Master's thesis

NTNU
Norwegian University of Science and Technology
Faculty of Information Technology and Electrical Engineering
Department of Electric Power Engineering

Maria Claire Westad

A Stochastic Simulation Tool for Generating Hourly Load Profiles for Residential EV Charging, Based on Real-World Charging Reports

Master's thesis in Energy and Environmental Engineering
Supervisor: Karen Byskov Lindberg
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June 2021

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Kunnskap for en bedre verden

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Preface

This master thesis has been written at the Department of Electric Power Engineering at the Norwegian University of Science and Technology (NTNU) during the spring of 2021, with Karen Byskov Lindberg as supervisor and Åse Lekang Sørensen as co-supervisor. The thesis represent the end of the five-year MSc programme Energy and Environmental Engineering.

I would like to thank my main supervisor Karen Byskov Lindberg for her great help, organising meetings, good feedback, support and guidance during my work. I also owe a special thanks to Åse Lekang Sørensen for good inputs and guidance, and for providing the EV charging data used in my work. Finally, I must thank my fellow students, family and friends for providing me with support, encouragement and good times throughout the years of studying and through the process of writing this thesis.

Trondheim, June 2021.

Maria Claire Westad

Abstract

The electrical vehicle (EV) fleet is increasing in Norway. To plan and operate the long-term power system and evaluate EVs' effect on the power grid, accurate load-profile generation models are needed. Such models are also needed to analyse optimal EV charging strategies.

The purpose of this thesis is to develop a model to simulate realistic hourly load profiles for dumb private home charging, based on real-world EV-charging data. The data is provided by charging reports from charging point operators (CPOs), and gives information on the date, user type, user ID, plug-in and plug-out time, connection time, and charged energy for every measured charging session. Analysis of the data reveals that the factors EV type and day type impacts the EV user charging habits, as such these factors are considered in the model.

The model is a stochastic bottom-up model, providing single load profiles for EVs being charged at home in Norway for a year. The load profiles depend on two types of EVs defined as "large EV" and "small EV", referring to the battery size of the car. It is possible to simulate any number of EVs and composition of EV stock. In addition, information for plug-in and plug-out time, charged energy, charging frequency and idle hours for each EV user is extracted when running the model.

Three different cases simulating load profiles for 1000 EVs are used to analyse and evaluate the model: BASE, LOW, and HIGH. In LOW, the EVs are assumed to be "small EVs" with a maximum charging power of 3.6 kW. In HIGH, EVs are assumed to be "large EVs" with a maximum charging power of 7.2 kW. In BASE, the battery sizes and maximum charging powers reflect the composition of the EV stock of the data set and combines the two other cases.

The simulation results show that the aggregate load profiles have the same shape in all three cases, and the daily average peak power occurs at the same time for the different day types: between hour 17 and 18 on weekdays, between hour 18 and 19 on Saturdays, and between hour 18 and 19 on Sundays. As the load profiles presumes dumb charging, they reflect the distribution of the plug-in time for the different day types used in the model.

The power peak and annual energy need are largest in HIGH and smallest in LOW, while BASE is between the two. The results validate that the model can account for factors such as charging frequencies and energy need being dependent on the EV type. This is also seen in the idle hours and shiftable energy levels. Even though the idle hours are higher in LOW, the shiftable energy level is higher in HIGH.

To further study the model, load profiles are simulated for the same cases assuming flexible charging. In this thesis, flexible charging means distributing the charged energy equally over the connection time. Compared to the load profiles for dumb charging, the peak powers are reduced by 35-38%. In addition, they are moved to occurring at night in all three cases.

It is a perception that EVs with large EV batteries and high maximum charging powers are preferred if using EVs as a flexible source in the grid. From this work, it is seen that EVs with these characteristics have fewer idle hours and are therefore a less flexible resource. When planning to use EVs as a flexible source, it is important to be aware of this trend.

All in all, the model generates realistic results for the aggregate load profile. However, to make it more robust, more charging data should be analysed and included.

Sammendrag

Antall elbiler i Norge øker fort. For planlegge og drifte det langsiktige kraftsystemet og analysere elbilers effekt på strømnettet trengs gode modeller som kan simulere realistiske lastprofiler. I tillegg trengs slike modeller for å analysere optimale ladestrategier for elbiler.

Målet for denne oppgaven har vært å utvikle en modell som kan brukes til å simulere realistiske timesbaserte lastprofiler for dum privat hjemmelading, basert på faktiske elbil-ladedata. Dataene som er brukt er laderapporter fra ladeoperatører som gir informasjon om dato, brukertype, bruker-ID, plug-inn og plugg-ut tid, tilkoblingstid og ladet energi for hver målte ladingsøkt. Dataene viser at ladevaner avhenger av elbiltype og dagtype. Dette er tatt hensyn til i modellen.

Modellen er en stokastiske bottom-up-modell, og simulerer lastprofiler for elbiler ladet hjemme i Norge gjennom et år. Lastprofilene avhenger av to typer elbiler definert som "stor elbil" og "liten elbil", og henviser til batteristørrelsen til bilen. Modellen kan simulere lastprofiler for hvilket som helst antall elbiler og sammensetning av elbiltyper. I tillegg gis informasjon for plug-in- og plugg-ut tid, energi ladet, ladefrekvens og antall timer elbilen er koblet til uten å lade.

For å analysere og evaluere modellen som er utviklet brukes det tre forskjellige case til å simulere lastprofiler for 1000 elbiler: BASE, LOW, og HIGH. I LOW er alle elbiler antatt til å være "liten elbil" med en lav maksimal ladeeffekt på 3,6 kW. I HIGH er alle elbiler antatt til å være "stor elbil" med en høy maksimal ladeeffekt på 7,2 kW. I BASE reflekterer batteristørrelse og maksimal ladeeffekt sammensetningen av elbiler slik den er i dataene, og er en kombinasjon av de to andre casene.

De aggregerte lastprofilene har samme form i alle de tre tilfellene, og den gjennomsnittlige toppeffekten inntreffer på samme tid for de ulike dagtypene: mellom klokken 17 og 18 i ukedagene, mellom klokken 18 og 19 på lørdager, og mellom klokken 19 og 20 på søndager. Siden lastprofilene er basert på dum lading, vil de reflektere distribusjonen av ulik plug-in tid for de ulike dag-typene.

Effekttoppen og det årlige energibehovet er størst i HIGH og minst i LOW. BASE ligger mellom de to. Resultatene validerer at modellen tar hensyn til faktorer som ladefrekvenser og energibehov, og at disse er avhengig av elbiltype. Dette vises også i antall timer ladere er koblet til nettet uten å lade og hvor mye energi som kan flyttes i tid. Selv om LOW har flere timer koblet til nettet uten å lade, har HIGH mer energi som kan flyttes i tid.

For å ytterligere vurdere modellen er det også laget lastprofiler for de samme casene med fleksibel lading. Her betyr fleksibel lading at energien som lades fordeles likt over tilkoblingstiden. Sammenlignet med dum lading reduseres effekttoppene kraftig, med 35-38%. I tillegg inntreffer nå effekttoppene om natten i alle de tre tilfellene.

Det er en oppfatting at elbiler med store batterier og høy maksimal ladeeffekt er foretrukket dersom elbiler skal brukes som en fleksibel last i nettet. Gjennom denne oppgaven, sees det at elbiler med disse egenskapene har flere timer koblet til nettet uten å lade. Skal elbiler planlegges til å brukes som en fleksibel last, er det viktig å være klar over denne trenden.

Alt i alt gir modellen realistiske resultater. Likevel, for å gjøre den mer robust, bør mer ladedata analyseres og inkluderes.

Contents

Abbreviations

BEV Battery electric vehicle

CPO Charging point operators

EV Electrical vehicle

GHG Greenhouse gas

HEV Hybrid EV

ICE Internal combustion engine

PHEV Plug-in hybrid electrical vehicle

RES Renewable energy sources

SoC State of charge

V2G Vehicle to grid

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1 Introduction

1.1 Motivation

As a result of the Paris Agreement, Norway aims to limit global warming to below 2 degrees Celcius, compared to pre-industrial levels. In addition, according to Norway's Climate Change Act, greenhouse gas (GHG) emissions are to be reduced by at least 50% by 2030 compared to 1990-levels [1].

Unlike most countries in Europe, where the main goal is a green transfer in the energy generation sector, Norway's electricity generation is already mostly renewable from the large share of hydropower [2]. Today, only 3,2% of the total GHG emissions are estimated to come from the energy supply [3]. Consequently, for Norway to reach the climate targets, emissions from other sectors such as the transport sector have to be reduced.

Road traffic is recognised as one of the significant sources of GHG emissions, accounting for 17% of the total GHG emissions in Norway [3]. As a part of reducing these emissions, the Norwegian parliament has set a target for the new passenger and light commercial car market to only consist of zero-emission vehicles from 2025 [4]. The share of electric vehicles (EVs) is rapidly increasing in Norway, with a market share of 54,3% battery electric vehicles (BEVs) in 2020, compared to a market share of 20,8% in 2017 [5]. This continuous growth will increase the electricity demand and significantly impact the power grid and system reliability. Today, most EVs operate with dumb charging, meaning the EV starts charging immediately after plug-in time [6]. If many EVs plugs in simultaneously, this can lead to an overload of the distribution grid. However, EVs can also be used as a flexible source. They are often connected to the grid longer than the charging time, and by introducing smart charging and vehicle to grid (V2G), EVs have several flexibility potentials.

To evaluate EV's effects on the power grid and analyse EV flexibility and EV optimal charging, realistic load-profile generation models based on realistic data are needed. In addition, such models are needed for planning and operation of the long-term power system [7].

1.2 Scope

This thesis gives an overview of EVs, their impacts and different methods for generating EV load profiles. The goal is to develop a model to simulate realistic EV load profiles based on real data from EV charging reports.

Today, most EV load profile generation tools are based on detailed bottom-up models, mainly using assumptions on driving distance, EV battery capacity, plug-in time, plug-out time and the initial state of charge (SoC) of the battery when plugging in. However, these data are not available from real-world measurements, and therefore these models are solely based on assumptions. In this thesis, instead of these assumptions, real measurement data provided by charging reports from charging point operators (CPOs) from [8] are used. The data provides information on the date, user type, user ID, plug-in time, connection duration, and charged energy for every measured charging session. The goal is to develop a stochastic simulation tool to generate realistic load profiles for dumb private home charging based on these data. Because the model will also provide information on the connection time, the perspective of using it in other applications is taken into account.

1.3 Approach and limitations

The thesis focuses on EVs and EV load profiles in Norway. Different impacts, charging habits, and assumptions typically utilised when generating load profiles are presented through a literature review. Data from the private EV users in [8] are analysed, presented and further used to develop the model predicting EV load profiles.

The model is limited to simulating yearly load profiles for private home-charging on an hourly scale. The goal is to generate realistic aggregate load profiles for dumb charging. Still, the individual EV characteristics are taken into account, and single EV load profiles are provided.

Because maximum charging powers and battery sizes of the EVs in the data set are unknown, assumptions are made to distinguish the EVs. In addition, the results from running the model are not compared to AMS-meters measuring. This should be done to validate the model.

1.4 Structure

Chapter 2 introduces EVs, how they can be used as a flexible load, typical factors affecting EV charging, and different methods used to generate load profiles.

Chapter 3 presents and analyses the EV data from [8].

Chapter 4 gives an overview of the stochastic bottom-up model used to generate EV load profiles and presents a case study to analyse the model.

Chapter 5 presents, compare and discuss the results obtained from the different cases in the case study.

In Chapter 6, some findings of the case study are further discussed. In addition, limitations of the model are pointed out and improvements are suggested.

2 Theory and Literature Review

Remark: In the following chapter, subchapter 2.2, 2.5, 2.8, subsubchapter 2.6.1 and parts of subsubchapter 2.9.3 build on work from the specialization project TET4520, resulting in extensive reproduction or usage of its content [9].

This chapter introduces EVs in Norway and presents an overview of the Norwegian EV fleet, EV impacts, typical charging factors and how EVs can be used as a flexible load. In addition, different methods for generating load profiles are presented through a literature review.

2.1 Electrical vehicles

EVs can broadly be divided into Hybrid EVs (HEVs) and Plug-in EVs. Because the battery in HEVs can not be recharged from an external power source , plug-in EVs are in this thesis incorporated with EVs [10].

Plug-in EVs are typically divided into two main types; battery electrical vehicles (BEV) and plug-in hybrid vehicles (PHEV) [10].

2.2 EV fleet in Norway

In 2019, 30% of the GHG emissions came from the transport sector in Norway, where more than half came from the road traffic [11]. To reach the EU's goal of reducing the transport sector's GHG emissions by 60% by 2050 compared to 1990-levels, Norway has a goal to only sell emission-free cars from 2025 [4].

The electrical car fleet is rapidly increasing in Norway and is the global leader in terms of electric car market share, with a market share of 46% in 2018 [12]. Compared to the market share of 29% in 2016, this is a significant increase [13]. Figure 2.1 shows the amount of BEVs and the market share over the last years. As of the end of 2020, Norway had a number of 345 921 BEVs and 142 858 PHEV [14]. Figure 2.2 shows the total number of both BEVs and PHEVs over the last years. In total, BEVs and PHEVs represent 17% of Norway's total car fleet as seen in figure 2.3.

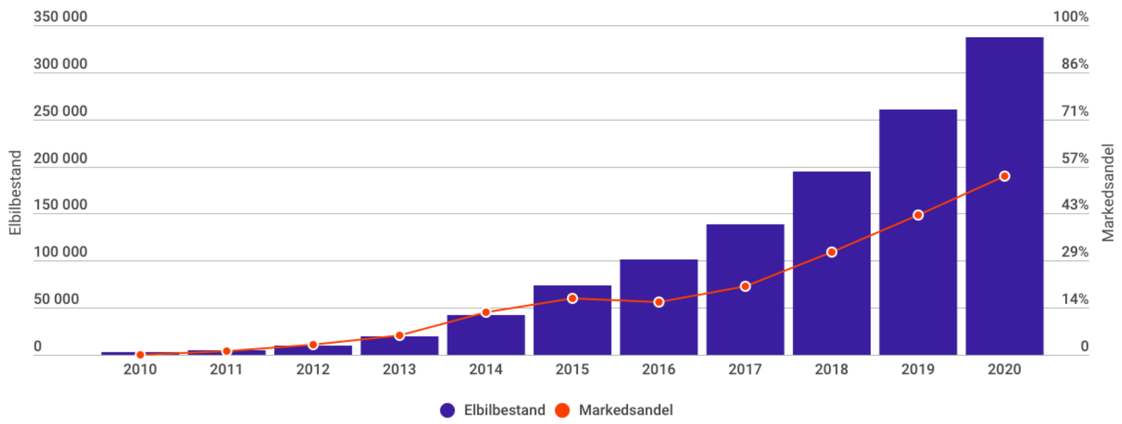


Figure 2.1: The amount of BEVs in Norway. Orange line represents the market share. Figure from [5]

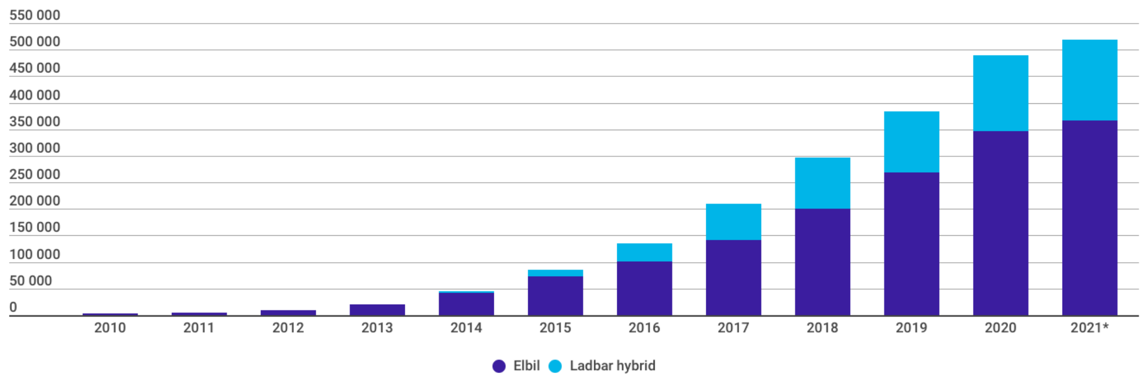


Figure 2.2: The amount of EVs in Norway. Dark blue represents BEV and light blue represents PHEV. Figure from [14]

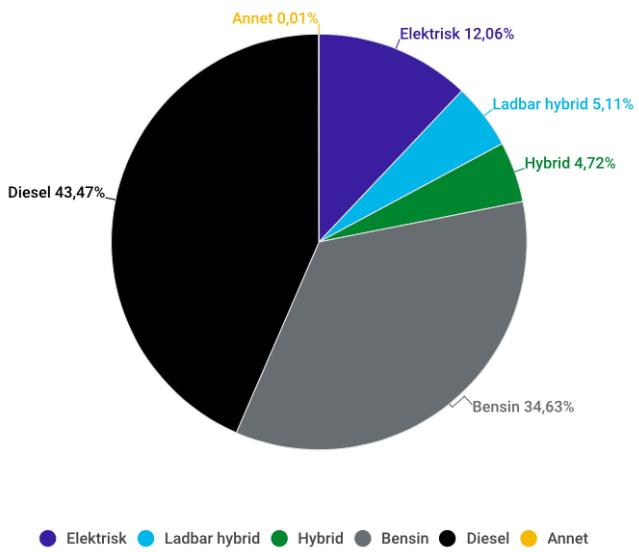


Figure 2.3: The car fleet in Norway at the end of 2020. Grey color represents gasoline cars, dark blue represents BEVs, light blue represents PHEVs. Figure from [14]

2.3 EV impacts

Habib et al., 2018 [10] has performed extensive research to study the EVs' impact. Figure 2.4 shows the three categories evaluated: impacts on power network, environmental impacts and economic impacts. The information provided in the three following sections is based on [10].

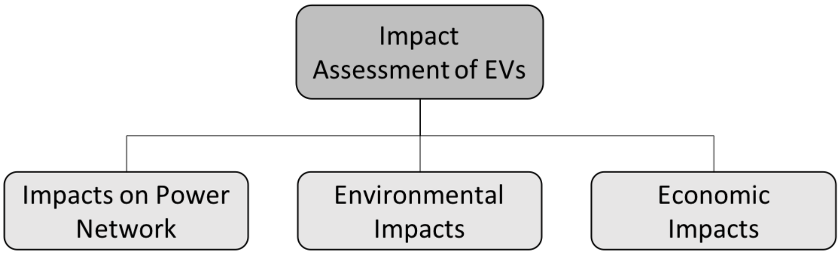


Figure 2.4: Categories of EV impacts. Figure from [10]

2.3.1 Economic impacts

EV economic impacts can be examined from the utility power grid and EV owner perspective. From the power grid point of view, an increase in the EV fleet will lead to an increased load, introducing additional power generation costs in terms of generation capacity. However, through controlled EV charging, up to 60% savings can be realised in the system cost and reduction in peak demand.

From the owner point of view, factors such as increased generation capacity, fuel cost, and high initial costs result in the negative economic impact of EVs. At the same time, several benefits can be achieved from EVs, such as lower operating costs due to the high efficiency of electric motors and comparatively lower costs of electricity. Moreover, research concludes that *"with the introduction of improved charging strategies and advanced infrastructure, electricity policies, trade incentives, and different reward policies, EV development and deployment can be gainful in both perspectives"* [10]. Also, users can benefit from supporting V2G.

2.3.2 Environmental impacts

Electrification of the transportation sector and integrating EVs into power networks provides a friendly environment based on reduced levels of CO_2 emissions. By integrating EVs with renewable energy sources (RES), several environmental benefits can be achieved, and dependency on fossil fuel can reduce using V2G technology.

The term "Well-to-Wheels" is introduced to evaluate EV environmental impact performance compared with the conventional internal combustion engine (ICE) vehicles. The term takes lifetime emissions, including exhaust pipe emissions, material, and energy utilized to power the vehicle into account. Some studies suggest that EVs are the vehicles with the least intensity of carbon gas emission. However, it is stated that charging of EVs through power plants including coal, natural gas and various fuel generating units with significant emission of pollutants may cause a comparable increase in "Wells-to-Wheels".

Different studies show different results for which vehicle has the least intensity of carbon emission. In the studies where electricity production comes from coal resources, EVs have a higher GHG emissions impact on the environment. However, with the *"increase in renewable energy integration to power network and optimized charging strategies, a significant reduction in "Well-to Wheels" emissions can be expected"* [10]. As Norway's electricity generation is mainly renewable, EVs are assumed to reduce GHG emissions [2].

2.3.3 Impacts on the power system

Electrification of the transport sector will introduce additional charging demand, which will impact and give challenges to the power system. The EV impacts on distribution grids can be categorised, as seen in figure 2.5. Moreover, each impact's substantial level depends on different factors such as the level of EV penetrations, charging strategies, EV battery characteristics, charging habits like charging location and time, driving distances and EV driving patterns, tariffs, and demand response techniques.

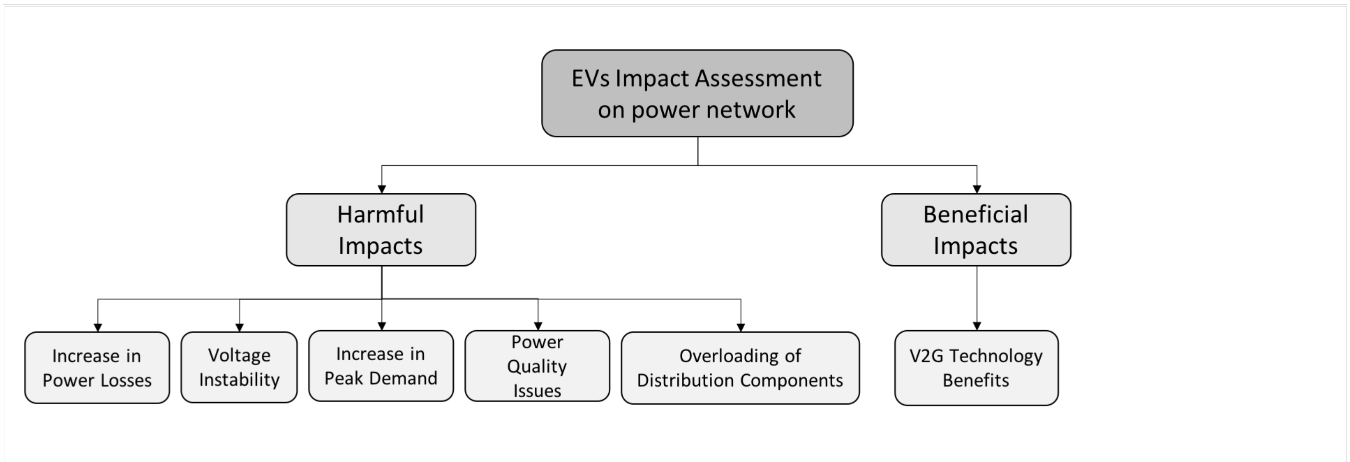


Figure 2.5: Classification of EVs impacts on distribution grid. Figure from [10]

2.4 Power system flexibility classification

Flexibility has many definitions and is not a unified term. In Degefa et al., 2021 [15], a unified definition for power system flexibility, characterisation and classification of flexibility resources are presented systematically. Here, power system flexibility is defined as *"the ability of power system operation, power system assets, loads, energy storage assets and generators, to change or modify their routine operation for a limited duration, and responding to external service request signals, without inducing unplanned disruptions"* [15].

To classify flexibility resource characteristics, they are grouped into two main categories: technical characteristics and economic characteristics. Technical characteristics are further classified into "quantitative technical characteristics", "qualitative technical characteristics", and "control technical characteristics", while the economic characteristics are classified into "Capital (investment) economic characteristics (CAPEX)", and "Operational economic characteristics (OPEX)" [15].

In literature, different methods are used to classify flexibility resource, as their place in the electricity supply chain, the roles of flexibility resources in the power system, and load shifting direction. Furthermore, other classifications methods based on aspects as the control mechanism, offered motivation, flexibility availability, and flexibility need are used. To systematise flexibility solutions, [15] propose a comprehensive classification of flexibility resources and their enablers. Here, EV's are classified as flexible resources having a mobile storage and demand side, shiftable advance.

2.5 Electrical vehicles as a flexible load

A large population of EVs will lead to an overall increased power load, especially in the local distribution network. It might cause a power peak exceeding the power grid's dimensions for capacity. By using the EV's potential as a flexible load, the need for investing in new power grids can be avoided [16].

