Norwegian School of Economics
Bergen, Spring 2022

Optimizing Charging Strategies for Electric Vehicle Owners

A Comparison of Charging Strategies to Schedule Optimal Home Charging

Thea Kristin Enger & Maria Melby Nøstvik

Supervisor: Mario Guajardo

Master thesis, Economics and Business Administration

Major: Business Analytics

NORWEGIAN SCHOOL OF ECONOMICS

Acknowledgements

This thesis was written as a part of our Master of Science in Economics and Business Administration, with a major in Business Analytics, at the Norwegian School of Economics (NHH). The process of writing our thesis has been exciting and educational.

First and foremost, we would like to express our deepest gratitude to our supervisor, Mario Guajardo, for encouraging us to create something ourselves, and whose excellent guidance and quick replies has helped us throughout the process of writing our thesis. We send our sincerest appreciation for all the engagement and inspirational thoughts.

Finally, we would also like to thank our friends and families, who have supported us in life and in the process of writing this thesis. Thank you.

Norwegian School of Economics

Bergen, June 2022

Thea Kristin Enger

Maria Melby Nøstvik

Abstract

The rapid growth in the Norwegian electric vehicle market has put Norway in a unique position as the leading country in electric vehicle adoption. With few challenges in the establishment of charging infrastructure, most electric vehicle owners will at some point charge their vehicle at home. The charging process of the vehicles can utilize business analytics to schedule the charging to optimize the desired objectives.

In this thesis, we performed a comparison of charging strategies for electric vehicle owners to schedule optimal charging at home. The charging strategies differ in the time periods of charging and are based on the charging behavior of electric vehicle owners in Norway. In order to compare the strategies, we developed a linear programming model that minimizes the charging cost. The spot prices of electricity for 2021 was retrieved as the thesis is conducted in a retrospective manner.

The thesis finds that the flexible night strategy would have experienced the lowest annual charging cost of 1935.36 NOK. In addition, we find the most costly annual charging cost of 2584.01 NOK associated with the forced afternoon strategy. This is a cost increase of approximately 34% compared to the strategy with the lowest annual cost. The results imply that the flexible strategies which can charge at any hour during the day choose to charge the most at night.

This thesis further investigates how the charging costs would be affected if the new network tariff model, to be implemented on July 1, 2022, was implemented in 2021. The results show that the new network tariff would lead to an increase in the variable charging cost for the strategies charging in the afternoon. In contrast, the results imply that the strategies utilizing the off-peak hours of electricity would have experienced a decrease in the variable cost. Lastly, adjustments in the battery capacity and driving range of the electric vehicle were made to investigate the cost effect on the strategies. The results show a decrease in the charging cost as the range increases. The most considerable cost reduction is seen when the range increases from 200 km to 300 km for all the charging strategies.

Abbreviations

A	Ampere
AMPL	A Mathematical Programming Language
EV	Electric vehicle
kV	Kilovolt
kW	Kilowatt
kWh	Kilowatt per hour
MW	Megawatt
MWh	Megawatt per hour
NEDC	New European Driving Cycle standard
NVE	Norges vassdrags- og energidirektorat
OFV	Opplysningsrådet for veitrafikken
TSO	Transmission System Operator
DSO	Distribution System Operators
V	Volt
V2G	Vehicle-to-grid
WLTP	Worldwide Harmonized Light Vehicles Test Procedure standard

Contents

List of Figures

List of Tables

1 Introduction

1.1 Background and Scope of Research

The Norwegian electric vehicle (EV) market has experienced rapid growth over the last years. At the end of 2021, the total share of EVs accounted for approximately 16% of the Norwegian car fleet (SSB, 2022). The rapid growth is a unique phenomenon in a global context considering Norway is a relatively small country as regards population size and the car market. Consequently, no other country in the world has more registered EVs per citizen.

Since its introduction, EV technology has developed exponentially as many businesses are investing heavily to conquer a larger market share of the booming industry. As technology evolves, car manufacturing companies strive to be the preferred choice for EV buyers. Naturally, EVs will have different car-specific characteristics, such as battery capacity and driving range. To meet the growing appetite for EVs, the companies strive to produce the vehicle with the longest range and largest battery capacity. As the industry develops as a whole, new technology and devices for EV charging are developed. Hence, the charging effect from the charging device installed at home evolves.

More than 94% of EV owners charge the vehicle at home, making the charging process flexible as the EV owner can decide which hours to charge (Figenbaum, 2018). Many EV owners plug the vehicle into the charger when coming home from work in the afternoon. Another typical charging behavior is to charge the vehicle during the night. As the EV owner can charge at preferred hours, the charging can be scheduled at hours when the spot prices for electricity are relatively lower.

As the number of EVs is expected to continue to increase, this might impact the stability of the power grid. Therefore, the demand for charging will increase; thus, greater peak demand on the power grid is expected. In June 2021, the Ministry of Petroleum and Energy resolved a new regulatory requirement to facilitate better utilization of the power grid and contribute to a reasonable distribution of the network costs between the end-users. The new network tariff model aims to motivate consumers to shift their electricity consumption to off-peak hours of electricity (Ministry of Petroleum and Energy, 2021a).

Based on the unique situation of the Norwegian EV market, it is of great interest to study different charging strategies based on the charging behaviors of the typical EV owner. In this way, we aim to gain insight into how charging strategies would have performed based on the spot prices of electricity in 2021. In order to do this, we utilize business analytics to develop a charging optimization model which is used in a retrospective manner.

