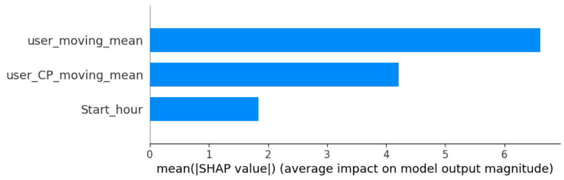
(a) Cluster 0



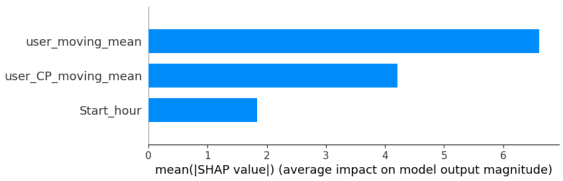
(b) Cluster 2



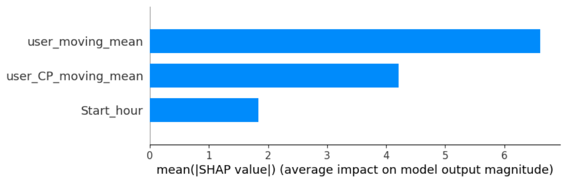
(c) Cluster 7



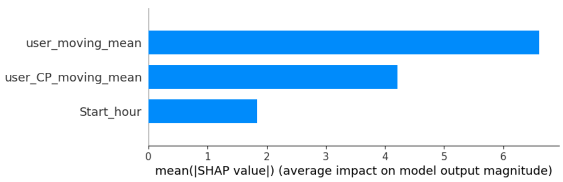
(d) Cluster 5



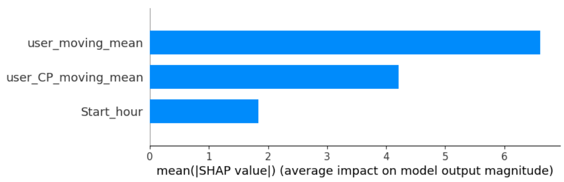
(e) Cluster 6



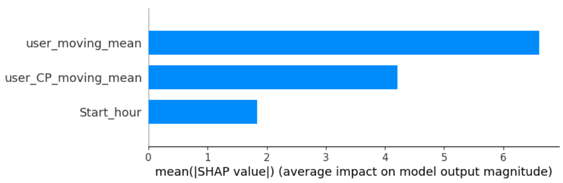
(f) Cluster 3



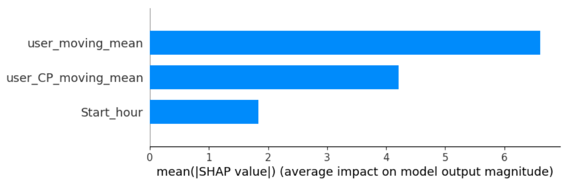
(g) Cluster 10



(h) Cluster 9



(i) Cluster 20



(j) Cluster 13

Figure H.2: Features importance with CP cluster models for energy consumption prediction