Cars are usually parked 80% of the time, or more [17]. Because EVs only require to be charged enough before usage, this makes load shifting possible without reducing user comfort. A better insight of charging habits can be used to develop smarter charging solutions to take advantage of this potential. As of today, different solutions are already developed. However, most solutions are still in the research stage.

Skotland et al., 2016 [18] states that Norway has a capable electrical grid, based on the average load from charging EVs in the future. Nevertheless, it is assumed that the distribution grid will experience challenges related to transformers and lines if many people in the same area charge simultaneously. Also, the increased number of EVs might lead to disturbances in the voltage, giving challenges related to the voltage quality. This especially happens when using a one-phase charger in an already weak power grid, causing an imbalance in the three-phase grid.

To meet the goal of having a fully electric transport sector in the future, knowledge about how this transition should be implemented and might affect the power grid is necessary.

In 2019, the FuChar project started with the goal to minimise investment and operation costs associated with the grid integration of electric transport [19]. The project aims to optimise the grid and the charging infrastructure by developing optimal methods and tools and increasing electrical charging and user behaviour knowledge.

Today, different types of charging exist, but uncontrolled, dumb charging is of yet the most used type. This type of charging starts at maximum power immediately after connecting the charger. Another type is timely controlled charging, where the charging does not happen immediately after connecting the charger but at a predefined time. In addition, there is smart charging and V2G [6].

2.5.1 Smart charging

There is no common definition of EV smart charging. The Belgian research collaboration EnergyVille describes smart charging as using EV flexibility to intelligently manage the charging process according to the operator preference, described through a peak shave scenario, a renewable scenario, and a balancing scenario [20].

In the peak shaving scenario, the aim is to reduce the power peak. This can be solved by charging the EV when the capacity in the grid is high or by spreading several EVs in the same area's demand over time by managing simultaneous charging. In the renewable scenario, charging occurs when the available amount of intermittent renewable energy production is high. In the balancing scenario, the aim is to solve the issues related to balancing the grid by using charging to balance the demand/supply. Figure 2.6 presents different load profiles for different charging strategies as dumb charging, smart charging and V2G. As seen, smart charging leads to shiftable and interruptible charging.

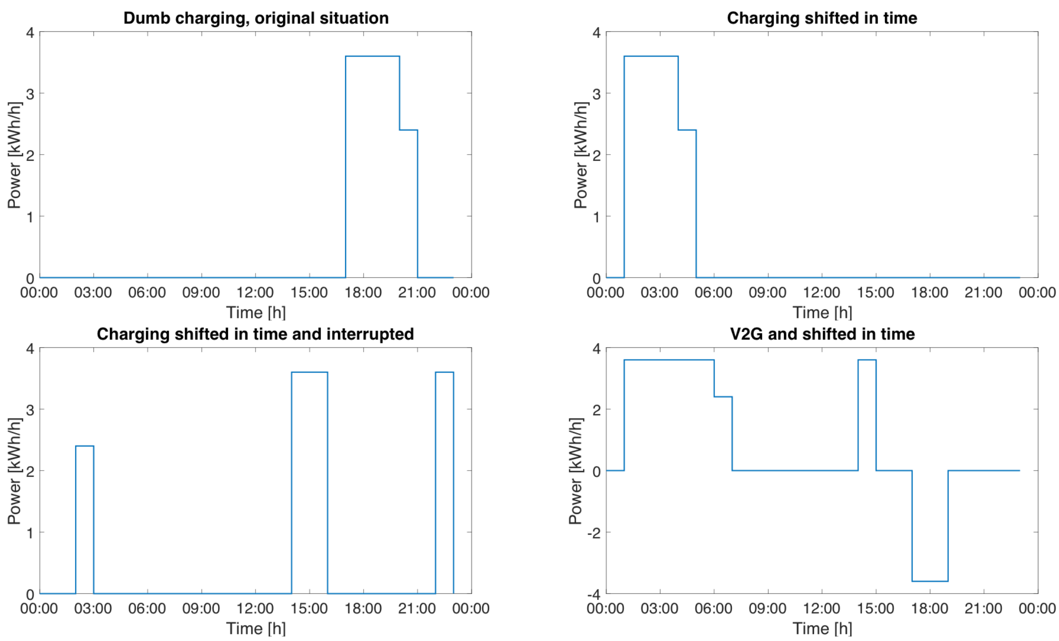


Figure 2.6: 13,2 kWh charging with a charging power of 3,6 kW. Figure based on [21].

Information such as connection and disconnection time, battery (SoC) when connecting the EV and charging demands or preferences are essential to operate smart charging [21].

Tibber is the leading company when it comes to offering flexible and smart solutions for EV charging to consumers in Norway [22]. They offer smart charging technology where charging happens at low energy prices. By having the consumer set the time for when the car needs to be done charging in an application, charging happens at the lowest price, always ensuring that the car is charged in time. Some car models in the market are already integrated with the application, and owners of these cars do not need any extra equipment to implement smart charging. Consumers having other car models need a charging box from Easee. When using smart charging with this box, Tibber guarantees its customers a cost reduction of 20% [22].

In [23], possible future power grid savings are predicted by using three different charging scenarios, assuming the whole car fleet to be electrical by 2040. The three scenarios are (a) charging every afternoon, (b) charging in the afternoon when needed and (c) charging at nighttime. In scenario a, the peak power increases 750 MW representing 5% of the load in the local distribution network. For scenario c, the peak power did not increase. Further, when comparing the total investment cost, they are predicted to be 11 billion for scenario a and 4,4 billion NOK for scenario b, considering reinstallation of some old power grids. For scenario c, no extra costs are obtained (The costs are not discounted and represent costs for 2019). This shows the value of having coordinated charging [23].

2.5.2 Vehicle-to-grid

V2G is a smart charging technology that allows bidirectional charging systems where energy can flow from the grid to the car and from the car to the grid. This way, EVs can store and dispatch electrical energy and operate as one collective battery fleet. This enables peak shaving by sending energy back when the demand is high or valley filling by charging at times when the demand is low [24].

The charging technology exists, but the systems are complicated and still in the research phase. Nissan and Renault are the only two car brands offering the technology, but they can only be used in a few countries without affecting the car's warranty. In addition, the CHAdeMO standard is the only charging standard available today, and it is reasonable to assume that it will take some years until V2G is commercially possible [6].

Today, the lifetime of the car battery will degrade faster when using V2G, as a result of the extra charging cycles used to transfer power back to the grid [6]. This makes V2G more expensive than the one-directional smart charging system. In addition, large price variations are needed to obtain a profitable V2G. Horne et al., 2019 [6] states that this is more likely to happen in 2030 and that the technology might get more relevant in the future.

2.6 EV batteries

2.6.1 Lithium-ion batteries

Today, lithium-ion batteries are the market leader for use in EVs, much because of their high efficiency, cycle life, and high energy density [25, 26]. Most likely, it will be the battery dominating the electric vehicle market for the next decade [27]. The batteries consist of two electrodes: one anode and one cathode, separated by a separating membrane allowing lithium ions to pass between the electrodes, preventing an internal short circuit [25, 26]. Graphic carbon is used as the anodes, while different materials can be used as the cathodes [26]. Today, nickel cobalt aluminium oxide (NCA), nickel manganese cobalt oxide (NMC) and lithium iron phosphate (LFP) are the most widely used for lithium-ion batteries [27].

EVs use a series of lithium-ion battery cells in a pack [26]. A battery cell monitoring is used to investigate the cell's conditions, as the battery cell may behave differently during the run-time. In addition, a battery management system (BMS) is needed to avoid overcharging, which can cause cell explosion and undercharging, potentially damaging the chemical properties of the battery and shorten the life of the battery cells. An ideal working range of the SoC can be between 20%-90% [26].

A charging convention with constant current and constant voltage (CC-CV) is recommended by most manufacturers [25]. The system provides constant current until the battery reaches the maximum charging voltage [26]. After this, the current drops to maintain the charging voltage to prevent overcharging of the cells, shown in figure 2.7.

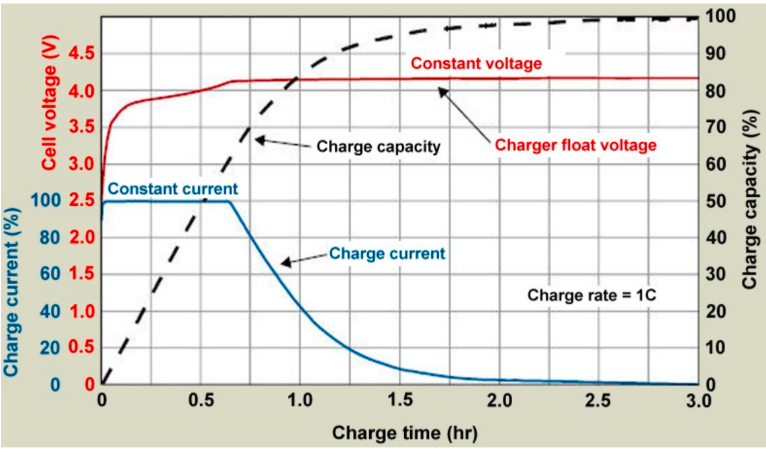


Figure 2.7: Characteristics of the lithium-ion battery when charging with CC-CV. Figure from [25]

The battery technology is developing, and the overall lithium-ion battery capacity is increasing. The average pack size across light-duty electric vehicles sold in 2018 was 37 kWh, compared to 44 kWh in 2020 [27]. In addition, there has been a marked reduction in the cost of batteries in the last decade [28]. This is seen in figure 2.8.

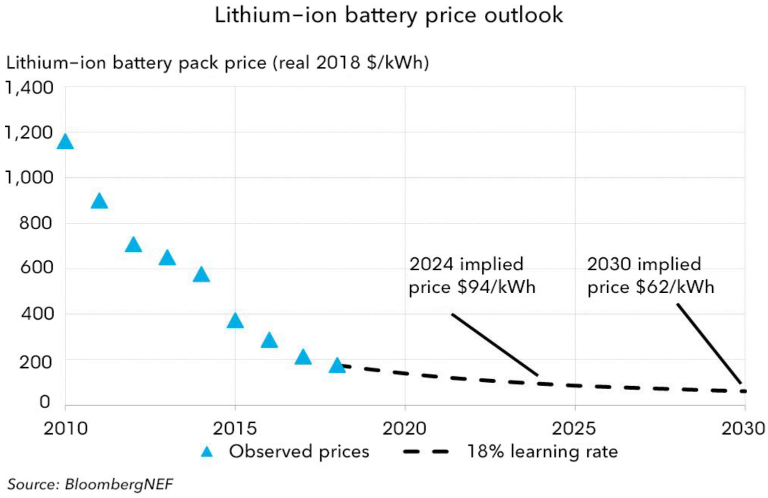


Figure 2.8: Development of the lithium-ion battery price. Figure from [28]

2.6.2 Battery aging and degradation

Battery degradation is an important aspect for EVs as it largely determines their cost, performance, and environmental impact [29]. By optimizing the battery operation conditions, battery life can be extended [30]. However, battery ageing depends on different factors and has a non-linear behaviour.

Battery ageing results from parasitic physicochemical reactions between components in a battery cell, resulting in degradation of the storable energy (capacity) and maximum power (impedance). The degradation typically depends on factors as temperature (T), state of charge (SoC) and current (I). The battery life is a result of both the three factors' instantaneous value and their temporal variations [29].

Battery ageing can be classified into calendar and cyclic ageing. Calendar ageing occurs when there is no current flowing through the battery; the car is parked and not charging. Cyclic ageing occurs when the battery is charging or discharging; the car is charging or driving [29].

The primary calendar ageing mechanism is the growth of the Solid Electrolyte Interface (SEI) layer on the negative electrode, typically accelerated at high levels of temperature (T) and State of Charge (SoC). For cycling ageing, the most representative mechanism is the lithium plating on the negative electrode and typically occurs at high current rates or low temperatures [29].

According to [30], cyclic ageing increases with lower temperature, and calendar ageing increases with higher temperature. This means that temperature should be kept low during storage periods and higher when cycling the battery, especially when charging. Furthermore, when a battery is charging for a longer time at low temperatures, current rates should be kept low to reduce lithium plating. In addition, to minimize battery ageing, a high SoC should be avoided when possible, and discharge depth should be reduced during cycling.

2.7 Influencing factors on EV charging

There are many factors influencing EV charging. Harbrecht et al., 2018 [31] address them as crucial to a systemic understanding of EV charging impacts on the power system. The influencing factors are divided into three subcategories: behaviour-, technical- and spatial factors.

Behavioural factors can be divided into driving behaviour and connection decision. Here, the driving behaviour includes the usage frequency, meaning the number of trips per day, the distance driven, and the arrival and departure times for different locations. Further, the connection decision will include battery SoC aspects when arriving at different locations, charging location, the frequency of recharging, where and when charging occurs, and the type of charging, typically divided into uncontrolled charging and user-controlled charging [31].

For the technical factors, the most important aspect influencing EV charging is the energy consumption typically measured in kWh per 100 km. This consumption depends on many physical factors as the driving velocity, vehicle weight, the ambient temperature and the use and application of auxiliary devices such as heating or cooling the passenger cell. Also, the battery size and usable battery share influence the EV charging and can especially be an essential aspect of the charging frequency. Furthermore, both the nominal internal EV charging power and the nominal external charging power at the charging station, together with their particular efficiencies, will primarily influence the charging time [31].

In addition, spatial factors such as the expected market penetration of both EVs and charging stations and their location will be important from a systemic perspective. Primarily, this yields when charging occurs at distribution grids already having challenges due to the high share of intermittent and decentralized electricity production [31].

2.7.1 Battery life cycle and EV driving range

An important technical aspect of EV charging is energy consumption per 100 km, as already described. This factor is directly related to the battery life cycle and EV driving range and depends on several physical factors, such as the driving conditions.

In [32], the impacts of driving conditions on a battery life cycle are studied. The mileage travelled by the vehicle before battery EOL are analysed for different conditions as driving cycles, ambient temperature, charging mode and trip distance. It is found that speed and acceleration can affect the driving range, where low speed and low acceleration is favourable. Furthermore, a low-temperature environment (0 °C) and high-temperature environment (40 °C) significantly reduces the driving range when the reference temperature environment is 20 °C. This is as expected as the ambient temperature directly affects the electrochemical performance and ageing rate of the battery pack [32].

Nissan also states that factors such as acceleration, driving velocity, topography and weather conditions affect the EV driving range [33]. They are one of few car manufacturers providing a range calculator where the user can set different factors as temperature, driving velocity and the number of people in the car. Figure 2.9 shows the Nissan Leaf's driving range for different average driving speeds dependent on the ambient temperature when assuming a family is in the car.

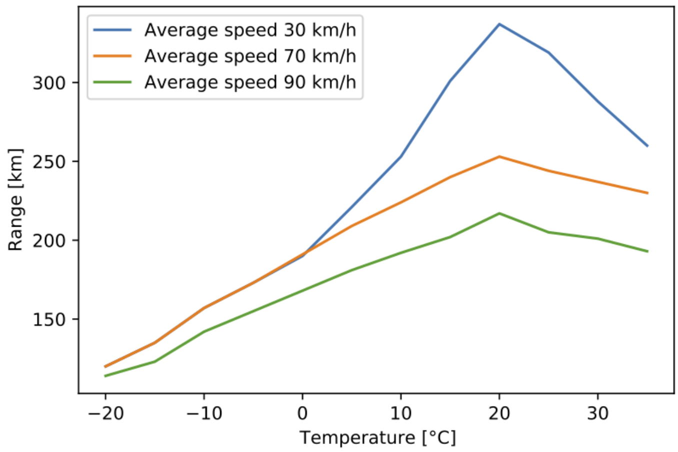


Figure 2.9: Driving range for different temperature levels and average speed levels, Nissan Leaf. Data from [33]

2.7.2 Charging point types

EV charging points can be divided into three main categories based on the charging function and power, categorised as normal charging, flexi charging, and fast charging [34]. According to [34], normal charging is the most used EV charging, which occurs at home at night or at work during the day. Flexi charging or public charging happens at a destination, where it is customary to stay some hours, such as at a mall. Fast charging is defined as charging at or above 50 kW and is usually placed in urban areas, often along arterial roads. Table 2.1 shows an overview of the three main charging points in Norway today.

Table 2.1: Categorising three types of charging points. Table from [34]

Charging point	Power	Where	Charging standard	Duration
Normal charging	3-4 kW (AC)	Typically at home at night or at work during the day, where the car is parked anyways.	Type 2 connector EU standard	6-7 hours
Flexi-charging	11-22 kW (AC)	At a destination, a place where you stay some hours, such as a mall	Type 2 connector EU standard	2-4 hours
Fast-charging	>50 kW (DC)	Urban areas, arterial roads	Three standards: 1. Combined Charging System (CCS/Combo) EU standard 2. CHAdeMO 3. Tesla's solution "Supercharger"	

In [35], the results from a BEV owner survey, collecting information from about 12.000 respondents with BEV owners from all over Norway, are presented. When splitting the respondents into two groups based on the housing type, the BEV owners living in detached houses charge to a substantial degree at home. People living in apartment buildings charge to a larger degree at public charging stations and use fast charging more. However, fast charging does not occur weekly, and normal charging is still the dominating charging method independent of the housing type.

In [18], NVE estimates 75% home charging, 15% charging at work, and 10% charging at fast-charging stations.

2.8 EV types and charging habits in Norway

2.8.1 Charging power

As described earlier, many factors affect the EV charging profile. A higher charging power results in a shorter charging time for the same amount of energy charged. It also leads to a higher power load, as more power is used at the same time. Also, the flexibility potential increases with increasing charging power, making it possible to shift a greater amount of energy [36].

Two limiting factors when charging an EV is the onboard charging power and the available AC power at the point where the charging happens [36]. The onboard battery characteristics for the ten most sold EVs in Norway (representing 75% of the whole EV fleet) are shown in table 2.2, based on data from [37] and [38]. Here, the charging power is typically between 3,6 kW and 11 kW. Renault Zoe offers the highest battery charging capacity of 43 kW and 22 kW. Based on findings in [36], there are typically five onboard charger capacities for EVs in Norway today: 3-3,7 kW, 6,6-7,4 kW, 11 kW, 16,5 kW and 22 kW.

Moreover, the charging power is limited by the charging power level for the home charger. [39] states that most home chargers have a charging power between 3 kW and 7 kW.

Table 2.2: Battery characteristics for the 10 most sold EVs in Norway. Data from [37] and [38]

Model	Total	%/total	Charging power [kW]	Plug-in [type]	Phases
Nissan Leaf	67 544	17.39%	3,6/6,6	Type 1	1
Volkswagen Golf	47 730	12.30%	3,6	Type 2	1
Bmw I3	28 813	7.42%	3,6/7,3/11	Type 2	1/1/3
Tesla Motors (Model 3)	26 030	6.71%	11	Type 2	3
Tesla Motors (Model S)	21 126	5.44%	11/16/22	Type 2	3
Kia Soul	21 004	5.41%	6,6	Type 2	1
Audi E-tron	17 704	4.56%	11	Type 2	3
Renault Zoe	14 564	3.75 %	43/22	Type 2	1
Tesla Motors (Model X)	13 838	3.57%	11	Type 2	3
Hyundai Ioniq	12 203	3.09%	6,6	Type 1	1

2.8.2 Driving range and charging frequency

The driving range depends on the EV battery size [kWh] and the energy demand per kilometre [kWh/km] and can be factors deciding how often and how much EVs need to charge. For BEVs, most cars have nominal battery sizes between 40 and 100 kWh [36]. Figure 2.10 shows last years development of battery capacity and the onboard charger for the different EVs on the market in Norway. It is seen that both the battery capacity and the onboard charging power has increased since 2011.

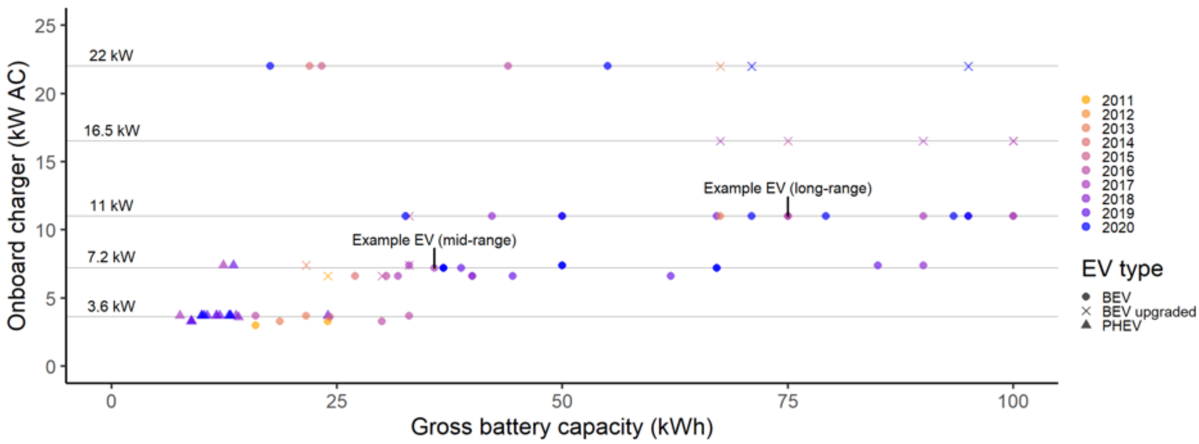


Figure 2.10: Nominal onboard charger capacity and gross battery capacity for BEVs and PHEVs on the market. Figure from [36]

How the driving range will affect the charging habits and charging frequency is uncertain. According to [40], nine out of ten charge at home. 96% of people living in single-family homes and 65% of people living in apartments charge at home at least once every week. In average, charging occurs 4,4 times at home and 1,1 times at work [40]. Based on findings in [36], the average charging frequency depends on having a private charger or a shared charger, found to be 4,4 times a week for the users having private chargers and 1,2 times a week for the users having shared chargers.

2.8.3 Energy demand

The EV's energy demand depends on the battery SoC, mainly resulting from the driving distance before charging. In Sørensen et al., 2021 [36], the average charging energy for each charging session was 11,2 kWh for private chargers and 14,2 kWh for shared chargers. 90 % of the charged energy was below 22 kWh for private chargers and below 39,3 kWh for shared chargers. In addition, the average yearly energy use was found to be 2150 kWh and 1500 kWh. This confirms the expectation in [36] that users with shared infrastructure charge less at home than users with private chargers.

As already described, the energy demand is also weather dependent and much higher in the winter season than in the summer season [18]. This is seen in figure 2.11, where the summer and winter energy demand are compared for different EV models. This means that EVs use more energy in the winter season when energy use is already high.

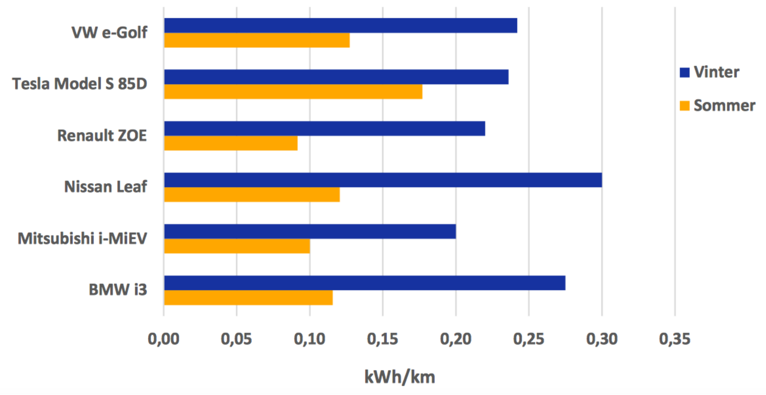


Figure 2.11: Energy demand per km for winter and summer for different EV models. Figure from [18]

2.8.4 Plug-in-, plug-out- and connection time

Today, plug-in time is the main factor for when the charging happens, as most charging bases on dumb charging [6]. Plug-out time decides the connection time, which is a factor deciding the possibilities for shifting load in time, hence the flexibility potential of the EV. The longer the EV is connected without being charged, the more flexible it is.

Sørensen et al., 2021 [36] found the plug-in and plug-out times correlating with the local hourly traffic data. Around 15% of the plug-ins occur between hour 16 and 17. This also corresponds to when the workdays typically end in Norway. For the plug-out time, it is observed a difference between the shared and private chargers. The users of shared chargers are encouraged to charge their EV for less than 3 hours, resulting in a less substantial morning peak. For EVs having private chargers, the peak with around 20% of the plug-outs happens between 7 and 8 on the weekdays. This is also present in the traffic density.

For the weekends, the traffic density is more evenly distributed during the day, which also is transferred to the corresponding plug-in and plug-out times [36].

The study also observed an average connection time of 12,8 h for the EVs having private chargers and 6,5 h for the EVs having shared chargers. However, there is no direct relationship between the charged energy and the time of connection. Generally, private chargers are connected longer than shared chargers for the same amount of energy charged.

2.9 Load profiles

Load profiles consist of energy demand information of an hourly or sub-hourly scale used to determine the energy system capacity and how they are operated [41]. In addition, load profiles play an essential role in the planning and operation of the long-term power system [7]. To be able to generate accurate load-profile generation models, realistic real-time network data are needed.

When charging an EV at home using a private home-charger, a new load adds to the original domestic electricity demand. Resultingly, the EV consumption might change the original load-profile shape completely, moving the peak power from occurring in the morning to occurring in the evening. Thus, understanding how EV load profiles depend on charging habits, charging capacity, and charged energy will be essential for future grid planning and operation. Additionally, EV load profiles will be important to decide on EV flexibility potential and EV optimal charging methods. As of yet, most literature on EV load profile generation is based on theoretical models [42].

2.9.1 Bottom up models

Because modelling of domestic electricity demand also depends highly on the user habits, the modelling approach is assumed to be comparable to EV load profile modelling. According to [41], there are two common approaches for modelling domestic electricity demand in literature; statistical models and bottom-up models. Statistical models base on a set of measured load profiles and use characteristics of the input parameters as season or household size to explain its variance. However, [41] states that the model lacks in investigating effects from user behaviours.

In bottom-up modelling, the smallest units of a system are used and aggregated to reach the higher system levels [43], starting from the individual electric device and its usage. In domestic load profile modelling, the energy consumption is found by modelling occupant behaviour, often done by combining time-of-use statistics with measured load traces of various electric devices [44].

2.9.2 Bottom up modelling of domestic electricity demand

Richardson et al., 2010 [45] presents a bottom-up model to represent domestic electricity demand. The model uses the appliance (an individual domestic electricity load) as the basic building block and maps the occupant activity to appliance use resulting in stochastically created synthetic demand data. It uses daily activity profiles as input, representing the likelihood of people performing different activities at different times of the day, based on time-use data derived from the UK 2000 Time Use Survey (TUS). Then, each dwelling in the system is assigned an active occupancy data series and a set of installed appliances. Using the appliance power use-characteristic and information about when the appliance switch-on occurs, the total electricity demand can be found.

In [41], SynPRO, a stochastic bottom-up model is used to generate electric load profiles to investigate the effects of occupant behaviour, appliance stock and efficiency on the electric load profile of an individual household. The load profile is generated from probability, based on a national time of use survey for Germany to decide the number of starts, start times, and duration of each activity. Use-frequency depends on user habits, and behaviour and seasonal effects are considered by using changing probability sets during the course of the year. When the model was tested against measured data, the results were 91% accurate and showed a correlation up to 0.98.

2.9.3 EV load profile models

Lopes et al., 2011 [46], generates load profiles by using a theoretical model based on three different rated power: 1.5 kW for a hybrid vehicle, 3 kW for a medium EV and 6 kW for a large EV. Further, it is assumed to have an average charging time of 4 hours and a daily charging energy of 2.3 kWh, 10.9 kWh, and 22.4 kWh for the hybrid, medium EV, and large EV.

Wu et al., 2016 [47], generates load profiles by using Markov chain modelling to decide the plug-in time, plug-out time and charging need. Plugs-ins and plugs-outs are assumed once a day. For the simulation done in this specific paper, a plug-out time between 7:00 AM-08:00 AM and a plug-in time between 16:00-17:00 AM is used. Further, it is assumed that the EV only charges at home and drives between work and home. The trip time is decided by using ten individual daily driving schedules over 3197 work-days in an office in Chengdu, China. A 12 kWh battery energy demand, equipped with a 10kW Tesla single charger, is used.

In [48], a Monte Carlo based simulation method is utilised to create EV charging and discharging profiles. It assumes that EV charging solely occurs in EV's owner's residence, only using a single-phase EV connection. For the typical EV load profile creation, Peugeot ION (16.5kWh), Volkswagen GOLF (26.5kWh) and Nissan LEAF (25kWh) are used. The battery capacity is randomly selected within three values in each iteration of the simulation. The average power demand is 3.5 kW, which assigns to a typical EV power level in slow charging mode. Battery SoC is linearly dependent on the daily driving distance, randomly sampled from the driving distance distribution and allocated to every charging behaviour through the Monte Carlo method. Starting charging time is randomly selected within a specific time scope decided in the simulation for three different analysed scenarios.

In [49], a method for simulating and analysing the time-dependent EV demand flexibility is presented, using charging information as connection time, charging time and plug-in time from a Dutch charging case study, assuming perfect forecast. Three methods are used for simulating the charging power. The first method uses a fixed constant charging power based on the maximum power of the charging point or the EV. The other two methods use charging power values varying per simulated transaction, with a maximum constant charging power in method 2 and an average constant charging power in method 3.

[42] presents a method to generate realistic EV profiles based on statistical data to identify their effect on the distribution grid with and without the use of demand response. The daily duration of charging is linked to the driven distance per day [km/day]. The probability of

each driving distance has a different probability provided from a Norwegian EV ownership survey conducted in 2017. Further, the EV battery energy and charging power are set based on ownership statistics in Norway. The method uses the probability of charging at home at each hour of the day to decide when charging occurs. Then, a monte-carlo approach is used to generate 1-minute level daily charging profiles.

Harbrecht et al., 2018 [31] presents a stochastic bottom-up model to generate EV load profiles, to analyse the impact on load profiles at different parking location and EV load management potential. A large dataset on German mobility is used to identify influencing factors on residential charging behaviour. In addition, a set of household and BEV configurations, behavioural decision parameters for grid connection and charged energy, BEV model data and other technical parameters are used as input parameters. They are further used to generate individual driving profiles where an inhomogeneous Markov Chain is used to sample a sequence of destinations of each car trip. Different probability distributions of the driven distance, duration, and parking duration determine the electricity demand. The model takes socio-economic, technical and spatial factors into account, which influences charging behaviour and location. It considers work pattern, weekdays, season, place of residence and family situation, resulting in detailed load profiles for typical charging locations and battery SoC history for all the charging events.

3 Data

This chapter presents the measurement data from [8], used to make the EV load profile generation model in this thesis. The EV data set consists of charging reports collected from a housing cooperative at Risvollan in Trondheim, Norway. It provides information such as date, user type, user ID, plug-in time, connection duration, and charged energy for every measured charging sessions between 21.12.2018 and 31.01.2020. In this thesis, only private users are evaluated. Consequently, a total number of 5466 charging sessions will be analysed to find EV charging habit connections and aspects.

Figure 3.1 shows the number of users per week and the weekly charged energy. As observed, the number of EVs increases throughout the year, which reflect the increase of the EV fleet in Norway. As expected, the total weekly energy increases as the number of users charging per week increases.

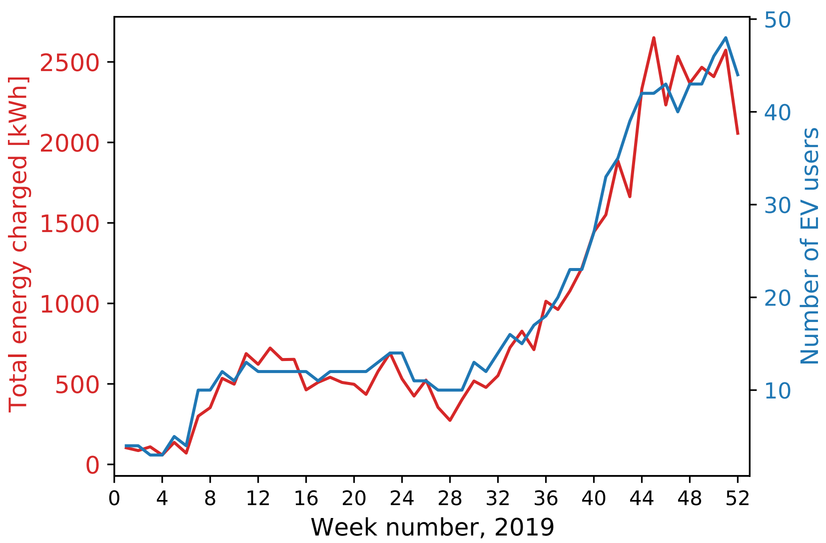


Figure 3.1: The total energy charged per week and the number of EV users charging

3.1 EV types

In [36], charging habits such as the weekly charging frequency and charged energy is seen to depend on the EV using a private or shared charger. Generally, people with private chargers charge their EV at home long before the battery SoC is low. Still, for private chargers, it is expected that EVs with large battery sizes will charge less frequently than EVs with small battery sizes. Further, EV load profiles depend highly on maximum charging power. Therefore, to analyse any differences, factors such as the battery size and maximum charging power must be identified. In this case, information for these factors is only provided for nine EVs. Resultingly, alternative methods are used to distinguish the data set's EV types.

The maximum charging powers are estimated by using equation 3.1:

$$P_{max} = \max_{i=\{1,...,n\}} \left(\frac{E_i}{C_i}\right) = \max\left(\frac{E_1}{C_1}, \frac{E_2}{C_2}, ..., \frac{E_n}{C_n}\right) \tag{3.1}$$

E_i is the charged energy, C_i is the connection duration, and $i = \{1, ..., n\}$ is the charging session number, where n is the total number of charging sessions. The maximum is selected and stored as the maximum charging power, P_{max}. Running this for each EV user, a maximum charging power of approximately 3.6 kW or 7.0 kW is obtained for each EV, and can be seen in figure 3.2.

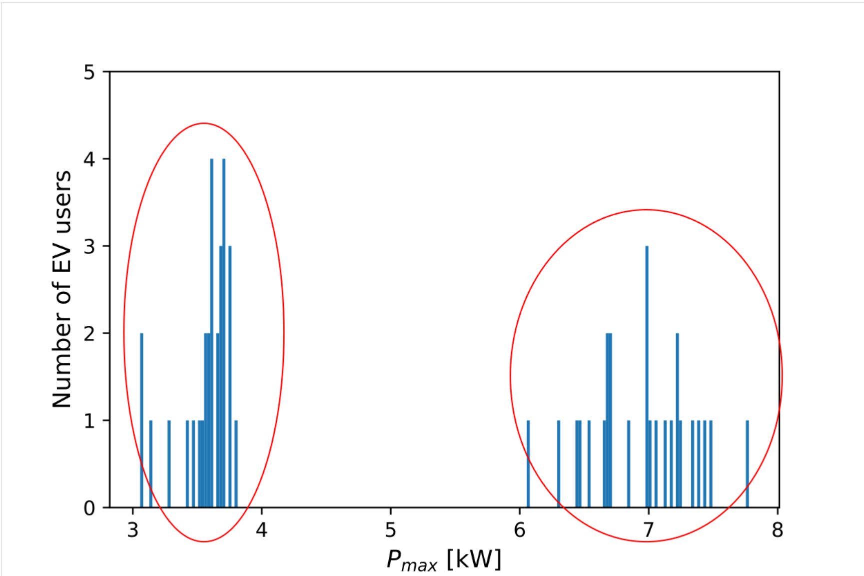


Figure 3.2: Maximum charging power per EV user

Based on this, the EVs are divided into two groups, charging at the typical charging power levels of 3.6 kW or 7.2 kW. Further, to estimate the EV battery sizes, the maximum charged energy per EV user per session is used. Figure 3.3 shows the maximum charged energy per EV user per session for the two charging power groups.

EVs having a maximum charging power of 3.6 kW typically have lower maximum charged energy per session than the EVs having a maximum charging power of 7.2 kW. This relation is expected and can be justified from figure 2.10 in chapter 2.8.2, showing how battery capacity size and charging power are related and has increased over the years.

The maximum charged energy per session is more distributed for the EVs charging with 7.2 kW. If this results from different charging habits for EVs having the same battery size or reflect different battery sizes, is uncertain. However, based on the figure, it is assumed that a maximum charged energy of 25 kWh per session can be used to roughly distinguish the EV battery sizes of the EV users in the data. In the following, the "large EV" refers to the EVs having a large battery size with maximum charged energy per session greater than

25 kWh, and a "small EV" refers to the EVs having a small battery size with maximum charging per session smaller than 25 kWh. Even though the maximum charging powers will not be used further to analyse the data explicitly, they are used to group the EV types in the data, which can be seen in table 3.1.

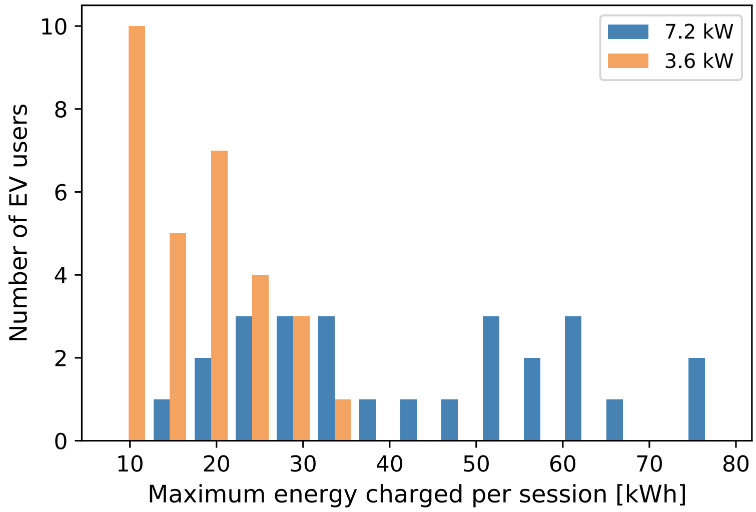


Figure 3.3: Maximum charging power and maximum energy charged per EV user per session

Table 3.1: EV types in data set

	% of all EVs	**3.6 kW [%]**	**7.2 kW [%]**
Large EV	46	19	81
Small EV	54	87	13

3.2 Weekly charging frequency

By separating the large EVs from the small EVs, differences in charging frequencies can be analysed. Figure 3.4 shows the weekly plug-in frequencies for the different EV types. Generally, the charging frequencies are lower for large EVs than for small EVs. As an EV with a lower battery size needs to charge the car more frequently for the same amount of charged energy, this is expected. For large EVs, 30% charge two times per week. The weekly charging frequency is much more distributed for small EVs, with a peak of around 12% for the charging frequencies of two and three times per week.

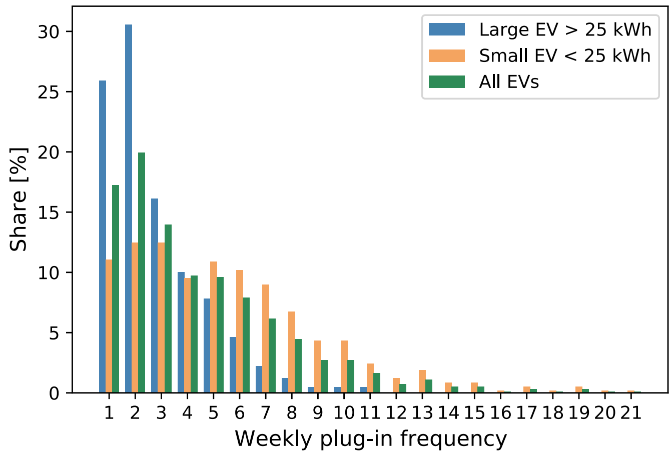


Figure 3.4: Weekly charging frequency different EV types

3.3 Energy charged versus weekly charging frequencies

Figure 3.5 shows the mean charged energy per charging session for different weekly charging frequencies and EV types. In general, the mean energy charged per charging session decreases as the weekly plug-in frequency increases. However, for small EVs, the mean charged energy per charging session is approximately uniform for weekly charging frequencies above 12. For charging frequencies above this level, an increased charging frequency might imply longer total weekly driving distances.

The mean charged energy per charging session is higher for large EVs than for small EVs, for the same weekly plug-in frequency. This might imply that users with a smaller battery size generally drive shorter distances and use the car less than users with larger battery sizes.

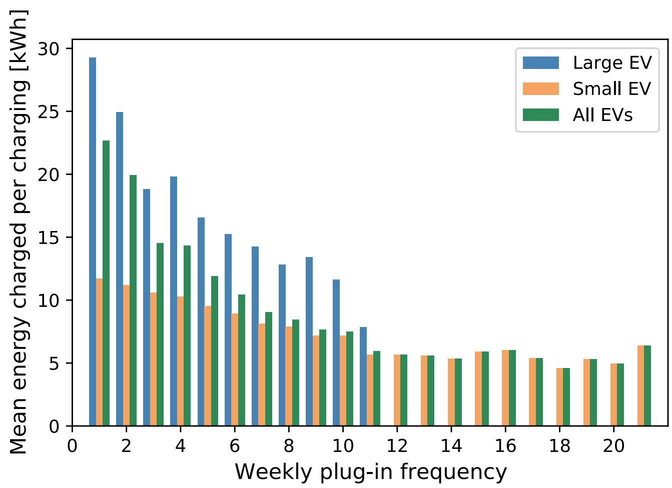


Figure 3.5: Mean energy charged per charging for the different charging frequencies and EV types

3.4 Energy versus temperature

EV energy need depends on the ambient temperature. Because the data does not provide any information on the driving distance before charging or the battery SoC when plugging in, a temperature dependency can not be analysed directly. Instead, to determine any temperature dependency, the temperature levels are compared to the actual charged energy.

Figure 3.6 shows the energy charged per EV user compared to the average weekly temperature. No clear correlation is found on this level, which is not surprising as the charged energy mainly results from different driving and charging habits. However, on a monthly level, a negative correlation is found and can be seen from figure 3.7. Month 1 and 2 do not include enough EV users and are therefore not taken into account. Still, even though a negative correlation is found, this might result from different monthly driving distances.

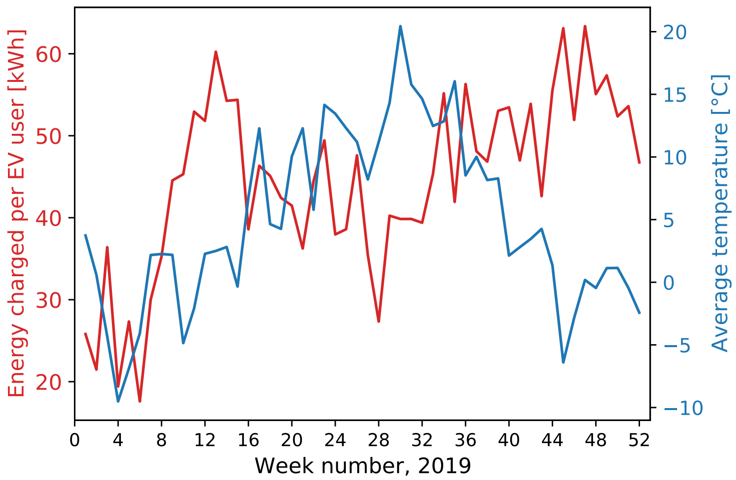


Figure 3.6: The total energy charged per week and the average weekly temperature

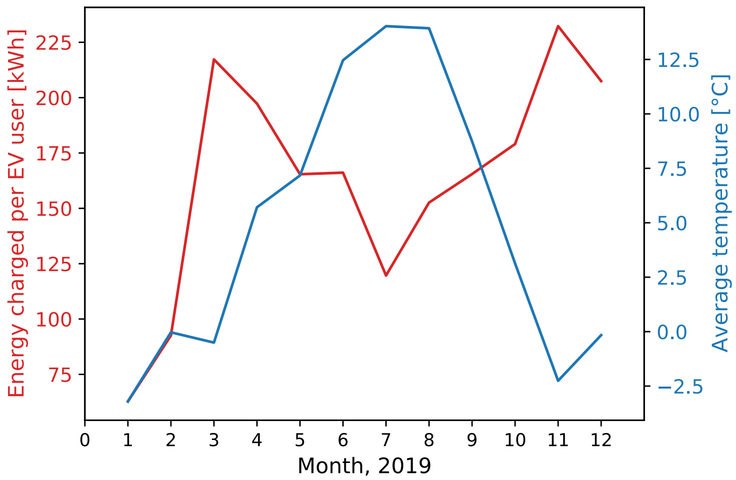


Figure 3.7: The total energy charged per month and the average monthly temperature

3.5 Plug-in times

There is not found any relationship between weekly charging frequencies and plug-in time, and the plug-in time follows, to a certain extent, the overall plug-in distribution for all plug-in frequencies. Figure 3.8 shows the plug-in time distribution for every day of the week. Because the plug-in times from Monday to Friday are similar, they are plotted as "weekdays" in the plot to the right, together with the plug-in times for Saturdays and Sundays. The plug-in times seem realistic and peak between hour 16 and 17, which is when most people typically arrive home from work on weekdays (Monday to Friday). For Saturday and Sunday, the plug-in times are more distributed over the day.

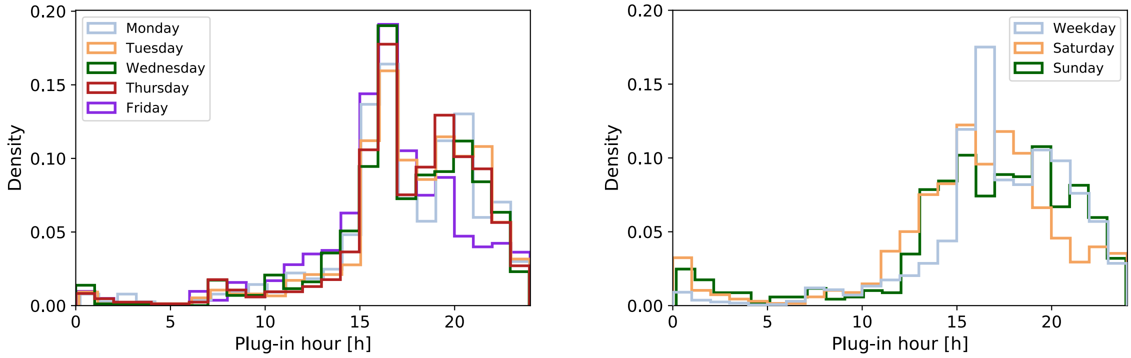


Figure 3.8: Plug-in times for all days of the week

3.6 Plug-out times

Plug-out time together with the plug-in time decides the connection time, which is an essential parameter to model the flexibility potential from charging of EVs. For fast charging, plug-out time is mostly related to the energy need, and the car is usually not connected for more hours than it is charging. However, for home charging, plug-out time often results from how long the EV is parked for the specific charging session. Consequently, for home charging, the EV is typically connected longer than the charging time. Thus, there is no particular relationship between the connection hours and the charged energy [36].

When comparing plug-out time for the seven days of the week, the plug-out time is similar for the weekdays (Monday-Friday), with a plug-out time peaking between 7 and 8. This reflects when most people typically go to work in Norway. For Saturday and Sunday, the plug-out time is more distributed over the day. This can be seen in figure 3.9.

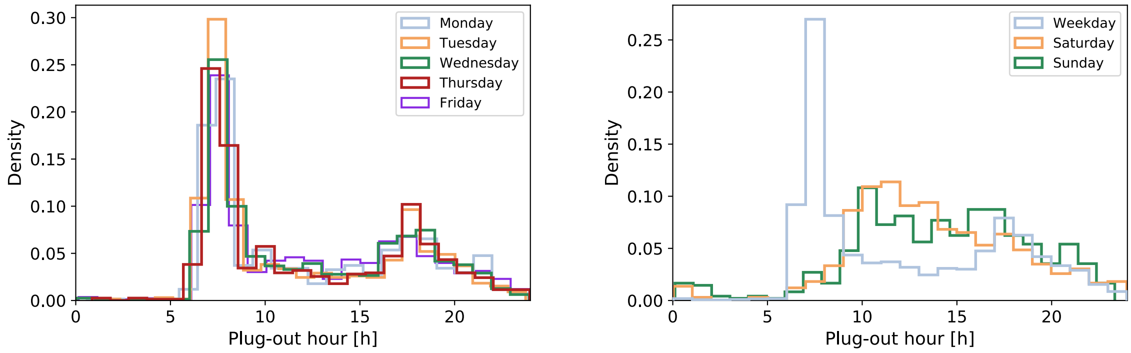


Figure 3.9: Plug-out times for all days of the week

EVs are often connected overnight, and hence the plug-out time is also related to the day of plugging in the car. In figure 3.10, the different plug-out times can be seen for the different days of plugging in when only taking the charging sessions being connected for less than 24 hours into account. Because the plug-out times are approximately the same for plug-in days from Monday to Thursday, they are plotted together. From this graph, it can be seen that the plug-out times have a similar shape for the plug-in days where the following day is of the same day type: weekend or weekday.