Appendix I

Flexibility prediction

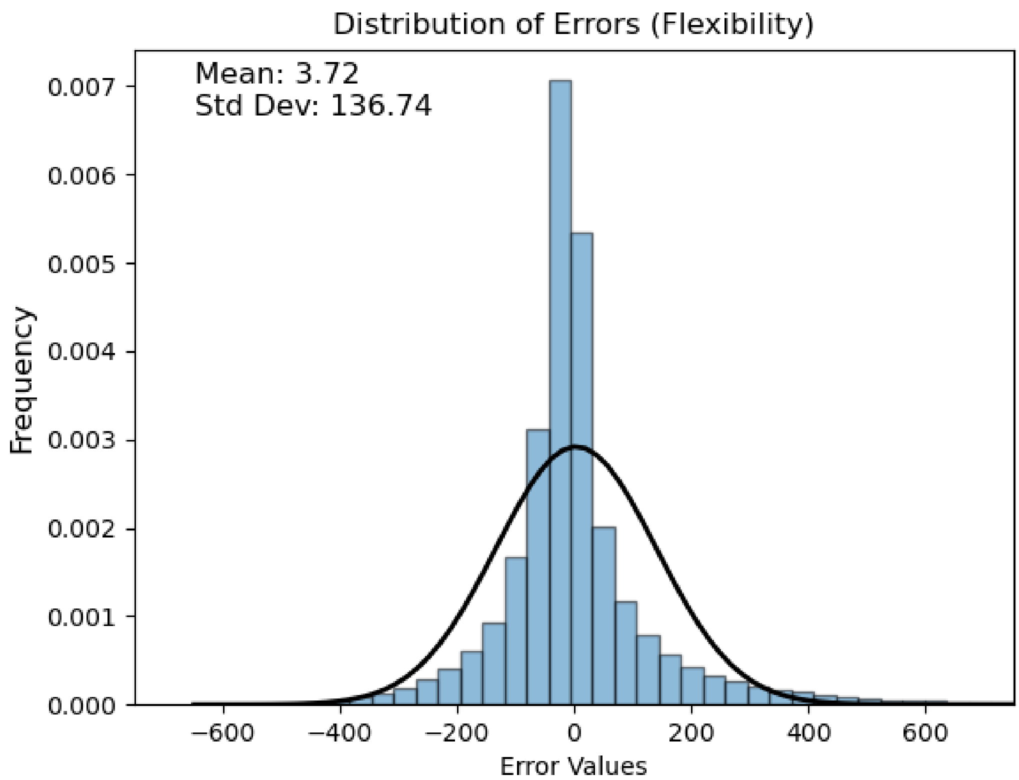


Figure I.1: Prediction error for flexibility on the test data

Appendix J

Survey results

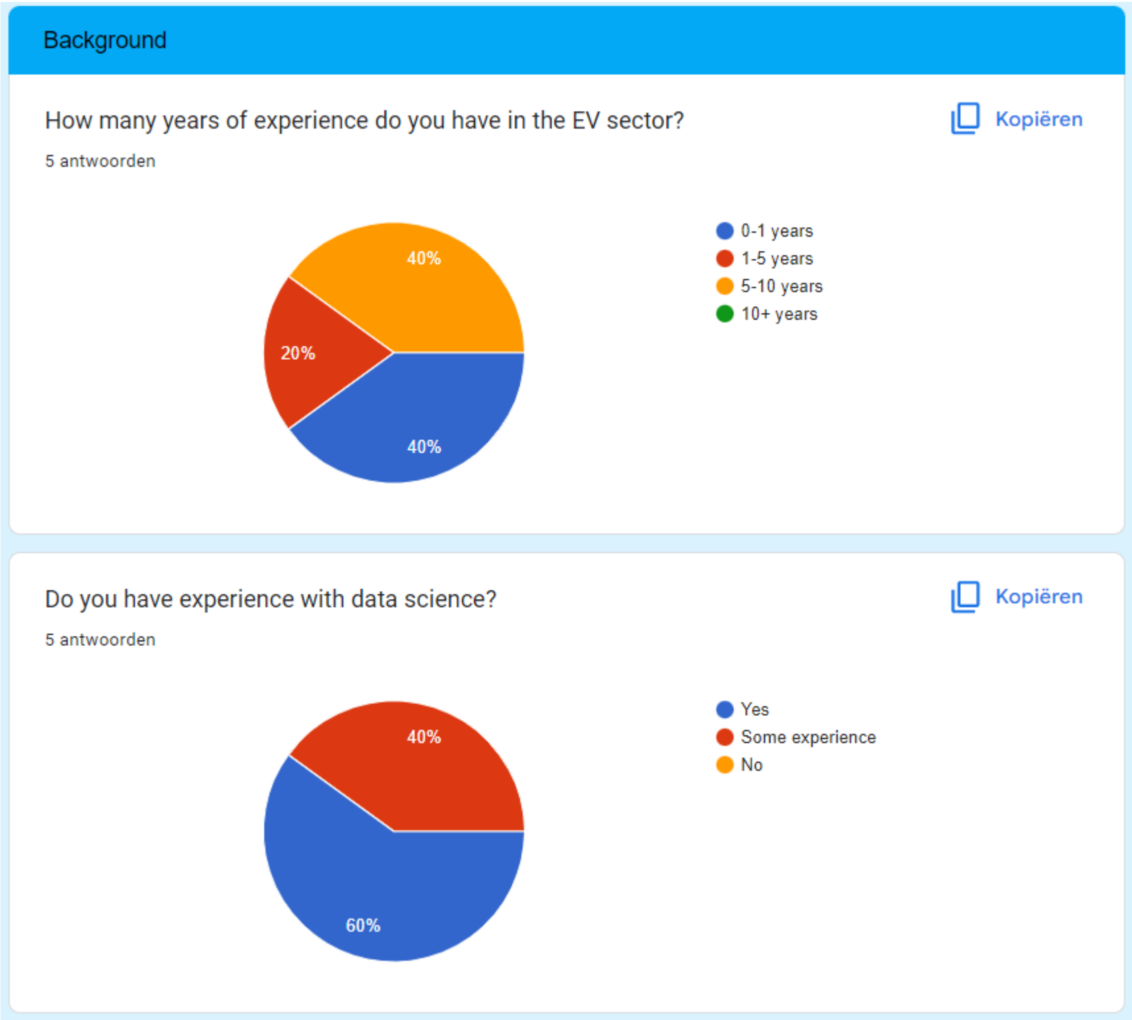


Figure J.1: Background survey