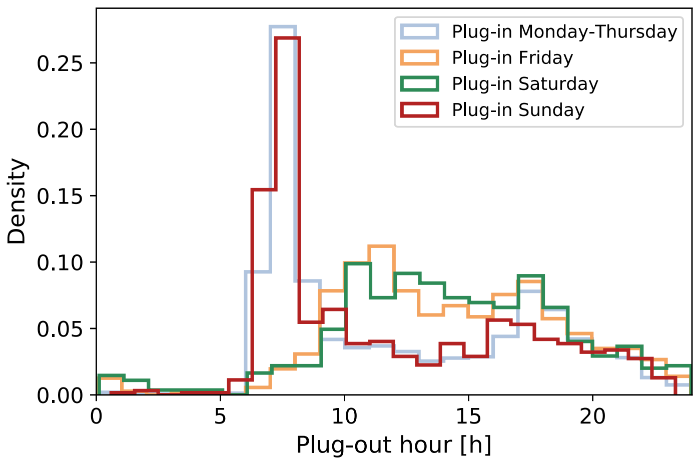


Figure 3.10: Conditional plug-out times for different days of plugging-in

3.7 Connection duration

A correlation between the plug-in time and connection time is identified in [36]. As the connection time is directly connected to the resulting plug-out time, plug-in time also correlates with the plug-out time. An earlier plug-in often means a shorter connection and a plug-out later the same day. A late plug-in often has a longer connection time and a plug-out the following day.

This aspect can be explained by figure 3.11, showing the connection time for different day types having similar connection time distribution: the days followed by a weekday (Sunday-Thursday), and the days followed by a day in the weekend (Friday and Saturday). The connection duration shows two peaks for both day types, and the charging sessions plugged in earlier on the day usually connect to the first peak, while the charging sessions with a plug-in later on the day connect to the second peak.

For charging sessions with a plug-in on Sunday-Thursday, around five per cent are connected for more than 24 hours. When the plug-in day is Friday or Saturday, the connection time is more distributed. Generally, the connection time is longer, and approximately 17% are connected for more than 24 hours.

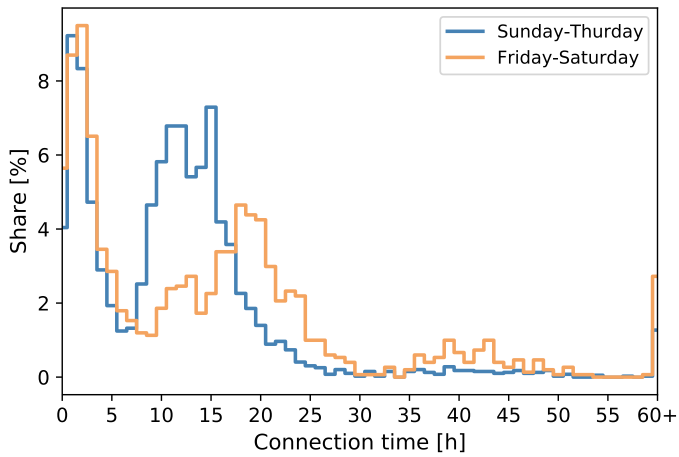


Figure 3.11: Connection time for different days

4 Method

This chapter presents the stochastic bottom-up model used to simulate EV load profiles for private home charging. In contrast to other models, it bases on real-world EV-charging data presented in chapter 3. The simulation tool is written in Python, using Spyder IDE.

The model is built using a similar approach as presented in [41], described in chapter 2.9.2. EV load profiles depend strongly on user behaviour, such as weekly charging frequency, plug-in time and plug-out time. In addition, load profiles depend on the type of car, such as battery capacity, charging power level and energy need. These are all parameters used directly or indirectly in the model to simulate the aggregate load profile.

Figure 4.1 shows a simplified overview of the model developed in this thesis. The distributions needed to create the stochastic input parameters are identified by the data set described in chapter 3. A Monte-Carlo approach is indirectly implemented when simulating aggregate load profiles for a significantly large number of EVs.

The goal is to make a realistic aggregate hourly load profile for all EVs, each day of the year, assuming dumb charging. Still, the model provides individual EV characteristics such as plug-in and plug-out time, charged energy, charging frequency and idle hours for each EV user. Hence, it is also possible to use the model to analyse EV flexibility potentials. In addition, the model can be used to simulate load profiles when assuming other charging strategies than dumb charging.

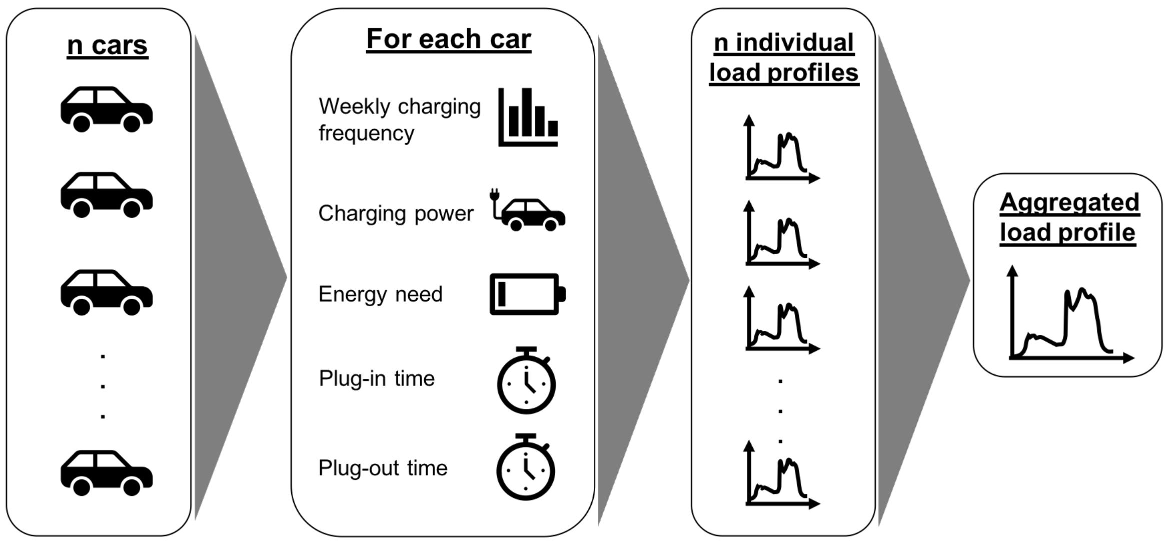


Figure 4.1: Simplified system model for generation of EV load profiles

4.1 Identifying probability distributions

Several distributions are analysed to find the best-fitted distribution for all the continuous stochastic parameters such as charged energy, plug-in time and plug-out time. A Kolmogorov–Smirnov test is used and implemented in a Python script to estimate the goodness of fit between the data and the tested distributions to find the best-fitted distribution.

Figure 4.2 shows how the EV-charging data is divided to obtain the probability distributions used to decide the stochastic parameters in the model.

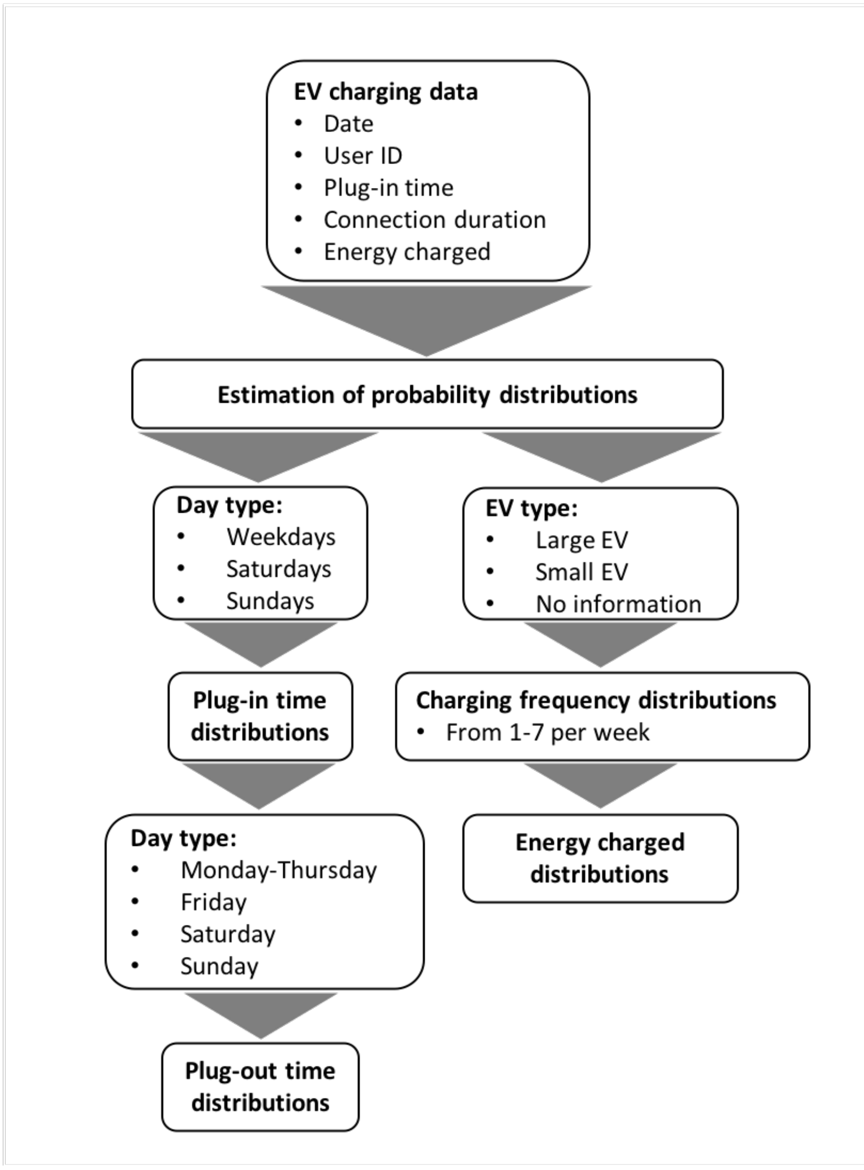


Figure 4.2: Flow chart of how the data set is divided to obtain the distributions used to find the stochastic input parameters in the model

4.1.1 Charging frequency

Charging frequency is usually a result of the driving behaviour and battery SoC. Because the EV charging data does not provide information for the battery SoC when plugging in, this can not be used. However, weekly charging frequency probability information can be extracted. In addition, weekly charging frequency is seen to depend on the EV type, where a lower battery size typically leads to a higher charging frequency. This is used set the charging frequency in the model.

Due to ease of implementation, the modelled weekly charging frequency is limited to a maximum of one plug-in per day meaning a maximum of seven charging sessions per week. Because only 15% of the charging sessions in the data belong to a weekly charging frequency higher than seven, it is reasonable to assume that this simplification will not significantly affect the aggregate EV load profiles.

Figure 4.3 shows the probability for each weekly charging frequency for the different EV types. The probability of charging seven times per week results from the probability of charging seven times or more per week. Thus, charging frequency is a discrete number from 1 to 7. Based on the different probabilities, a random weekly charging frequency is randomly drawn for each car in the system depending on the EV type.

The total number of plug-ins are approximately equal for all the days of the week. Consequently, based on the weekly charging frequency, which days of the week charging occur are set randomly.

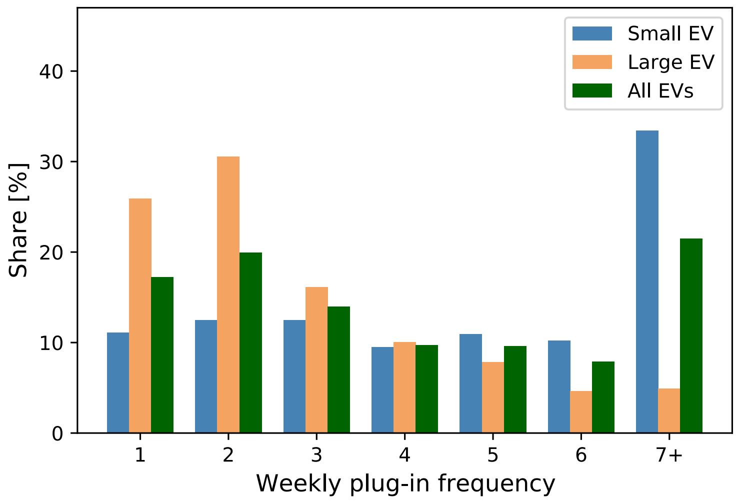


Figure 4.3: Weekly charging frequency probability for different EV types

4.1.2 Charged energy

In real life, energy need per charging session depends on driving distances, battery charging efficiency and outside temperatures. Because the data does not provide any information on the driving distances, factors such as the weekly charging frequency, EV type and ambient temperatures are used to decide the energy need in the model.

Figure 4.5, 4.6 and 4.7 shows the distributions for the charged energy for different weekly charging frequencies, for small EVs, large EVs and all EVs, respectively. An example of the best fitted distribution is shown in figure 4.4, showing the energy charged for all EVs charging three times per week. The different distributions for the different EV types can be seen in table A.2.1 and A.2.2 in the Appendix.

When setting the energy need for a charging session in the model, the first step is to draw a random number from the correct distribution according to the EV type and weekly charging frequency.

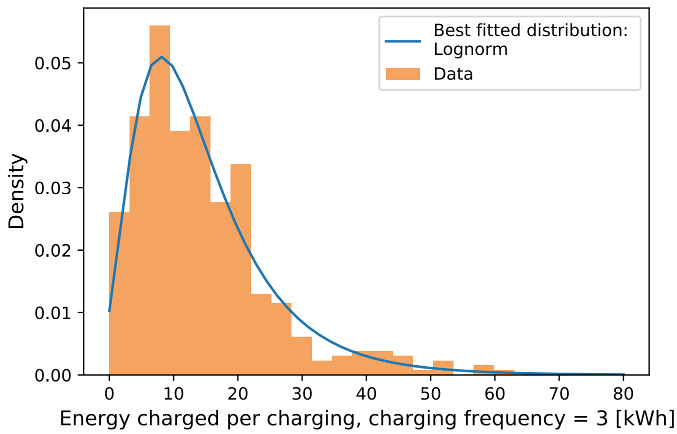


Figure 4.4: Example of a distribution fitted to the data

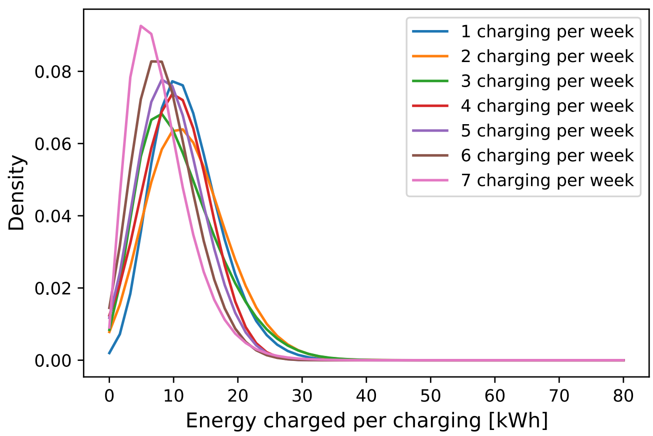


Figure 4.5: Distribution of energy charged per charging session for different weekly charging frequencies. Small EV

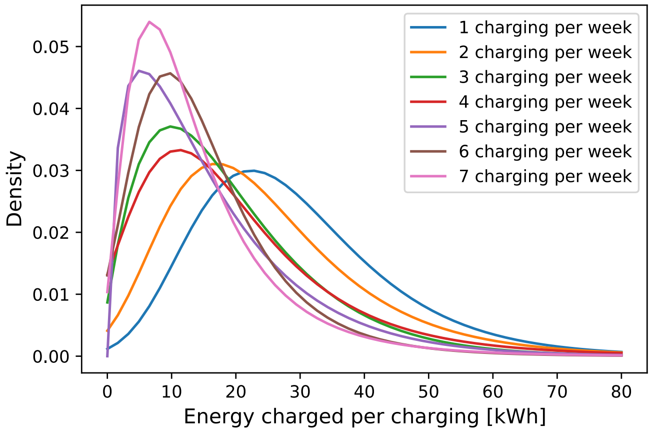


Figure 4.6: Distribution of energy charged per charging session for different weekly charging frequencies. Large EV

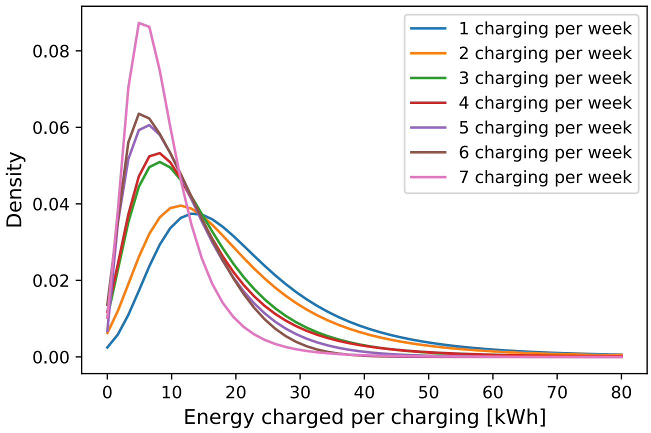


Figure 4.7: Distribution of energy charged per charging session for different weekly charging frequencies. All EV

In addition, the EV energy need will depend on the ambient temperature, and should be scaled accordingly.

In chapter 3, a temperature-dependent charged energy level is found on a monthly level. As this might result from different monthly driving distances, the dependency needs to be validated. This is done by comparing the temperature dependency found in the data to the temperature-dependent range of Nissan Leaf, as presented in chapter 2.7.1. In this case, an average speed of 70 km/h is used, assuming a family is in the car.

The same unit is obtained in both cases by transferring Nissan Leaf's range in kilometre to the total energy need per car per month. This is done using Nissan Leaf's battery size of 40 kWh and assuming a monthly driving range of 1000 km [33, 50]. Figure 4.8 shows the temperature-dependent monthly energy charged per user for the two methods. As observed, they are in the same range. Thus, the temperature dependency found from the data is used to scale the energy need in the model. Because the data provides no information for temperature levels above 20°C, Nissan Leaf's temperature dependency is used when temperatures are above this level.

The average temperature for the period of the measurement data is 5°C. Resultingly, the energy need is scaled according to this temperature level. The final temperature scaling factor can be seen in figure 4.9. By multiplying the scaling factor with the randomly drawn energy need, the final energy need is found.

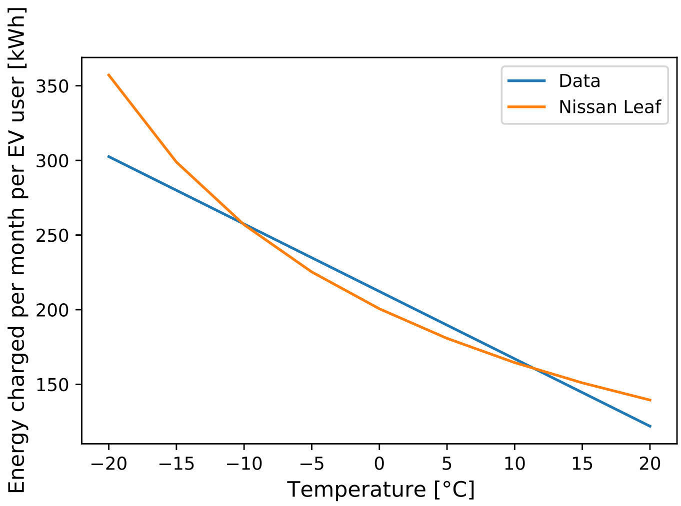


Figure 4.8: Temperature dependent energy charged per EV user per month for Nissan Leaf and data

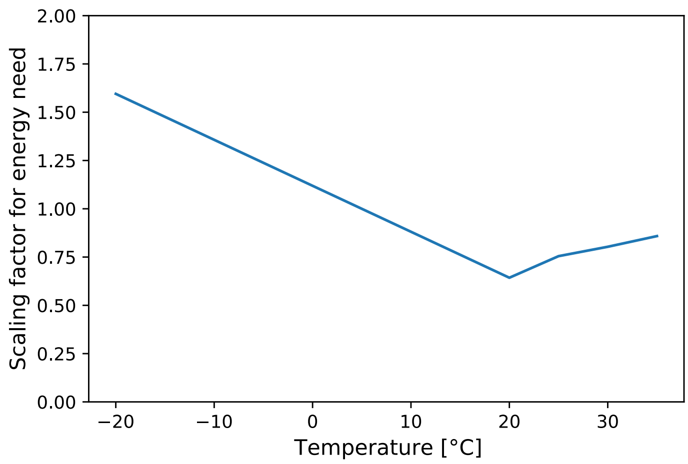


Figure 4.9: Scaling factor used for temperature scaling the energy need in the model

4.1.3 Plug-in time

The plug-in time distribution will not be affected by the EV type and is generated randomly based on the day types of the week: weekdays, Saturdays and Sundays. Because not a single distribution fits the plug-in time data, a combination of different distributions will be used. This can be seen in figure 4.10, 4.11 and 4.12, showing the plug-in time distributions for weekdays, Saturday, and Sundays, respectively. The plug-in time is set by first randomly drawing which distribution to use, followed by randomly drawing a plug-in time from this distribution. The plug-in distribution and the relating parameters can be seen in table A.3.1 in the Appendix for the three day types.

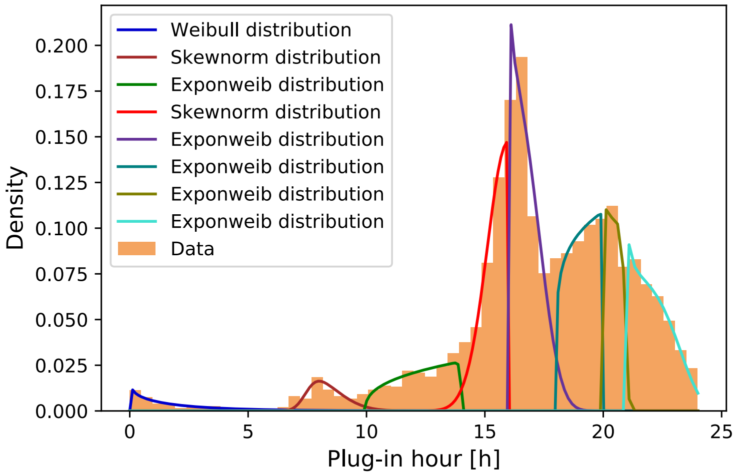


Figure 4.10: Best fitted distributions for plug-in times, weekdays

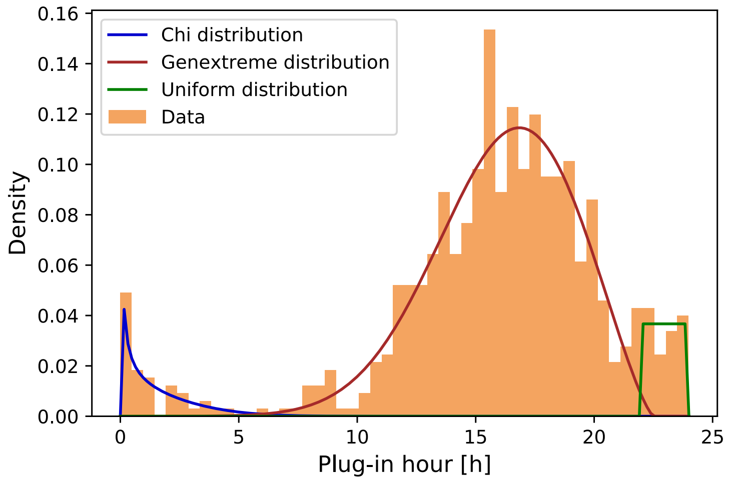


Figure 4.11: Best fitted distributions for plug-in times, Saturday

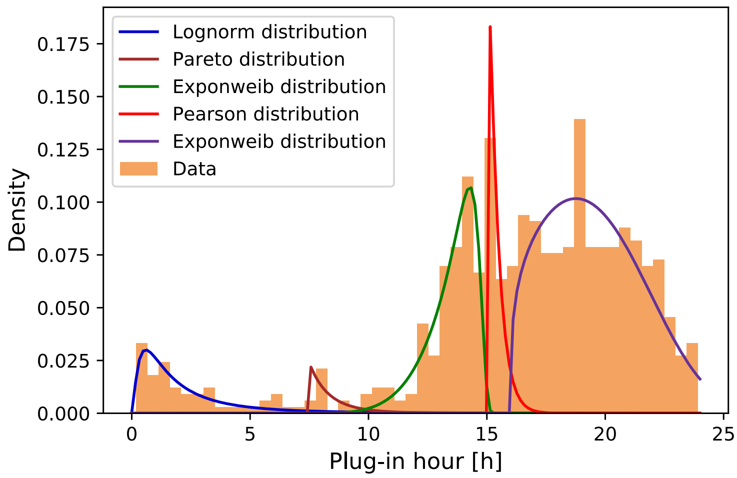


Figure 4.12: Best fitted distributions for plug-in times, Sunday

4.1.4 Plug-out time

In the model, connection time is limited to a maximum of 24 hours. Consequently, the plug-out time can be modelled and used directly to find the connection time. As the main goal is to simulate load profiles for dumb charging, and the battery sizes today are usually not large enough to charge as long as 24 hours, the simplification will not significantly affect the result. If using the model for optimisation purposes, and load profiles are simulated using smart charging, this aspect becomes more crucial. However, as most of the charging sessions in the data are connected for less than 24 hours, the simplification is still assumed to give a realistic output.

When the plug-in day is from Monday to Thursday, the simplification guarantees that the plug-out day is a weekday. When this is the case, plug-out time is modelled using the correlation to the plug-in time. The plug-in times are grouped into "Early and late-night (0-6)", "Early morning (6-9)", "Late morning (9-12)", "Early afternoon (12-15)", "Late afternoon (15-18"), "Early evening (18-21)" and "Late evening (21-23)", and different distributions are found for the plug-out time for each of these plug-in groups. Figure 4.13 shows an example of the distribution for the plug-out time when the plug-in time is between hour 18 and 21. Depending on the group of plug-in time, plug-out time is set by randomly drawing which distribution to use, and then randomly drawing a number from this distribution.

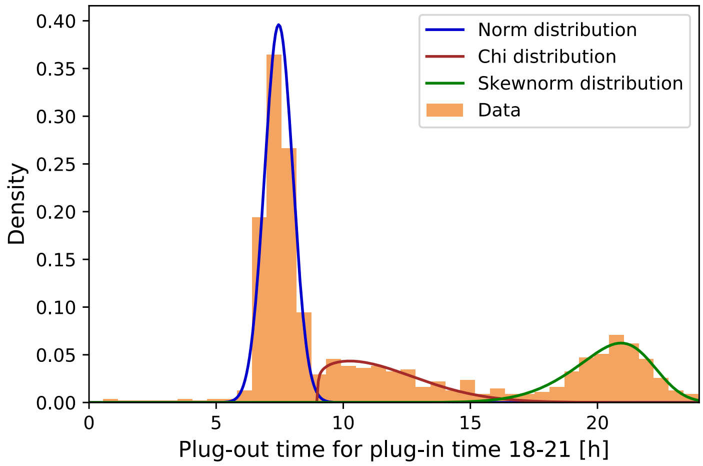


Figure 4.13: Best fitted distributions for plug-out times, when plug-in is between 18 and 21 on a weekday (Monday-Thursday)

When the plug-in day is a Friday, Saturday or Sunday, there is not enough data to find the plug-in time dependent plug-out times. For these days, the plug-out time is instead modelled depending on the day of plugging in the EV. Figure 4.14 shows the distributions for the plug-out time when the plug-in day is Saturday. The plug-out time is set the same way as when the plug-in day is a weekday, apart from not depending on the plug-in hour group.

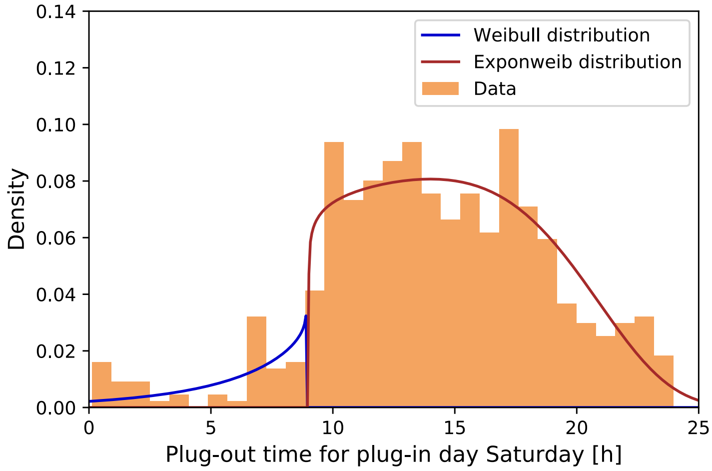


Figure 4.14: Best fitted distributions for plug-out times, when plug-in day is Saturday

The simplification of having a maximum connection time of 24 hours and a maximum of one charging per day reduces the probability of drawing a plug-out time occurring later than the plug-in time of the next charging session. However, if this happens, a new plug-out time is drawn to avoid overlapping charging sessions.

Information of all plug-out time distributions can be seen in the Appendix, in table A.4.1

for plug-ins on weekdays (Monday-Thursday) and table A.4.2 for plug-ins on weekends (Friday-Sunday).

4.2 Mathematical model

The mathematical model is presented to systematically give an overview of the steps for obtaining the final connection profile and charging profile in the model.

4.2.1 Index sets

The following table provides the index sets used in the model:

Name	Description
$t \in T$	Time periods (e.g. hours)
$d \in D$	Day of week or year
$u \in U$	EV user (EV ID)
$D^A \subseteq D$	Weekdays (Monday - Friday)
$D^B \subseteq D$	Weekdays (Mondays - Thursday)
$D^C \subseteq D$	Fridays
$D^E \subseteq D$	Saturdays
$D^F \subseteq D$	Sundays
$U^L \subseteq U$	Large EV
$U^S \subseteq U$	Small EV

The set of time periods can be written as $T = 1, \ldots, N$

4.2.2 Parameters

The following table provides the input data stochastic parameters required by the model and the associated unit:

Name	Description	Units
$P_u^{\max}$	Maximum charging power for EV user u	kW
$E_{d,u}$	Charging need per session	kWh
F_u	Weekly charging frequency (1...7)	-
L_t	Duration of period t	h
$T_{d,u}^{\mathrm{S}}$	Plug-in time (1...24)	h
$T_{d,u}^{\mathrm{E}}$	Plug-out time (1...24)	h
$C_{d,u}$	Connection duration (1...24)	h
$\Gamma_{d,u}$	EV user u plugs-in at day d	0/1

Where the connection duration $C_{d,u}$ is a result of the plug-in time and plug-out time expressed as:

$$C_{d,u} = \begin{cases} T^{\mathrm{E}}_{d,u} - T^{\mathrm{S}}_{d,u}, & \text{if } T^{\mathrm{E}}_{d,u} \geq T^{\mathrm{S}}_{d,u} \\ 24 - T^{\mathrm{S}}_{d,u} + T^{\mathrm{E}}_{d,u}, & \text{if } T^{\mathrm{E}}_{d,u} < T^{\mathrm{E}}_{d,u} \end{cases} \tag{4.1}$$

4.2.3 Flow chart for stochastic input parameters

Figure 4.15 shows a detailed flow chart of how to obtain the modelled stochastic input parameters for each EV and all days.

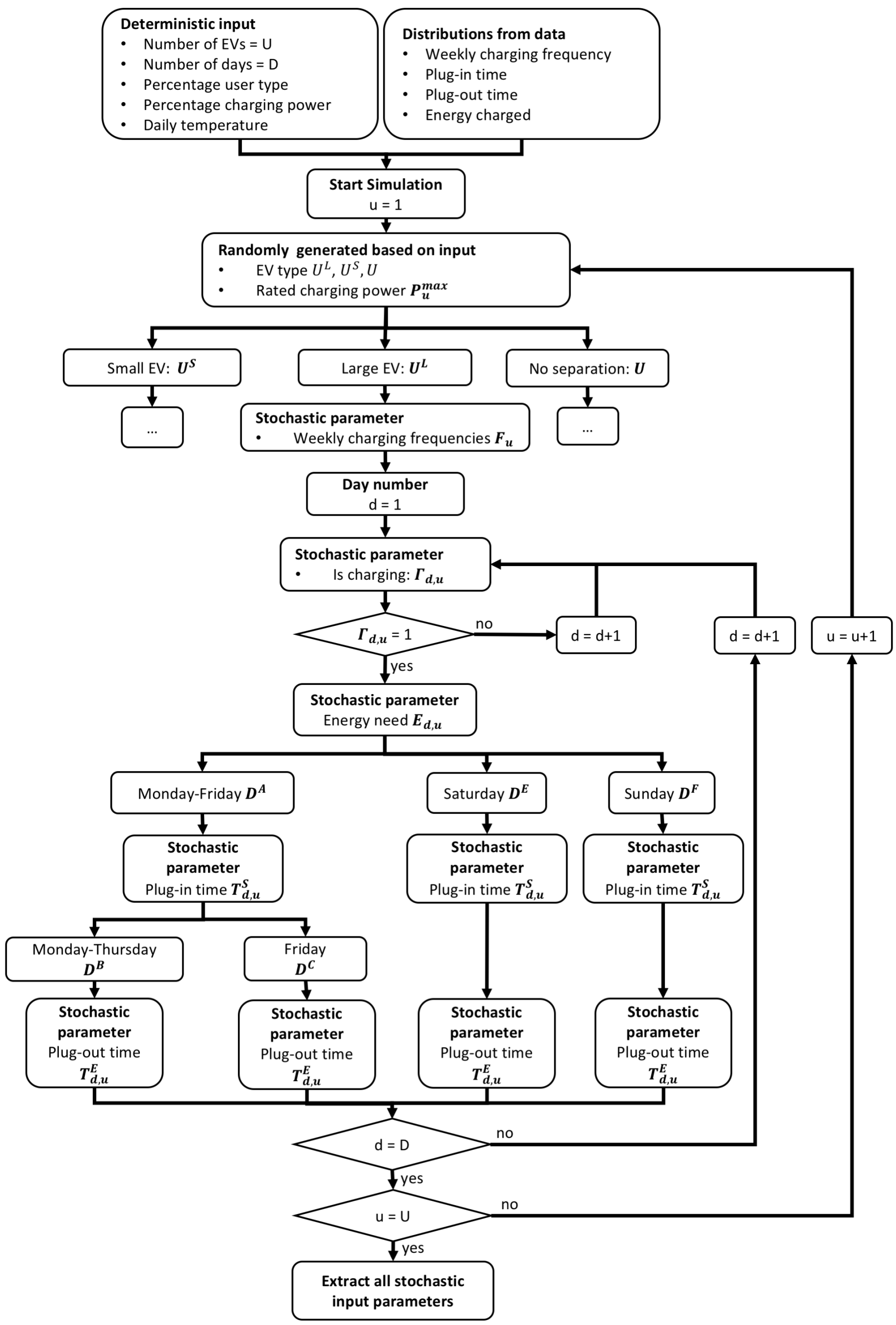


Figure 4.15: Detailed flow chart of the stochastic parameter model

4.2.4 Variables

The model has four sets of variables:

Name	Description	Unit
$y_{t,d,u}$	Load at time t, day d, for EV user u	kWh/h
$z_{t,d,u}$	Remaining charging need at time t, day d, for EV user u	kWh
$\alpha_{t,d,u}$	EV user u is charging at time t, day d	0/1
$\beta_{t,d,u}$	EV user u is connected at time t, day d	0/1

y and z are continuous and non-negative variables, while α and β are binary variables.

4.2.5 Equations

The hourly load profile can be expressed by equation 4.2 as:

$$y_{t,d,u} = P_u^{\max} \times \alpha_{t,d,u} \tag{4.2}$$

where P_u^{max} is the maximum charging power level for EV u and $\alpha_{t,i,k}$ is a binary variable being 1 when the EV is charging. $\alpha_{t,d,u} = 1$ when the charging need $z_{t,d,u} > 0$, and the EV is connected $\beta_{t,d,u} = 1$ as expressed in equation 4.3.

$$\alpha_{t,d,u} = \begin{cases} 1, & \text{if } z_{t,d,u} > 0 \text{ and } \beta_{t,d,u} = 1 \\ 0, & \text{otherwise} \end{cases} \tag{4.3}$$

When the EV is not connected over night, meaning that $T^S_{d,u} + C_{d,u} \leq 24$ and $T^E_{d,u} > T^S_{d,u}$, the hourly charging need can be expressed by equation 4.4 as:

$$z_{t,d,u} = E_{d,u} - \sum_{t=T^S_{d,u}}^{N} P_u^{\max} \times \beta_{t,d,u} \times L_t, \qquad \text{for } T^S_{d,u} \leq t \leq 24 \tag{4.4}$$

Where N = 24, L_t is the duration of period t of one hour and $E_{d,u}$ is the charging need per session at day d for EV user u. $\beta_{t,d,u}$ is a binary variable being 1 when the EV is connected. When the EV is not connected over night, $\beta_{t,d,u}$ is expressed by equation 4.5 as:

$$\beta_{t,d,u} = \begin{cases} 1, & \text{if } T^S_{d,u} \leq t \leq T^E_{d,u} \\ 0, & \text{otherwise} \end{cases} \tag{4.5}$$

If the EV is connected over night such that $T^S_{d,u} + C_{d,u} \geq 24$ and $T^E_{d,u} \leq T^S_{d,u}$, the charging session's remaining charging need might be transferred to the next day as expressed in equation 4.6.

$$z_{t,d+1,u} = z_{24,d,u} - \sum_{t=1}^{T^E_{d,u}} P_u^{\max} \times \beta_{t,d+1,u} \times L_t, \qquad \text{for } 1 \leq t \leq T^E_{d,u} \tag{4.6}$$

When the EV is connected over night, $\beta_{t,d,u}$ is expressed by equation 4.7 and 4.8.

$$\beta_{t,d,u} = \begin{cases} 1, & \text{if } T^S_{d,u} \leq t \leq 24 \\ 0, & \text{otherwise} \end{cases} \tag{4.7}$$

$$\beta_{t,d+1,u} = \begin{cases} 1, & \text{if } 1 \leq t \leq T^E_{d,u} \\ 0, & \text{otherwise} \end{cases} \tag{4.8}$$

4.3 Input parameters

The input values set by the user running the model are:

- Number of EVs
- Percentage of EV type "Large EV" and "Small EV". If no input, then no distinction of EV type.
- Percentages of charging power 3.6 kW or 7.2 kW for the respective EV type.
- Daily temperatures for the modelled year, starting on Monday week 1.

4.4 Output

The input parameters will be used to extract the stochastic parameters used to simulate the hourly load profile for each EV user, each day of the year. The load profiles assume dumb charging, meaning that charging will start immediately after plugging in the car. Charging power is set to its maximum, and the car will charge with this power throughout the whole charging session. For the sessions connected long enough, charging will continue until the charged energy is equal to the energy need. When this is not the case, charging will last the entire connection duration.

In addition to extracting load profiles for dumb charging, it is possible to use the stochastic parameters to create hourly connection profiles. Hence, the model can be utilised to simulate load profiles when assuming other charging strategies than dumb charging.

As the EV fleet increases and because dumb charging is not the most optimal charging method, this aspect of the model is assumed to be of utmost interest.

4.5 Case study

In order to compare the output of the model, three different cases will be simulated and compared by changing the EV type input and the respective charging power.

In each case, an EV fleet of 1000 EVs is used. In addition, the daily average temperatures input is the same for all three cases, using daily temperature levels from Trondheim in 2019 [51]. Table 4.1 shows the different input parameters for the EV types and maximum charging powers. BASE case represents the composition of the EV stock of the data set. The LOW case represents the small EV type charging more frequently but for less charged energy each session, with a maximum power of 3.6 kW for all EVs. The HIGH case represents the large EV type charging less frequently but for more charged energy each session, having a maximum charging power of 7.2 kW for all EVs.

To further study the model, load profiles are simulated for the same three cases, assuming flexible charging, using the same stochastic input parameters as used to simulate the load profiles with dumb charging.

Table 4.1: Input parameters of the three cases

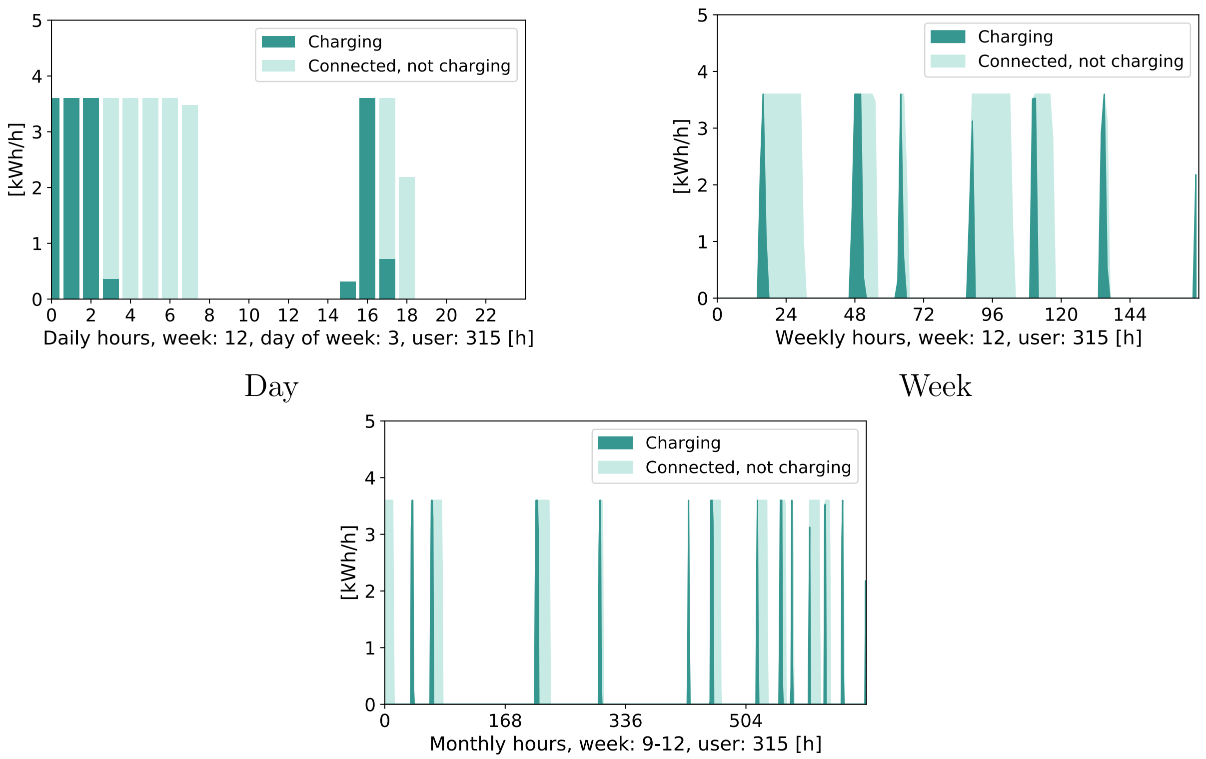
	EV type	**% of all users**	**3.6 kW [%]**	**7.2 kW [%]**
BASE	Large EV	46	19	81
	Small EV	54	87	13
LOW	Large EV	0	0	0
	Small EV	100	100	0
HIGH	Large EV	100	0	100
	Small EV	0	0	0
$\text{BASE}_{\text{flex}}$	Same numbers as BASE, but assuming flexible charging			
LOW_{flex}	Same numbers as LOW, but assuming flexible charging			
$\text{HIGH}_{\text{flex}}$	Same numbers as HIGH, but assuming flexible charging			

5 Results and Discussion of Case Study

The three cases will simulate different aggregate load profiles, giving different peak power and total energy demand. This chapter presents, compares and discuss the results of the three cases BASE, HIGH, and LOW introduced in chapter 4. Chapter 5.1 presents single load profiles of simulated EV users. Chapter 5.2 presents the results of the three cases of simulating 1000 EVs. Additionally, the three cases are run with the possibility of charging the EVs flexible, presented in chapter 5.3.

5.1 Single load profiles

In all three cases, single load profiles and connection profiles can be extracted for each car in the system. Figure 5.1 and 5.2 shows daily, weekly and monthly single hourly load profiles for a small EV with charging power of 3.6 kW and a large EV with a charging power of 7.2 kW, respectively. Even though charging occurs at the maximum power, the load profile is on an hourly scale. Hence, the charging power is lower when charging does not last the complete hour. This is apparent in the daily single load profile. Here, a more exact plug-in and plug-out time can be seen. The small EV typically charge more frequently and has a lower energy need than the large EV. However, both EV types are generally connected longer than the charging time.

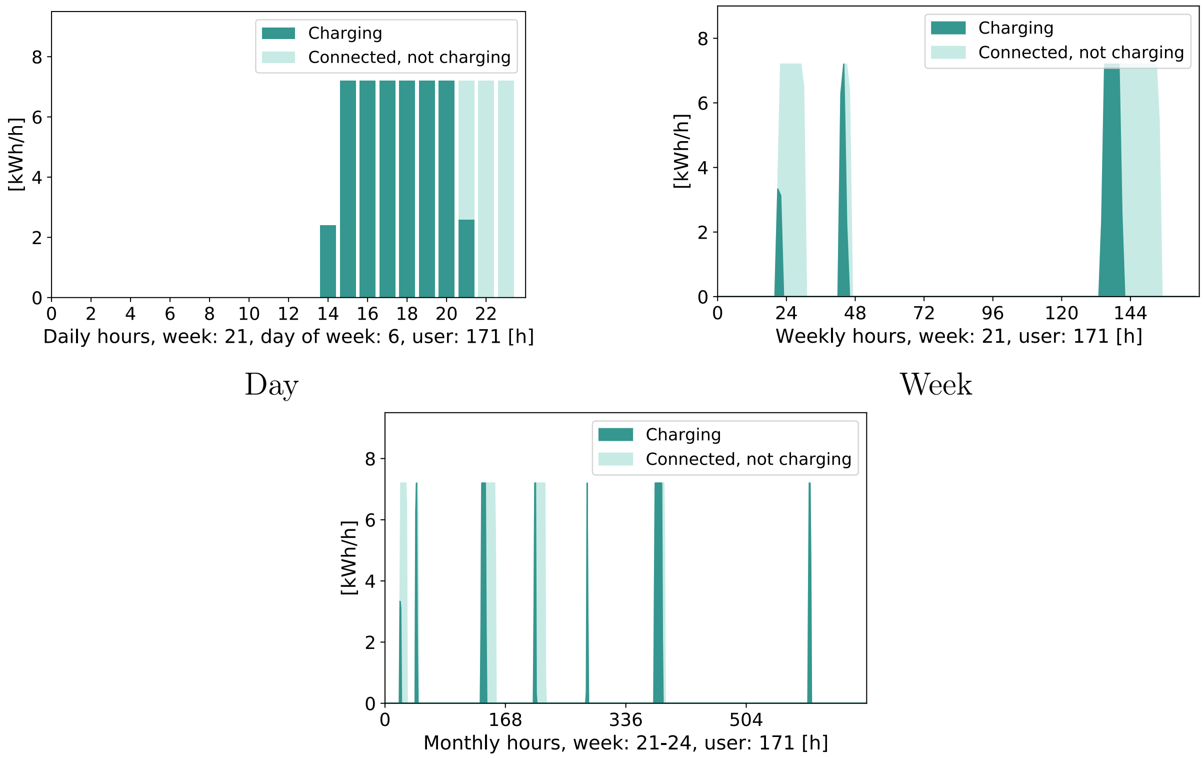


Day

Week

Month

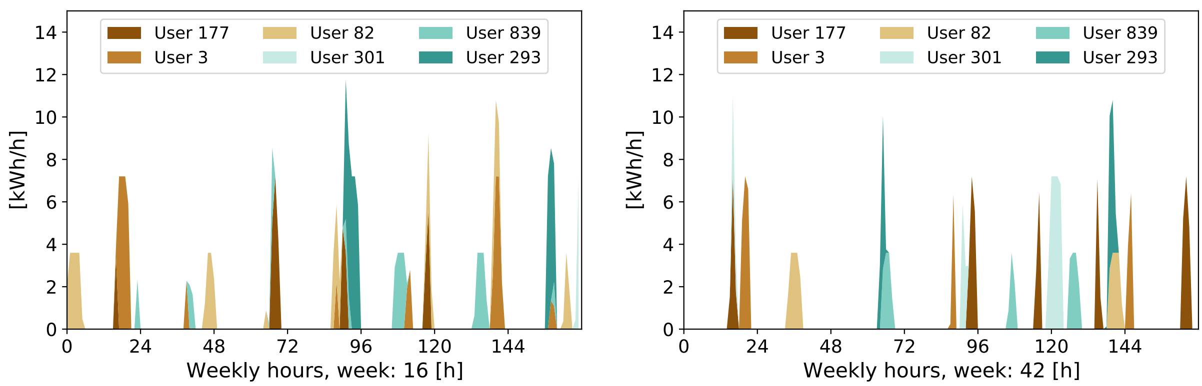
Figure 5.1: Daily, weekly and monthly load profiles for a small EV with charging power 3.6 kW



Day Week Month

Figure 5.2: Daily, weekly and monthly load profiles for a large EV with charging power 7.2 kW

To compare the three cases, aggregate load profiles for 1000 cars will be evaluated. Figure 5.3 shows the stacked load profile for two different weeks and six random cars from BASE to give an impression of how the aggregate load profiles are generated.



Week 16 Week 42

Figure 5.3: Stacked load profile for six random cars, BASE

5.2 Case study of 1000 EVs with dumb charging

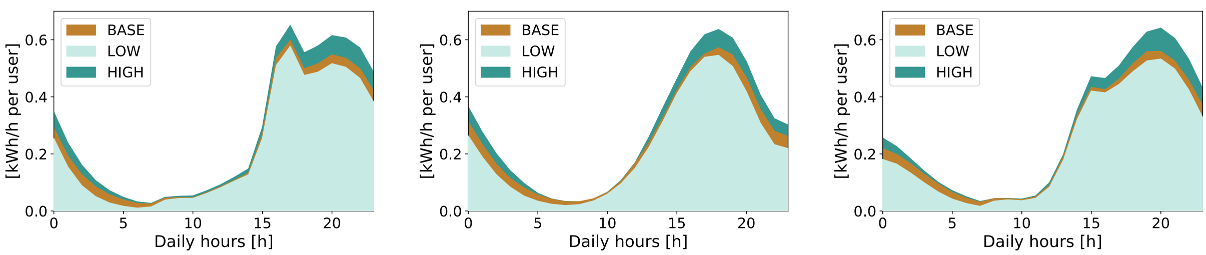
Load profiles are simulated for 1000 EVs in each of the three cases, assuming dumb charging. Table 5.1 shows the main results.

Table 5.1: Main results of all cases with dumb charging

	BASE	**LOW**	**HIGH**
Daily average charging demand (kWh per user)	5.80 (Weekday) 5.97 (Saturday) 6.05 (Sunday)	5.29 (Weekday) 5.36 (Saturday) 5.54 (Sunday)	6.54 (Weekday) 6.68 (Saturday) 6.74 (Sunday)
Daily average peak power demand (kWh/h per user)	0.59 (Weekday) 0.57 (Saturday) 0.56 (Sunday)	0.58 (Weekday) 0.54 (Saturday) 0.53 (Sunday)	0.65 (Weekday) 0.64 (Saturday) 0.64 (Sunday)
Hour of daily average peak power demand (h)	17-18 (Weekday) 18-19 (Saturday) 19-20 (Sunday)	17-18 (Weekday) 18-19 (Saturday) 19-20 (Sunday)	17-18 (Weekday) 18-19 (Saturday) 19-20 (Sunday)
Annual charging demand (MWh/year)	2136.66	1947.41	2405.72
Total number of sessions per year	196657	242520	144696
Average charged energy per session (kWh)	10.86	8.03	16.63
Peak power (kWh/h)	808.52	732.70	899.07
Hour of peak power (h)	17-18	17-18	22-23

5.2.1 Daily average EV load profiles

Figure 5.4 presents the daily average load profile per user for the three cases and the three different day types: weekdays, Saturdays and Sundays. The load profiles are found by dividing the average aggregate load profiles for the three day types on the total number of cars in the system.



Weekday Saturday Sunday

Figure 5.4: Daily average EV load profile per EV user, all day types, all cases

The energy need is modelled independently of the day type, and each day of the week has the same probability of having a charging session. However, the daily average charging demand is the highest on Sundays in all three cases. The charging demand of this day is approximately 4% larger than the lowest charging demand, occurring on weekdays in all three cases.

The average temperature level is seen to be lowest on Sundays when only including temperature levels below 20°C. On weekdays and Saturdays, the average temperature is approximately the same. However, for temperature levels above 20°C, Saturdays have a higher average temperature than the weekdays. Consequently, because the energy need increases for temperature levels lower and higher than 20°C, the difference in daily energy levels reflects the temperature differences for the three day types.

When comparing the three cases, the daily average charging demand is smallest in LOW and largest in HIGH for all the day types. This results from the different battery sizes and charging habits for the two EV types used in the model.

The average peak power occurs between hour 17 and 18 on weekdays, between hour 18 and 19 on Saturdays, and between hour 19 and 20 on Sundays, in all three cases. The peak hour reflects the time of the day when most EVs are simultaneously charging. Because of modelling load profiles for dumb charging, the peak hour results from the plug-in time distribution, which is the same in all three cases. As most EVs are plugged in between hour 16 and 17 on weekdays, reflecting when people typically arrive home from work in Norway, the peak power occurring one hour later, between hour 17 and 18, is expected. This is also the case for Saturdays and Sundays, where the peak power occurs one hour later than the peaking plug-in time.

Even though the daily average charging demand is highest on Sundays, the average peak power is highest on the weekdays in all three cases. This results from using different plug-in time distributions for the three different day types. Saturdays and Sundays are days off work in Norway, and for these days, the plug-ins are more distributed over the day. Consequently, the charging demands are also more distributed.

The average peak power demand for the weekdays is at 0.59 kW in BASE, 0.58 kW in LOW, and 0.65 kW in HIGH. These differences reflect the differences between the maximum charging power and charging habits for the EV types in the model.

5.2.2 Aggregate load profiles

Figure 5.5 shows the total hourly load profiles and duration curves for the whole year for the three cases.

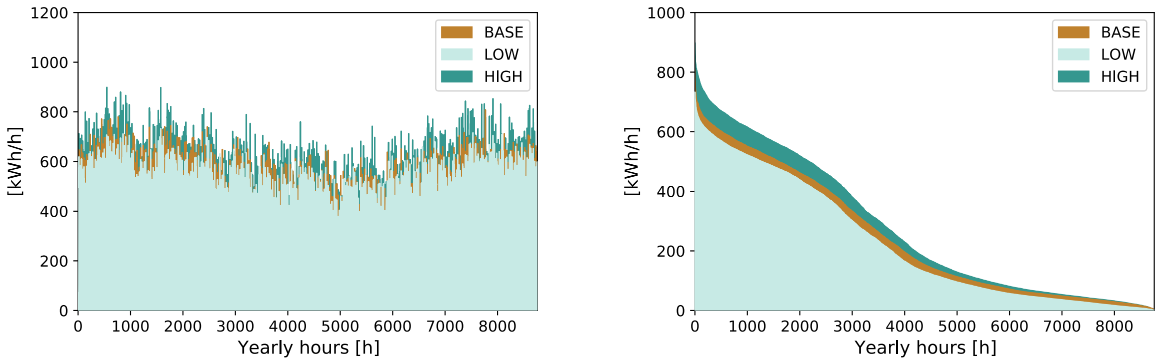


Figure 5.5: Yearly aggregate load profile and duration curve, all cases

The total yearly energy demand is 2136.66 MWh, 1947.41 MWh, and 2405.72 MWh in BASE, LOW, and HIGH, respectively. The differences can be seen clearer from the duration curve. Compared to BASE, the yearly energy demand is 8,8% smaller in LOW and 12,6 % larger in HIGH. This variation might result from the simplification of having a maximum of one charging session per day. Because the small EV has a higher probability of charging more frequently than the large EV, the small EVs are more affected by this simplification. On the other hand, as seen in chapter 3.3, even for equal charging frequencies, the charged energy is lower for small EVs than for large EVs. This can imply that EVs with a larger battery size also drive longer distances resulting in a larger total energy need.

The yearly average charged energy extracted from the data was 2150 kWh per EV [36]. This is very similar to the charged energy in BASE, of 2136.66 kWh per EV. As the BASE case reflects the composition of the EV stock of the data set, the model seems to give realistic energy levels.

The charged energy levels reflect a driving distance of 10 683 km in BASE, 9737 km in LOW, and 12 025 km in HIGH when assuming the simplified driving range of 5 km/kWh. Compared to the average yearly driving distance of 11 798 km in 2019 [50], this distance is similar to the driving distance in HIGH. However, the modelled energy levels are only a result of home charging. Because charging presumably also occurs at other places throughout a year, the actual driving distances are assumed to be longer. Resultingly, the difference in energy levels might also imply that an EV with a small battery size charge more frequently at other locations than at home than an EV with a large battery size when the yearly driving distances are the same for the two EV types.

From the yearly load profile, temperature variations can be observed from the fluctuating daily power peaks. HIGH generally has the highest daily peak powers, LOW generally has the lowest daily peak power, and BASE generally lies between the two other cases.

The average daily peak power is approximately 7% higher in HIGH than in LOW. However, if the maximum charging powers were the only difference between the two cases, HIGH would have had power peaks twice as high as LOW. Thus, the slight difference in power peak results from the differences in the charging patterns for the different EV types in the model. This is especially apparent in the total number of charging sessions for the three cases, whereas a LOW has 242 520 charging sessions, BASE has 196 657 charging sessions, and HIGH has 144 696 charging sessions. Consequently, LOW will have more simultaneously charging, resulting in a higher total power peak than what could initially be expected from the small maximum charging power.

Figure 5.6 presents the weekly aggregate load profile for a random week. By the differences in power peaks, the randomness of the model is seen clearer. Moreover, the load profiles show a twin peak for the weekdays, whereas the second peak typically occurs between hour 20 and 21 of the day. Again, because the model is based on dumb charging, this twin peak can be explained by the twin peak in the plug-in time.

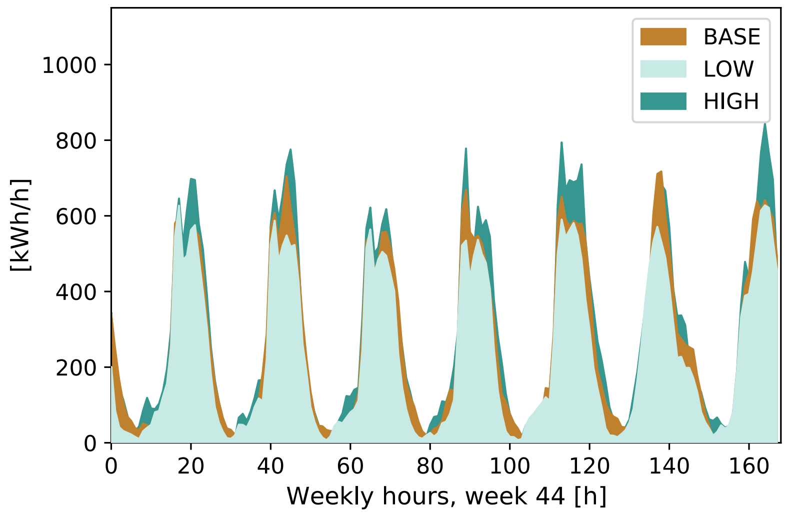


Figure 5.6: Aggregate load profile for week 44, all cases

5.2.3 Day with maximum peak load

Figure 5.7 shows the load profile for the day when the maximum power occurs for the three cases.

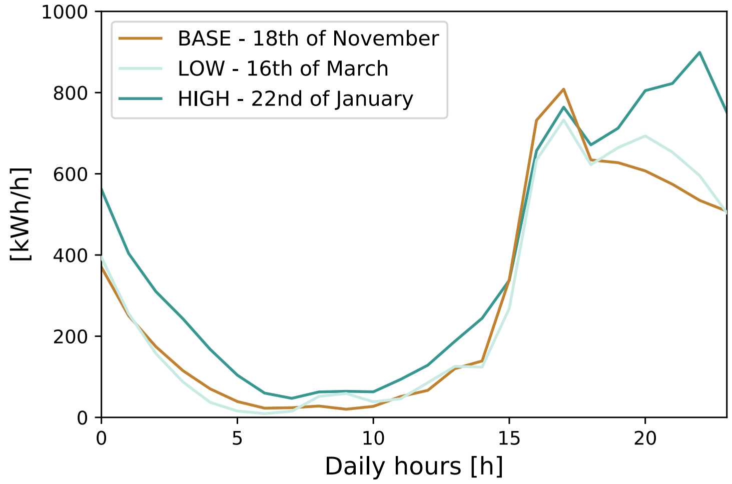


Figure 5.7: Day of maximum peak load, all cases

In BASE, the peak power of 808.52 kW occurs on the 18th of November, with an input temperature of -0.4°C. In LOW, the peak power of 732.70 kW, occurs on the 16th of March, with an input temperature of -9.7 °C. In both cases, the peak power occurs between hour 17 and 18. In HIGH, the peak power occurs on the 22nd of January, with an input temperature of -12,1°C. This power peak of 899.07 kW occurs between hour 22 and 23. The difference in peak power hour shows the randomness of the model. For all three cases, the day type is a weekday.

As seen, the temperature levels are below zero in all three cases. This is expected as the level is a factor when modelling the energy need for each charging session. Decreasing temperature levels leads to an increased energy need and will result in EVs charging for an extended period. Hence, the probability of having more overlapping charging sessions increases, leading to a potentially higher power peak.

5.2.4 Daily energy versus ambient temperature

Figure 5.8 compares the daily charged energy and the input temperature levels. The figure shows how the charged energy depends on the temperature levels. In addition, it can be seen that the daily energy need is higher in HIGH and lower in LOW when compared to BASE. This is because of the difference between the EV types, as already explained.

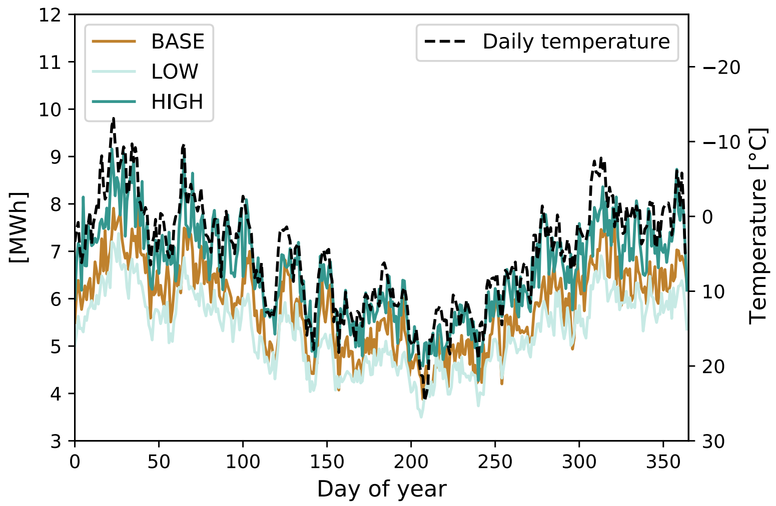


Figure 5.8: Aggregate daily energy versus input temperature levels, all cases

5.2.5 Coincidence factor and peak load per EV

Coincidence factor and coincident peak demand are important factors in network planning, especially for the dimensioning of the grid. These factors account for the diversity in loads and changes with the number of customers [52].

The coincidence factor is found by equation 5.1 based on [52].

$$c(n) = \frac{P_{s,max}(n)}{\sum_{i=1}^{n} P_{max}(i)} \tag{5.1}$$

$P_{s,max}$ is the system hourly peak load for n EVs, and P_{max} is the maximum charging power for EV user i. The peak load per EV is calculated by equation 5.2 based on [53].

$$P_{max}(n) = \frac{P_{s,max}(n)}{n} \tag{5.2}$$

To investigate the coincidence factor and peak load per EV for an increasing number of EVs, a fleet of 100 single load profiles is used. By drawing n single load profiles from this fleet, the aggregate load profile is found, and the coincidence factor and peak load per EV are calculated using the equations described above. This is done for $n = 1, ..., 50$. Because this method is stochastic, the procedure is repeated 50 times for each n, and the maximum, minimum and mean results are collected. Figure 5.9 shows the results for performing this when using 100 randomly drawn single load profiles from the BASE case. The orange area shows the maximum and minimum results obtained when repeating the procedure 50 times. The coincidence factor and peak load per car decrease rapidly as the number of cars increases and is reduced by 74% in both cases when moving from 1 to 50 cars.

The same is performed for LOW and HIGH, and figure 5.10 shows the mean coincidence factor, and the average peak load per EV as the number of EVs increases for all three cases. As seen, the coincidence factor is lower in HIGH than in LOW when the number of cars increases. This reflects the higher charging frequency in the LOW case, resulting in more overlapping charging sessions. Further, the peak load per car is higher in HIGH than in LOW, resulting from the higher charging power of 7.2 KW in HIGH and 3.6 KW in LOW.

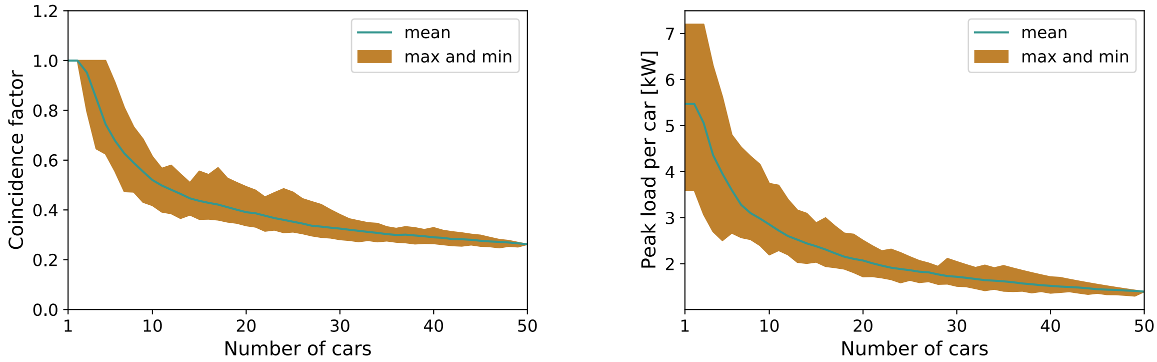


Figure 5.9: Coincidence factor and peak load per EV for an increasing number of EVs, BASE

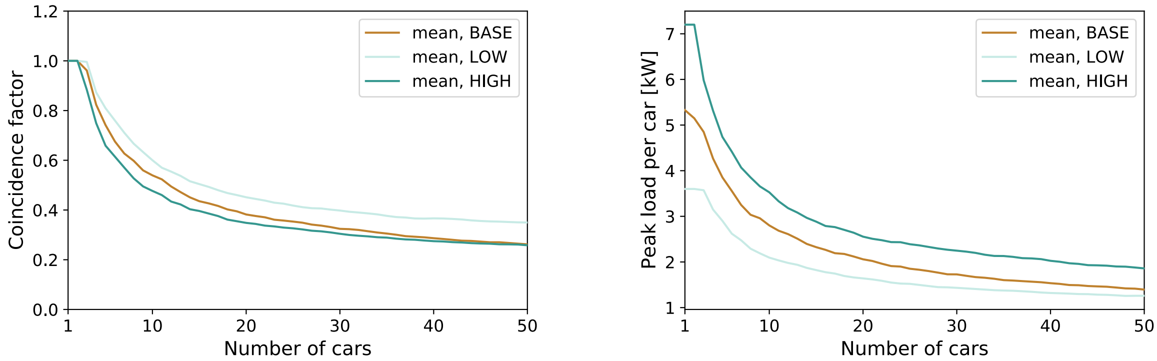


Figure 5.10: Mean coincidence factor and average peak load contribution to the coincident peak demand as the number of EVs increases, all cases

5.2.6 Flexibility potential

Because the model extracts parameters such as connection time and charging time, it is possible to use the model to look at different flexibility potentials.

EV's flexibility potential is presented as an important but rather complex aspect. Quantifying flexibility is complicated and depends on many factors, as described in chapter 2.4. In this thesis, flexibility potential is evaluated by the load shifting potential, as the number of hours connected without charging and the resulting amount of shiftable energy. This is seen in table 5.2, showing the flexibility potential for the three cases.

The hours of charging makes up 21% of the total hours connected when having dumb charging in all three cases. Nevertheless, in LOW, charging duration is 19% longer, and in HIGH, charging duration is 26% shorter than the charging duration in BASE. The total hours connected without charging, referred to as the total EV idle time, is higher in LOW than in HIGH.

Even though the total EV idle time is higher in LOW, flexibility potential is also affected by the charging power. By multiplying each EV's idle time with the respective charging power, the total shiftable energy is found. Compared to the BASE case, the LOW case has 12% less shiftable energy, while the HIGH case has 11% more shiftable energy. Consequently, even though the idle time is higher in LOW, the greatest amount of shiftable energy of 9209.6 MWh is in HIGH.

Table 5.2: Flexibility potential in the three cases

	BASE	**LOW**	**HIGH**
Total hours charging, all users (h)	452254	540949	334127
Total hours connected, all users (h)	2133054	2581080	1613238
Total hours connected, not charging (h)	1680800	2040132	1279111
Hours charging of hours connected (%)	21	21	21
Hours connected of total yearly hours (%)	24	29	18
Total shiftable energy (MWh)	8322.62	7344.47	9209.60

5.3 Case study of 1000 EVs with flexible charging

To show that the model can be used to simulate load profiles when assuming other charging strategies than dumb charging, load profiles are simulated for the same three cases assuming flexible charging.

To compare the load profiles with flexible charging to the load profiles with dumb charging, the same stochastic parameters are used in the cases both with and without flexible charging. In this thesis, flexible charging means distributing the energy charged equally over the connection duration of each charging session.

Table 5.3 presents the results with flexible charging.

Table 5.3: Main results of all cases with flexible charging

	BASE$_{\text{flex}}$	**LOW$_{\text{flex}}$**	**HIGH$_{\text{flex}}$**
Daily average peak power demand (kWh/h per user)	0.34 (Weekday) 0.33 (Saturday) 0.32 (Sunday)	0.32 (Weekday) 0.31 (Saturday) 0.30 (Sunday)	0.38 (Weekday) 0.36 (Saturday) 0.37 (Sunday)
Hour of daily average peak power demand (h)	01-05 (Weekday) 17-19 (Saturday) 00-01(Sunday)	01-05 (Weekday) 17-19 (Saturday) 00-01(Sunday)	01-05 (Weekday) 17-19 (Saturday) 00-01(Sunday)
Percentage reduction of average peak power* (%)	42 (Weekday) 42 (Saturday) 43 (Sunday)	45 (Weekday) 43 (Saturday) 43 (Sunday)	42 (Weekday) 44 (Saturday) 42 (Sunday)
Peak power (kWh/h)	502.71	471.49	587.52
Percentage reduction of peak power* (%)	38	36	35
Hour of peak power (h)	04-06	03-04	05-06

*compared to dumb charging

5.3.1 Daily average EV load profiles

Figure 5.11 shows the daily average charging profiles for the three different day types and cases. As seen, the shapes of the load profiles now reflect both the typical plug-in times and plug-out times.

On weekdays, the typical plug-out time is seen from the steep negative slope between hour 6 and 8, while the typical plug-in time is seen from the steep positive slope between hour 15 and 17. On Saturday and Sunday, the slopes are generally less steep, reflecting the more distributed plug-ins and plug-outs.

The average peak power occurs between hour 01 and 05 on weekdays, between hour 17 and 19 on Saturdays, and around midnight on Sundays in all three cases. When comparing each of the daily average power peak demands to the equivalent case for dumb charging, a reduction between 42% and 45% is found in all cases. Having approximately the same reduction makes sense as the number of hours charging compared to the hours connected was the same in all three cases.

Figure 5.12 compares the daily average EV charging profiles with and without flexible charging. Here, it can be seen clearly that the plug-out time plays a more significant role in the shapes of the flexible load profiles. Also, it can be seen that more energy is moved to the night than before.

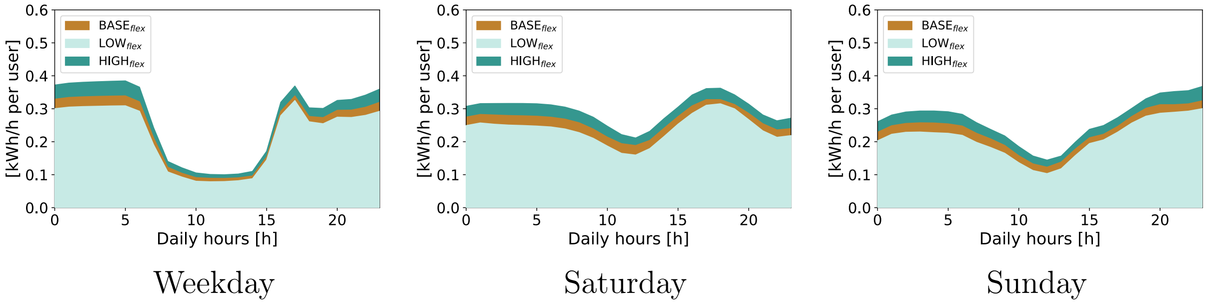


Figure 5.11: Daily average charging profile, with flexible charging, all cases

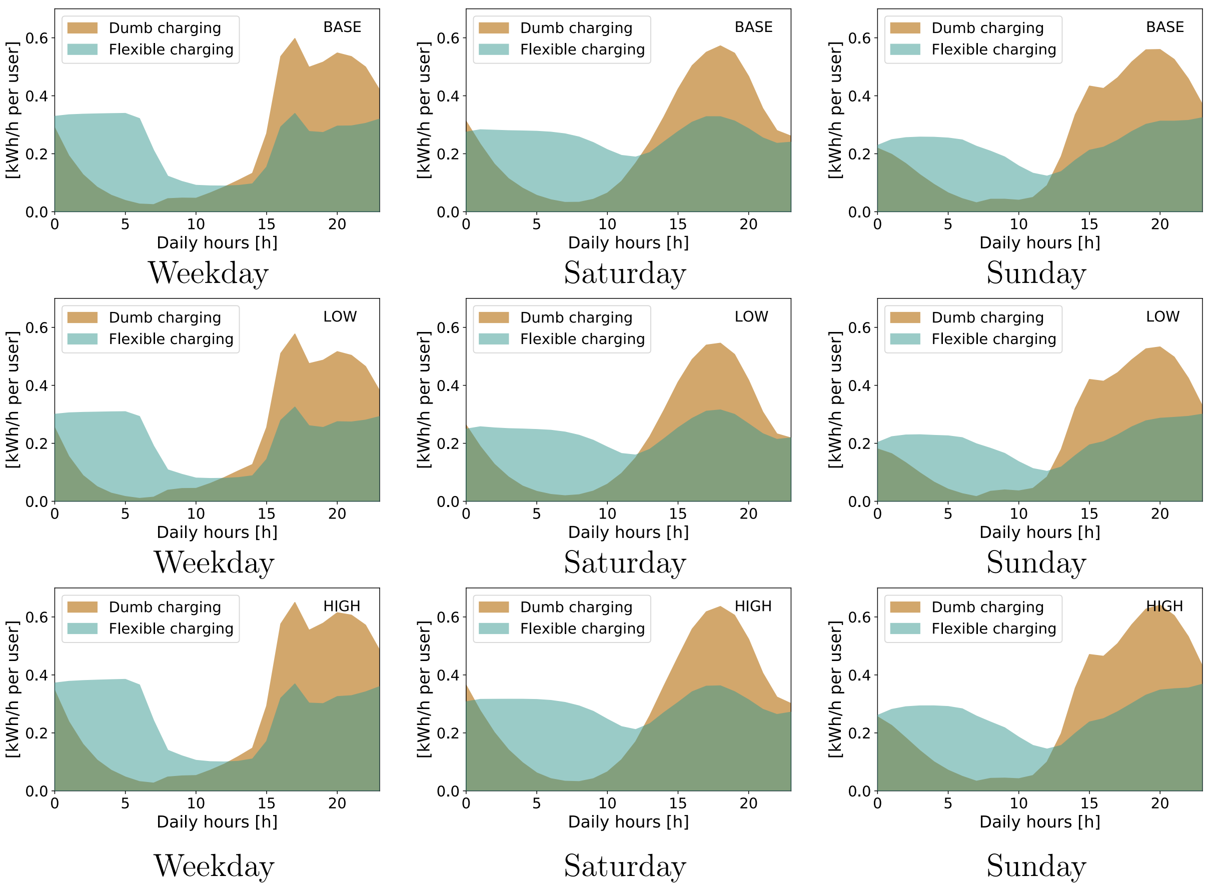
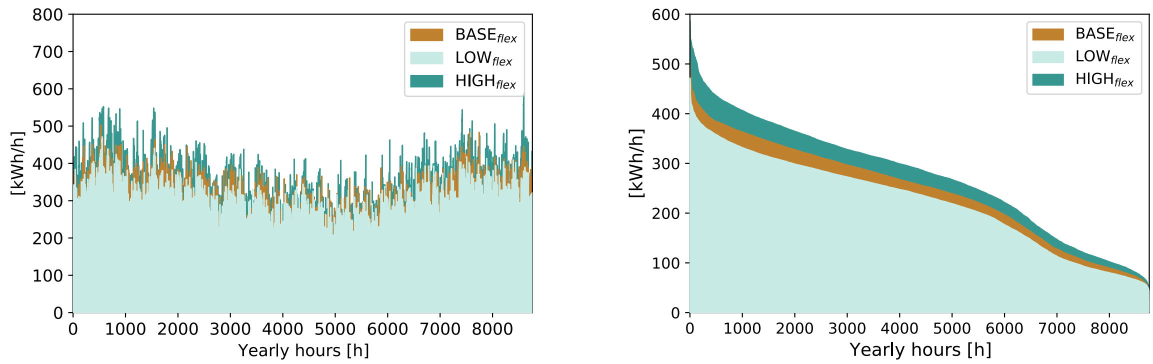


Figure 5.12: Daily average charging profile with flexible and dumb charging, all cases

5.3.2 Aggregate load profiles

Figure 5.13 shows the aggregate profiles and duration curves for a year when having flexible charging. The power peaks have reduced a lot in all three cases. Still, the power peaks are generally lower in LOW and higher HIGH, while BASE lies between the two. Because the energy is equally distributed over the connected hours, the total EV connection time is a more critical factor, while the maximum charging power is less crucial. Hence, because the total energy need is higher in HIGH, the difference between the power peak levels are as expected.

Figure 5.14 shows the aggregate load profile for a random week of the year. From this figure, it can be seen that the flexible load profiles are more distributed, and that more energy is charged at night.



Load profile Duration curve

Figure 5.13: Yearly aggregate load profile and duration curve, with flexible charging, all cases

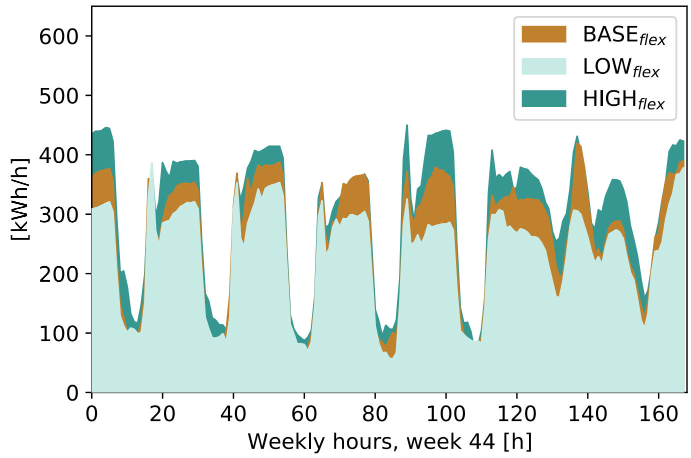


Figure 5.14: Aggregate load profile for week 44, with flexible charging, all cases

5.3.3 Day with maximum peak load

Figure 5.15 shows the days with the maximum peak loads, still being a weekday for all three cases. In BASE, the peak load of 502 kW takes place between hour 4 to 6. In LOW, the peak load of 471.49 kW occurs between hours 3 and 4, and in HIGH, the peak load of 587.42 kW occurs between hours 5 and 6. As seen, for all three cases, the peak load is shifted to the night. The temperature levels for the days with maximum peak load are 0.8°C, -9.6°C and -4.7°C in BASE, LOW and HIGH, respectively. Figure 5.16 compares the day with maximum peak load with and without flexible charging. Compared to the dumb charging load profiles, the peak loads are reduced by 38% in BASE$_{flex}$, 36% in LOW$_{flex}$ and 35% in HIGH$_{flex}$. As the power peaks are both reduced and moved to the night, this shows how flexible charging can avoid grid overload in the future.

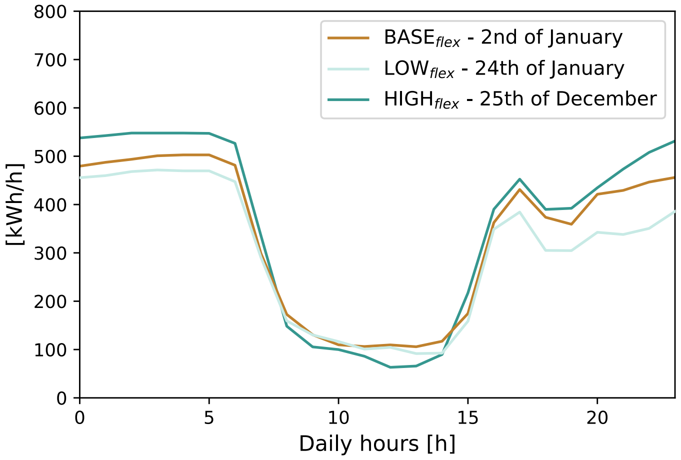
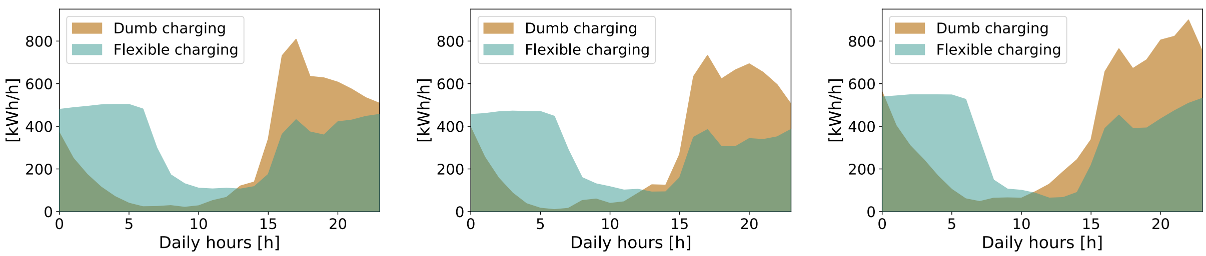


Figure 5.15: Day of maximum peak load with flexible charging, all cases



BASE LOW HIGH

Figure 5.16: Day of maximum peak load with dumb and flexible charging

6 Discussion

In this chapter, some aspects of the case results are further discussed. In addition, different limitations of the the model are pointed out, followed by some suggested measures.

6.1 Discussion of case results

6.1.1 Flexible charging

As seen in chapter 5, it is possible to use the model to simulate load profiles when assuming other charging strategies than dumb charging. In this thesis, flexible charging means to distribute the energy equally over the connection time. However, it is important to emphasise that optimisation aspects as the costs of moving the energy, focusing on user-friendly charging stations, battery aspects as degradation, and maximum and minimum capacity should be considered when moving the load and energy in real life.

6.1.2 Charging habit trends affecting EV flexibility

The data shows that charging habits such as charging frequency and energy charged depend on the EV battery size. Increasing battery sizes leads to decreasing weekly charging frequencies and larger energy need per charging session. This leads to less idle hours for larger battery sizes. It is important to be aware of this trend when planning to use EVs as a flexible source in the grid.

The goal is usually to reduce the total power peak in the power grid. To reduce the total peak, EVs should not charge when the power demand in the grid is already high. The maximum charging power is an important aspect for evaluating the EVs flexibility potential. Higher maximum charging power leads to shorter time needed to charge the same amount of energy, making the EV more flexible for load shifting. From the case study results, it could be seen that even though the idle time was higher in LOW, HIGH had a greater amount of shiftable energy. Thus, even though a larger battery size typically leads to less idle time, the maximum power is also important, and a larger maximum charging power increases the flexible potential [36].

V2G is an essential aspect when discussing EV flexibility potential. When this is utilised, the EV can operate as a source for energy flexibility, directly related to the power grid. The greatest load shifting potential is achieved by having a large battery size and a high maximum charging power. In the future, if V2G is widely used, this might affect people's charging habits, and the weekly charging frequencies might depend less on the battery size than it does today.

Summing up, both a larger battery size and maximum charging power are preferable.

However, to use EVs for flexibility purposes, they need to be connected even though the charging need is low.

6.2 Limitations of the model

Even though the EV load profile model is based on real-world EV charging data, some limitations and assumptions affect the output.

6.2.1 Charging frequency

A limitation of the model is the simplification of the maximum of one charging session per day. Because most EVs do not typically charge more than this, the aggregate load profile is expected to be realistic. However, if analysing single load profiles for small EVs, where a more frequent charging frequency is sometimes typical, the simplification will make a less realistic output.

Today, battery sizes and charging powers are increasing. However, EV charging habits are assumed to not change drastically in the near future. Therefore, when using the model for near-future EVs, the limitation of only one charging session per day is assumed not to affect the results significantly, and realistic output for the single load profiles are expected.

In future, one may expect that plug-in of cars will be unnecessary and that they automatically will start charging when parked. In such a future, the assumption of only one charging session per day will limit the validity of the model results.

6.2.2 Energy need versus energy charged

The energy need distributions in the model are made based on the charged energy distributions in the data. The energy charged in the model will be affected and limited by the connection time resulting in a final charged energy smaller than the modelled energy need. Consequently, the modelled charged energy might differ from the situation found in the data.

However, as seen in the case study, a similar energy level is found when comparing the total charged energy in the BASE case to the total charged energy in the data. Because the BASE case is supposed to reflect the composition of the EV stock of the data set, using the charged energy levels from the data to model the energy need is assumed to be valid.

In the future, initial battery SoC will most likely be available in EV charging reports. By using this factor to set the energy need, more realistic load profiles can be made. In addition, with this information, it is possible to analyse different charging patterns more correctly.

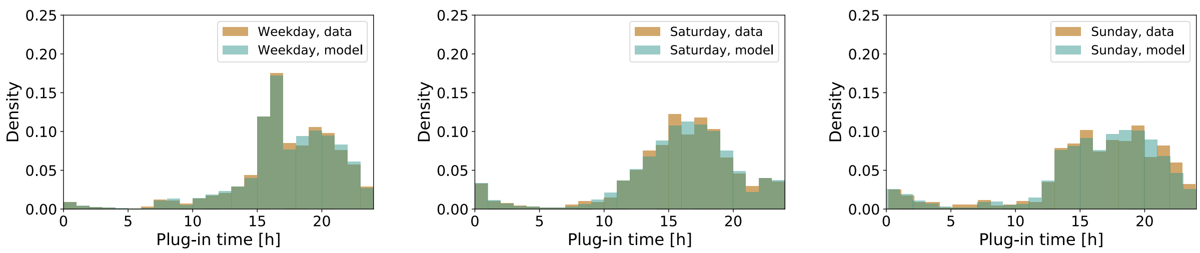
6.2.3 Plug-in, plug-out and connection time

The first step in the model is to randomly draw which days of the week charging occurs. For these days, all plug-in times are set by randomly drawing from the plug-in input distribution. Then, based on the plug-in times, all plug-out times are set by randomely drawing from the plug-out input distribution, and all resulting connection times can be extracted. This means that each charging session is modelled independently, which is not the situation in real life.

Even though the model does not follow the same order as in real life, the modelled plug-in times, plug-out times and connection times reflect the data. Figure 6.1, 6.2 and 6.3 compare the plug-in time-, plug-out time- and connection-time distributions resulting from the model and the data. As seen, plug-in times follow the data for each day type. Because the plug-in times are modelled based on the data and do not depend on any other parameters, this is expected.

The modelled plug-out times also reflect the data to a high degree. For Friday, Saturday and Sunday, they vary somewhat more. This is probably mainly a result of using model distributions slightly different from the data distributions. In addition, the plug-out times depend on the plug-in parameters. If charging happens two days in a row, the plug-out hour might get limited by the next day's plug-in hour.

Furthermore, regarding the connection times, the difference between the two modelling methods are seen clearly. For plug-in between Monday and Thursday, the plug-out time is modelled depending on the plug-in time, resulting in a more accurate connection time. For plug-ins on Friday, Saturday or Sunday, the plug-out only depends on the day of plugging in. Hence, the connection time is more likely to differ. To avoid this, more EV charging data is needed.



Weekday Saturday Sunday

Figure 6.1: Plug-in time from data and model for different day types

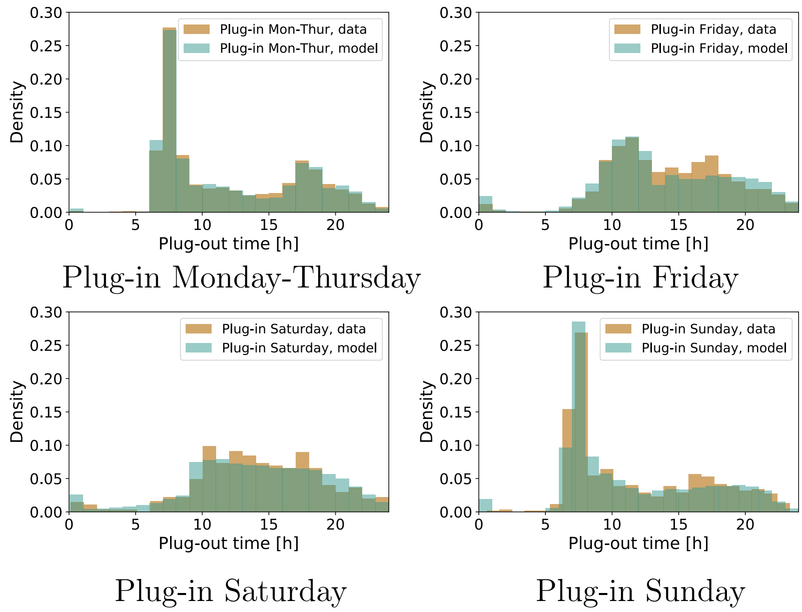


Figure 6.2: Plug-out time from data and model for different plug-in days

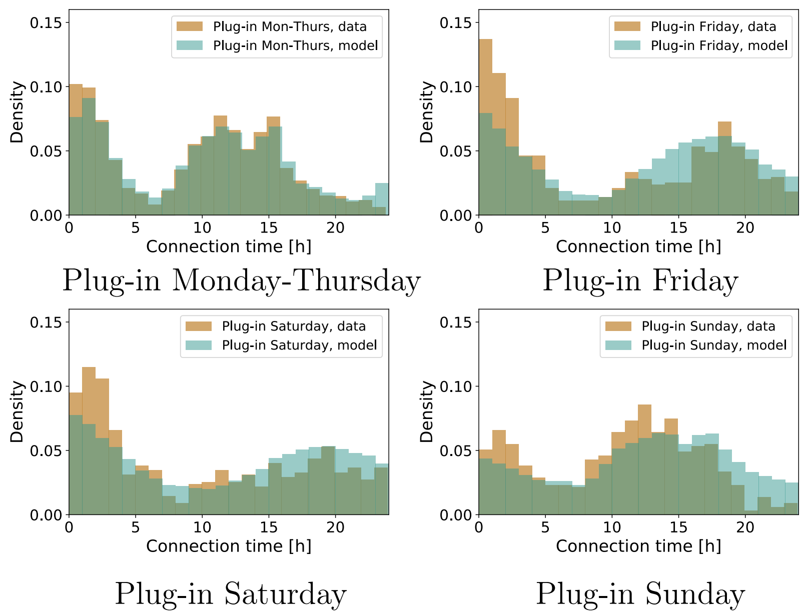


Figure 6.3: Connection time from data and model for different plug-in days

In this thesis, the goal is to generate realistic load profiles for dumb charging. Because plug-in times are the essential parameter reflecting the shape of the resulting load profiles, it is expected that the way of modelling the plug-in, plug-out and connection times are acceptable.

However, if a higher charging frequency is seen in the future, the model must be built differently to meet this change. One alternative could be to model the plug-in time based on the previous plug-out time by finding statistics of how long it typically takes from plugging out the car to plugging in the car. Then, both the maximum of one charging per day and maximum connection of 24 hours is avoided. However, this will make the model much more complex, and to get a realistic output when using this aspect, much more data is needed.

6.3 Further work

To make the model more robust, several aspects could be improved or included.

6.3.1 Place of charging

In this thesis, the goal is to predict load profiles for private home-charging. However, for home charging, there are usually also shared chargers. Because the data also provide information of EV's using shared chargers, this aspect could be analysed and included in the model to make a more representable load profile.

In addition, a diversity of charging patterns, including charging at work, charging at the store, fast chargers and home charging, could be included.

6.3.2 Holidays

As of now, the model does not take holidays into account. Charging habits are expected to differ on holidays. People might travel more from their home or drive less, affecting the home-charging habits patterns. A more robust and realistic model can be made by analysing this aspect and including it in the model.

6.3.3 Battery size

The data provides no information on EV battery sizes, and EV types are distinguished based on the maximum charged energy per session. If knowing the battery sizes, the distinction would reflect the actual size instead of being based on assumptions, which would improve the model.

The battery size will also define the possible maximum energy need for the respective car. By including this in the model, more realistic single load profiles can be obtained.

The battery size would also be a critical factor that should be included if using the model for optimisation purposes when V2G is used. Then, the battery size would set the maximum amount of energy that can be discharged from and charged to the EV battery.

7 Conclusion

A stochastic bottom-up model based on real-world EV-charging data is developed to simulate realistic load profiles for private dumb and flexible home charging. The model is based on evaluating typical charging patterns from the data, and identifying the impact of user behaviour. The user behaviour is evaluated through charging frequency, energy charged per session, plug-in time and plug-out time. The model can simulate all from 1 to 1 million EVs, providing the aggregate annual hourly load profile. Because the model also extracts connection profiles, it is possible to use the model for optimisation problems, analysing different load shifting opportunities.

The model was run and evaluated for the three cases: BASE, LOW and HIGH, having different input percentages for the EV types and charging powers. In all three cases, 1000 EVs and daily temperatures for Trondheim 2019 were used.

The simulation results show that the average peak power occurs on a weekday, between hour 17 and 18 in all three cases when assuming dumb charging. This is a result of most people arriving at home between hour 16 and 17 in Norway. The average peak power per EV varies in the three cases, at 0.59 kW, 0.58 kW and 0.65 kW in BASE, LOW, and HIGH. The total peak power is 808.52 kW in BASE, 730.70 kW in LOW and 899.07 kW in HIGH. For BASE and LOW, the peak power occurs on a weekday, between hour 17 and 18. In HIGH, the peak power occurs on a weekday between hour 22 and 23. The annual charging demand is lower in LOW than in HIGH, while BASE is between the two.

Further, the flexibility potential of the three cases were investigated by evaluating the idle hours (when the EV is connected but not charging), and shiftable energy per session. The idle time was higher in LOW than in HIGH. However, when taking the maximum charging power into account, the total shiftable energy was higher in HIGH than in LOW.

By assuming that the EVs will distribute their charging need equally over the connection time, new charging load profiles were obtained. When comparing the load profiles to the load profiles with dumb charging, the power peaks moved from occurring in the afternoon and evening to occurring at night in all three cases.

The results reflect that the model can account for different charging habits for the EV types and day types both when assuming dumb and flexible charging. In addition, the results reflect the randomness of the model.

Generally, EVs having larger battery sizes and maximum charging powers are seen to decrease the number of idle hours. It is important to be aware of this trend when planning to use EVs as a flexible source.

7.1 Further work

In this thesis, a model for making a stochastic bottom-up model based on real-world EV-charging data is developed to generate realistic dumb charging load profiles for private home charging. However, the model is based on EV charging data from only one place. Consequently, the load profiles reflect the charging patterns from this area. More EV data should be analysed and included to make the model more robust and reflect a more general situation.

The model still extracts realistic output, reflecting today's charging patterns. Hence, the model can be used for optimisation purposes to find load profiles for optimal charging when using different grid tariffs as capacity-based tariffs, energy-based tariffs, or Time of Use-tariffs (ToU).

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Appendix

A Probability distributions

A.1 Probability density functions

Equations from [54]

Chi distribution:

$$f(x,k) = \frac{1}{2^{k/2-1}\Gamma(k/2)} x^{k-1} exp(-x^2/2) \tag{A.1}$$

for $x \geq 0$, $k > 0$. and the gamma function is defined as

$$\Gamma(z) = \int_0^\infty t^{z-1} e^{-t} dt \tag{A.2}$$

Generalized extreme distribution:

$$f(x,c) = \begin{cases} exp(-exp(-x))exp(-x), & \text{for } c = 0 \\ exp(-(1-cx)^{1/c})(1-cx)^{1/c-1}, & \text{for } x \leq 1/c, c > 0 \end{cases} \tag{A.3}$$

Exponentiated Weibull distribution:

$$f(x,a,c) = ac[1 - exp(-x^c)]^{a-1} exp(-x^c) x^{c-1} \tag{A.4}$$

for $x > 0$, $a > 0$, $c > 0$.

Lognormal distribution:

$$f(x,s) = \frac{1}{sx\sqrt{2\pi}} exp\left(-\frac{log^2(x)}{2s^2} \right) \tag{A.5}$$

for $x > 0$, $s > 0$.

Pearson type III distribution:

$$f(x,\kappa) = \frac{\mid \beta \mid}{\Gamma(\alpha)} (\beta(x-\zeta))^{\alpha-1} exp(-\beta(x-\zeta)) \tag{A.6}$$

where:

$$\beta = \frac{2}{\kappa} \tag{A.7}$$

$$\alpha = \beta^2 = \frac{4}{\kappa^2} \tag{A.8}$$

$$\zeta = -\frac{\alpha}{\beta} = -\beta \tag{A.9}$$

and the gamma function is defined as

$$\Gamma(z) = \int_0^\infty t^{z-1}e^{-t}dt \tag{A.10}$$

Normal distribution:

$$f(x) = \frac{exp(-x^2/2)}{\sqrt{2\pi}} \tag{A.11}$$

for a real number x.

Weibull Maximum Extreme Value distribution:

$$f(x,c) = c(-x)^{c-1}exp(-(-x)^c) \tag{A.12}$$

for $x < 0$, $c > 0$

Weibull Minimum Extreme Value distribution:

$$f(x,c) = cx^{c-1}exp(-x^c) \tag{A.13}$$

for $x > 0$, $c > 0$

Normal Skewed distribution:

Let $\phi(x)$ be the PDF of the Normal standard distribution.

Let $\Phi(x) := \int_{-\infty}^{x} \phi(t)dt$ the corresponding CDF.

Then the Normal skewed distribution with a skewness parameter a can be defined as:

$$f(x,a) = \frac{\phi(x)\Phi(ax)}{\Phi(0)} \tag{A.14}$$

A.2 Distributions of charged energy per session

Table A.2.1: Distributions used to decide the energy need for different charging frequencies when the user is of "high energy" type.

Charging Frequency	Distribution	Variables
1	Genextreme	c = 0.01, loc = 22.27, scale = 12.28
2	Genextreme	c = -0.04, loc = 17.54, scale = 11.85
3	PearsonIII	κ = 1.32 , loc = 18.78, scale = 13.42
4	Genextreme	c = -0.11, loc = 12.19, scale = 11.11
5	PearsonIII	κ = 1.69, loc = 16.55, scale = 13.38
6	Genextreme	c = -0.07, loc = 9.94, scale = 8.06
7	Exponentiated Weibull	a = 10.27, c = 0.65, loc = -2.85, scale = 2.99

Table A.2.2: Distributions used to decide the energy need for different charging frequencies when the user is of "low energy" type.

Charging Frequency	Distribution	Variables
1	Genextreme	c = 0.12, loc = 9.78, scale = 4.76
2	PearsonIII	κ = 0.45, loc = 12.20, scale = 6.34
3	Skew-Normal	a = 3.66 , loc = 3.33, scale = 10.01
4	Normal	loc = 10.19, scale = 5.39
5	Genextreme	c = 0.19, loc = 7.61, scale = 4.81
6	Weibull Maximum	c = 7.18, loc = 38.43, scale = 31.78
7	PearsonIII	κ = 1.07, loc = 8.03, scale = 4.89

Table A.2.3: Distributions used to decide the energy need for different charging frequencies when the user type is not set.

Charging Frequency	Distribution	Variables
1	Genextreme	c = -0.17, loc = 15,08, scale = 9.94
2	Genextreme	c = -0.17, loc = 12.72, scale = 9.43
3	Lognormal	s = 0.51 , loc = -5.32, scale = 17.39
4	Genextreme	c= -0.18 , loc = 8.82, scale = 6.99
5	PearsonIII	κ = 1.37, loc = 11.89, scale = 8.40
6	Skew-Normal	c = 6.36, loc = 1.54, scale = 11.64
7	Genetreme	c = -0.12, loc = 6.05, scale = 4.18

A.3 Plug-in time distributions

Table A.3.1: Distributions used to decide the plug-in time for the different days of the week.

Plug-in day	Distribution	[%]	Variables
Weekday (Monday-Friday)	Weibull Minimum	2	c = 0.87, loc = 0.02, scale = 2.15
	Skew-Normal	3	a = 3.14, loc = 7.44, scale = 1.21
	Exponentiated Weibull	8	a = 0.02, c = 84.51, loc = 9.95, scale = 4.03
	Skew-Normal	16	a = -939739, loc = 15.98, scale = 0.88
	Exponentiated Weibull	26	a = 0.37, c = 2.46, loc = 16.02, scale = 1.43
	Exponentiated Weibull	19	a = 0.01, c = 111.88, loc = 18.01, scale = 1.97
	Exponentiated Weibull	10	a = 0.12, c = 8.26, loc = 20.02, scale = 0.91
	Exponentiated Weibull	16	a = 0.27, c = 3.34, loc = 21.02, scale = 2.23
Saturday	Chi	6	k = 0.49, loc = 0.02, scale = 2.96
	Genextreme	86	c = 0.43, loc = 15.30, scale = 3.10
	Uniform	8	loc = 22.02, scale = 1.97
Sunday	Log-Normal	7	s = 0.96, loc = -0.04, scale = 1.58
	Pareto	2	b = 8.99, loc = 0.09, scale = 7.59
	Exponentiated Weibull	21	a = 0.19, c = 29.79, loc = 6.79, scale = 7.84
	PearsonIII	10	κ = 0.19, loc = 15.41, scale = 0.37
	Exponentiated Weibull	59	a = 0.45, c = 2.86, loc = 16.00, scale = 5.55

A.4 Plug-out time distributions

Table A.4.1: Distributions used to decide plug-out time according to the plug-in hour group, plug-in days Monday-Thursday

Plug-in hour	Distribution	[%]	Variables
Early and late night (0-6)	Chi	100	k = 0.81, loc = 6.67, scale = 4.54
Early morning (6-9)	Skew-Normal	100	a = 12.06, loc = 6.92, scale = 6.05
Late morning (9-12)	PearsonIII	100	κ = 0.15 , loc = 13.58, scale = 2.93
Early afternoon (12-15)	Skewnorm	20	a = 4.63, loc = 6.88, scale = 1.89
	Weibull min	80	c = 2.55, loc = 6.71, scale = 10.12
Late afternoon (15-18)	Lognormal	37	s = 0.09 , loc = 1.56, scale = 5.96
	Genextreme	11	c = 0.06, loc = 10.58, scale = 2.96
	Skew-Normal	45	a = -0.93 , loc = 18.47, scale = 1.20
	Lognormal	8	s = 0.72 , loc = 19.84, scale = 1.02
Early evening (18-21)	Normal	57	loc = 7.46, scale = 0.56
	Chi	19	k = 1.17, loc = 9.00, scale = 3,06
	Skew-Normal	24	a = -2.38 , loc = 22.15, scale = 2.40
Late evening (21-23)	Exponentiated Weibull	65	a = 0.13, c = 10.90, loc = 6.20, scale = 1.98
	Chi	35	k = 0.80 , loc = 8,62, scale = 7.06

Table A.4.2: Distributions used to decide connection duration according to the plug-in day, Friday, Saturday and Sunday

Plug-in day	Distribution	[%]	Variables
Friday	Genextreme	2	c = -0.55, loc = 0.47, scale = 0.49
	Genextreme	48	c = 0.49, loc = 10,57, scale = 1.80
	Exonentiated Weibull	50	a = 0.24, c = 4.14, loc = 14.02, scale = 7.42
Saturday	Genextreme	9	c = 1.08, loc = 5.32, scale = 3.91
	Exonentiated Weibull	91	a = 0.25, c = 4.39, loc = 9.01, scale = 11.20
Sunday	Exonentiated Weibull	46	a = 4.21, c = 19.38, loc = -12.53, scale = 19.36
	Exonentiated Weibull	14	a = 0.07, c = 11.87, loc = 9.08, scale = 2.75
	Exonentiated Weibull	40	a = 0.16, c = 7.55, loc = 12.00, scale = 9.61

B Hourly peak load per EV

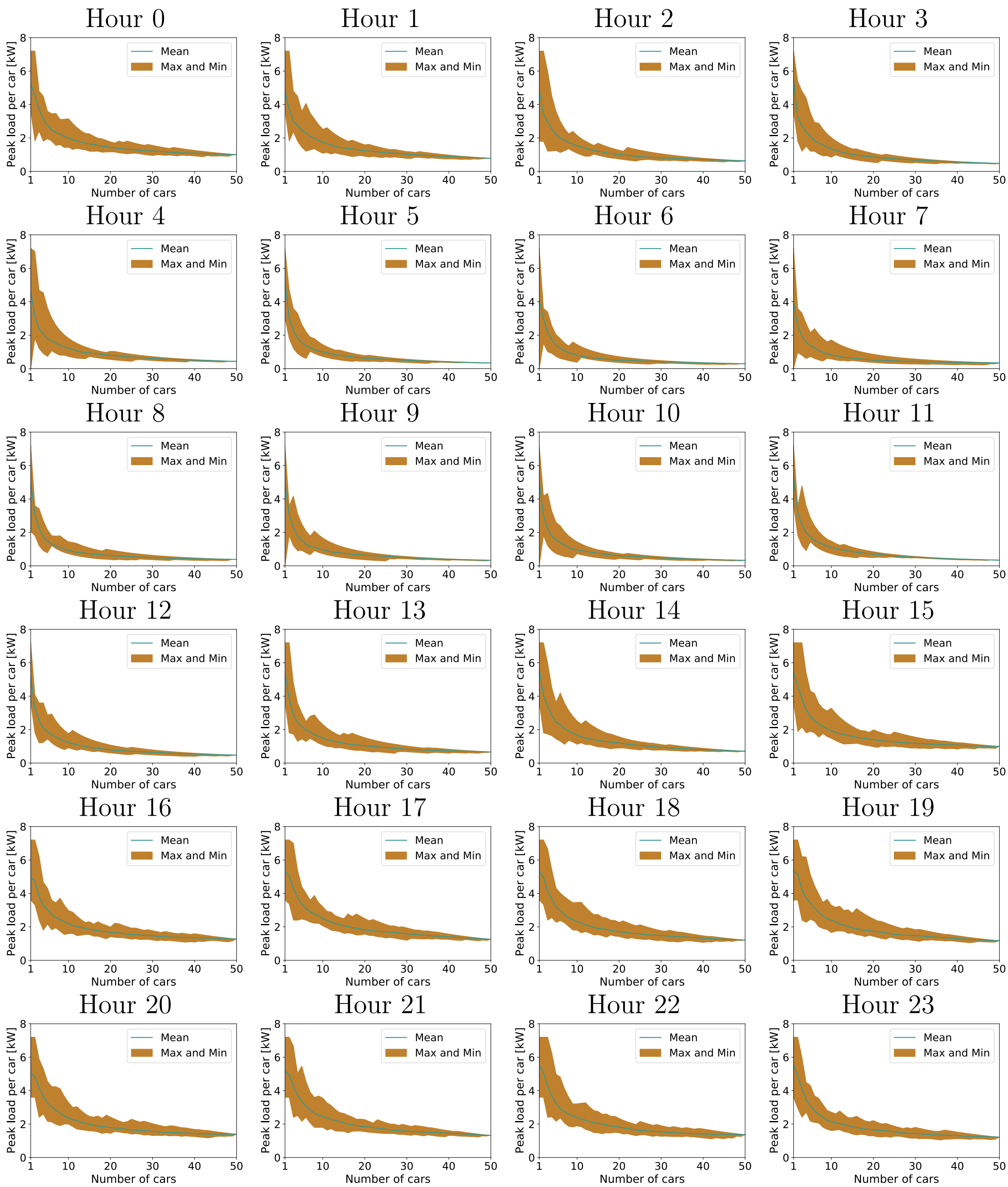

Figure B.0.1: Peak load per EV for an increasing number of EVs considered, BASE. The orange area shows the maximum and minimum results obtained from the 50 iterations.

C Hourly coincidence factors

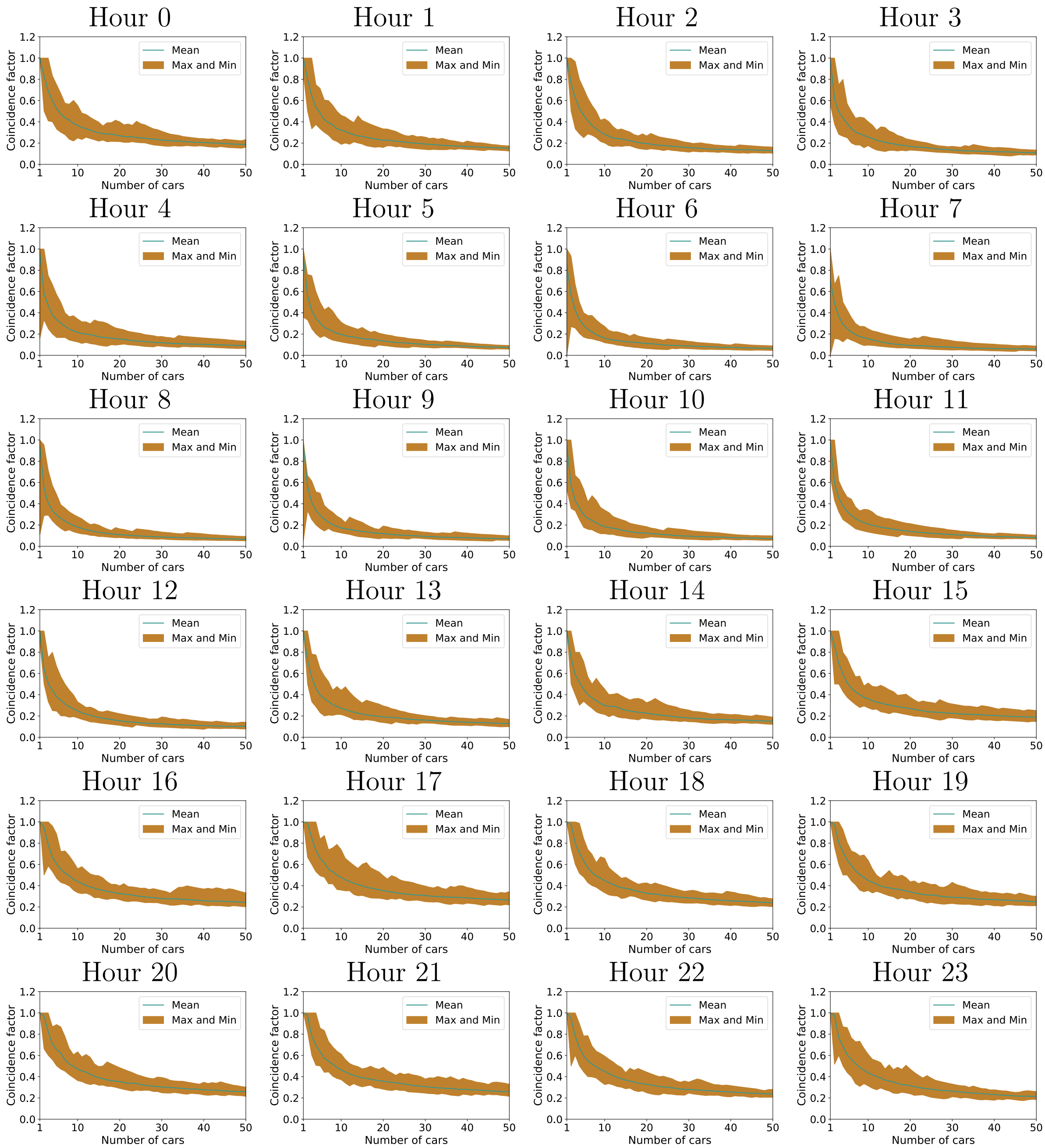

Figure C.0.1: Coincidence factor for an increasing number of EVs considered, BASE. The orange area shows the maximum and minimum results obtained from the 50 iterations.

D Model in Python

D.1 Stochastic input parameters

```python
import EV_functions_year as f
import Input as Input

import EV_functions_year as f
import Input as Input

''' Input parameters ---- (set by user)'''

Nr_of_charging_stations = 1000

#Percentage of EV type
percent_high = 46 #BASE
percent_low = 54 #BASE

#Percentage of maximum charging power when Large EV type
percent_high_3_6 = 19 #BASE
percent_high_7_2 = 81 #BASE

#Percentage of maximum charging power when small EV type
percent_low_3_6 = 87 #BASE
percent_low_7_2 = 13 #BASE


''' Stochastic input distributions '''
#Importing distributions used to make the stochastic input parameters
distribution = Input.Input()

# Distributions for charging frequencies
charge_freq_all = distribution.charge_freq_all
charge_freq_low  = distribution.charge_freq_low_e
charge_freq_high = distribution.charge_freq_high_e

# Distributions for energy need
energy_all = distribution.energy_all
energy_low = distribution.energy_low_e
energy_high = distribution.energy_high_e

#Distributions for plug-in time
plugin_weekday = distribution.plugin_weekday
plugin_sat = distribution.plugin_sat
plugin_sun = distribution.plugin_sun

#Distributions for plug-out time
```

```
plugout_weekdays = distribution.plugout_weekdays
plugout_friday = distribution.plugout_friday
plugout_saturday = distribution.plugout_saturday
plugout_sunday = distribution.plugout_sunday


temperature2019 = distribution.temperature2019['Gjennomsnitt']

''' Stochastic input parameters '''
#Using functions developed in EV_functions_year

#Setting EV type based on input
EV_type = f.charging_type(Nr_of_charging_stations, percent_high,
    percent_low)

#Setting charging frequency and making an array of days of the year
    charging
charging_freq_year,if_charging_year = f.generate_ifcharge(
    Nr_of_charging_stations, charge_freq_low, charge_freq_high,
    charge_freq_all, EV_type)

# Setting the maximum charging power
charging_power = f.charger_power_distribution(Nr_of_charging_stations,
    EV_type, percent_high_3_6, percent_high_7_2, percent_low_3_6,
    percent_low_7_2)

# Setting the energy need energy need for the days charging
energy_year = f.EV_energy_need(EV_type, charging_freq_year, energy_high,
     energy_low, energy_all, Nr_of_charging_stations, if_charging_year,
    temperature2019)


# Setting plug-in time for all days of charging
plugin_year = f.EV_plugin(plugin_weekday, plugin_sat, plugin_sun,
    Nr_of_charging_stations, if_charging_year)

# Setting plug-out time for all days of charging
plugout_year = f.EV_plugout(Nr_of_charging_stations, plugout_weekdays,
    plugout_friday, plugout_saturday ,plugout_sunday,  if_charging_year,
    plugin_year)

# Finding connection time based on plug-in time and plug-out time
connection_year = f.EV_connection_1(Nr_of_charging_stations, plugin_year
    , plugout_year, if_charging_year)
```

D.2 Function to make Connection Profile

```python
import numpy as np
import math

def EV_connection_profile(Nr_of_charging_stations, if_charging_year, plugin_year, plugout_year, connection_year):
    """ Generates EV connection based on the stochastic variables from Plugin time and connection time"""

    connection_profile = np.zeros((Nr_of_charging_stations,7*53*24))
    for i in range(Nr_of_charging_stations):
        for j in range(7*53):
            if if_charging_year[i,j] == 1:

                arr = math.floor(plugin_year[i,j]/1) #Finding arrival time

                #If still connected the next day
                if math.floor(connection_year[i,j] + plugin_year[i,j]) > 24 and j < (7*53-1): #If charging session last until next day
                    rest = math.floor(math.floor(connection_year[i,j] + plugin_year[i,j]) -24) #Finding hours charging the next day
                    for m in range(rest+1):
                        if m < math.floor(plugout_year[i,j]): #Connected the whole hour
                            connection_profile[i,j*(24+1)+m] = 1 #Setting whole hour charging
                        elif m == rest: #Not connected the whole hour
                            connection_profile[i,j*(24+1)+m] = (plugout_year[i,j]%1) #Setting part of hour when charging


                # Hours connected for same day as plugin
                for k in range(24):

                    # When hour = plugin hour
                    if (k == arr) and (math.floor(connection_year[i,j]) > 0):
                        connection_profile[i, j*24+k] = 1-(plugin_year[i,j]%1) #Setting part of hour charging

                    # When connected the whole hour
                    if k>arr and k < math.floor(connection_year[i,j] + plugin_year[i,j]):
                        connection_profile[i, j*24+k] = 1 # Setting whole hour charging

```

```
                    # WHen plugin and plugout happens the the same hour
                    if (k == arr) and (math.floor(connection_year[i,j]) == 0) and (arr == math.floor(plugout_year[i,j])):
                        connection_profile[i, j*24+k] = connection_year[i,j]  #Setting part of hour charging
                    # When plugout and plugin is not the same hour
                    elif k == math.floor(connection_year[i,j] + plugin_year[i,j]):
                        connection_profile[i, j*24+k] = (plugout_year[i,j]%1) #Setting part of hour charging

                    # When connected for less than an hour, plugin and plugout not the same hor
                    if (k == arr) and (math.floor(connection_year[i,j]) == 0) and (arr != math.floor(plugout_year[i,j])):
                        connection_profile[i, j*24+k] = 1-(plugin_year[i,j]%1) #Setting part of hour charging



    return(connection_profile)


```

D.3 Function to make Load Profile

```python
import numpy as np


def charging_profile_hourly(Nr_of_charging_stations, charger_power, energy_year, connection_profile):

    charging_profile_hourly= np.zeros((Nr_of_charging_stations, 7*53*24))


    for i in range(Nr_of_charging_stations):

        # Find charging power of EV
        charging_power = charger_power[i]

        #First connection is ready
        new_connection = 1

        #Still no residue of today
        Todays_residue = 0

        #Still no residue from last hour
        Yesterdays_residue = 0

        for j in range(7*53):
            for k in range(24):

                #When new connection is ready
                if new_connection == 1:

                    # Set todays residue as the energy need
                    Todays_residue = energy_year[i,j]

                    # When charging need is big enough to charge the whole time of connection
                    if (Todays_residue > 0) and (Todays_residue > charging_power*connection_profile[i,j*24+k]):
                        charging_profile_hourly[i,j*24+k] = charging_power*connection_profile[i,j*24+k] #Set charging
                        Todays_residue = Todays_residue - charging_power*connection_profile[i,j*24+k] #Find the energy need after charging

                        Yesterdays_residue = Todays_residue #Set energy that will be included the next hour
                        new_connection = 0 #Still same connection

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                # When charging need is less than needing to charge the whole time of connection
                else:
                    charging_profile_hourly[i,j*24+k] = Todays_residue #Set energy
                    Todays_residue = 0 #No energy need left
                    new_connection = 1 #ready for new connection

            # When already connected
            else:

                # Still energy need big enough to charge the whole time of connection
                if Yesterdays_residue >= (charging_power*connection_profile[i,j*24+k]):
                    charging_profile_hourly[i,j*24+k] = charging_power*connection_profile[i,j*24+k] #Set charging
                    Yesterdays_residue = Yesterdays_residue - charging_profile_hourly[i,j*24+k] #Find the energy need after charging
                # When charging need is less than needing to charge the whole time of connection
                else:
                    charging_profile_hourly[i,j*24+k] = Yesterdays_residue #Set charging
                    Yesterdays_residue = 0 #No energy need left

                #Update if new connection is ready
                # When connection session is over, but last charging session was to short to charge everything
                if Yesterdays_residue > 0 and connection_profile[i,j*24+k] == 0 and connection_profile[i,j*24+k-1] > 0  :
                    new_connection = 1 # Set ready for new connection
                # When charging session is over, and energy need s equal to energy charged
                elif Yesterdays_residue == 0 and connection_profile[i,j*24+k] == 0:
                    new_connection = 1
                # If still bigger energy need, and still connected
                else:
                    new_connection = 0 #Still same charging session

    return(charging_profile_hourly)
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