We intend to exploit and compare different charging strategies for electric vehicle owners to minimize the charging cost.

This is performed by using mathematical programming, where the model proposed is a linear programming optimization model. The objective function is to minimize the charging cost of the different charging strategies presented. The input data in the optimization model are spot prices of electricity and car-specific characteristics. Data on the spot prices are retrieved from Nord Pool, while the car-specific characteristics are retrieved from the Norwegian Road Federation (OFV). The solution of the optimization model returns the minimum cost the EV owner can achieve for each charging strategy. Additionally, the model can be used to see how the objectives will be affected if the new network tariff model was implemented and if car-specific factors are adjusted in 2021.

1.2 Structure of the Thesis

This thesis is divided into eight chapters. This chapter has presented the background and the scope of the research of the thesis. Chapter 2 presents relevant theory regarding the Norwegian electricity grid and EVs in Norway and ends with a literature review of research related to the field of EV charging. In chapter 3, a description of the development of the optimization model and charging strategies are presented. Moreover, chapter 4 presents and describes the optimization model in mathematical terms. In chapter 5, the computation and implementation of the data applied to the model are described. In chapter 6, the results of the model are presented, compared, and discussed before two scenarios are introduced. Furthermore, in chapter 7, a discussion of the model and data limitations and suggestions for further work are presented. In the final chapter, conclusions are drawn based on the results and discussion in the preceding chapters.

2 Background

This chapter is divided into two parts. The first part provides an overview of the Norwegian electricity grid. We present the technical characteristics of the power system, how the power market works, regulations, and costs of using the electricity grid. The second part elaborates on the EV market in Norway. This section includes a description of the development of the market, political measures, charging behavior, and the impact of the increasing number of EVs on the electricity grid. Lastly, a literature review is presented.

2.1 The Norwegian Electricity Grid

2.1.1 Production of Electricity

In its nature, electricity must be consumed at the same time as it is produced. This unique feature of electricity is known as the need for instantaneous balance. In order to maintain the instantaneous balance, the power supply system has three fundamental functions: production, transmission, and trade.

The resources for electricity production are often located far from where the actual consumption occurs. The energy sources are different in both location and form, including non-renewable energy sources like nuclear, oil, coal, and natural gas, and renewable energy sources like wind, solar, geothermal, and hydropower. Norway has the highest share of electricity produced from renewable sources in Europe, whereas hydropower is the mainstay of the power capacity (Energifakta Norge, 2021). The Norwegian hydropower system has a high storage capacity, and the production can be increased and decreased as needed at a low cost. The transmission function of the power supply system makes it possible to transmit the power from production to the end-user.

The Norwegian power system is closely integrated with the other Nordic power systems, which in turn are closely integrated with the rest of Europe through cross-border interconnectors to the Netherlands, Germany, Poland, Russia, and the Baltic states (Energifakta Norge, 2021). In Norway, the vulnerability to fluctuations in production between seasons and years is reduced due to the characteristics of hydropower as an energy source, a well-developed power grid, and integration with other power systems in other countries.

2.1.2 Infrastructure of the Electricity Grid

The function of the electricity grid is to transport the demanded volume of electricity from the producers to the consumers at the time requested by the consumers (Ministry of Petroleum and Energy, 2021b). The Norwegian power grid is a so-called natural monopoly as it is not considered efficient for society to build parallel power lines if the existing lines provide sufficient transmission capacity. The Norwegian electricity grid is divided into three levels: the transmission grid, the regional grid, and the distribution grid.

The transmission grid constitutes the nationwide main roads of the power system. The approximately 11000 km long transmission grid connects large producers and consumers and carries mainly a high voltage level of 300 kV to 420 kV (Energifakta Norge, 2019). In Norway, Statnett is the designated transmission system operator (TSO) and owns most of the transmission grid. Statnett is responsible for coordinating production and consumption to maintain an instantaneous balance in the power system.

The regional grid often links the transmission grid to the distribution grid. It carries a voltage level of 33 to 132 kV and has a total length of approximately 19000 km. The regional grid may also include production and consumption radials carrying higher voltage levels.

The distribution grid consists of the local electricity grids, which primarily supply power to smaller end-users. The distribution grid is divided into two segments, the high-voltage and low-voltage. The high-voltage distribution grid normally carries a voltage level of 1 kV to 22 kV, while the low-voltage distribution grid operates at a voltage-levels of 230 V or 400 V.

As defined by EU legislation, the regional and distribution grids are considered distribution systems (NVE, 2018). About 130 different distribution system operators (DSOs) operate on the distribution systems. The DSOs own the distribution networks and are responsible for distributing the power to the end-users.

2.1.3 Market-Based Power System

As electricity cannot easily be stored, the amount produced must equal the amount consumed. The standard microeconomic theory of price uses the concept of supply and demand to determine the appropriate price for a given commodity or service. In other commodity markets, the standard microeconomic theory implies that supply and demand will balance over time by using a pricing mechanism. In such markets, the price will increase when demand exceeds supply, resulting in a decrease in demand and an increase in supply until the balance is reached. The reverse logic is applied when supply exceeds demand. However, due to the need for an instantaneous balance of electricity, the standard microeconomic perspective of the pricing mechanism does not apply as the electricity prices cannot keep up. Therefore, the power market is an essential tool to ensure balance in the electricity system.

The power market can be divided into the wholesale market and the end-user market (Energifakta Norge, 2022). The wholesale market includes the day-ahead, continuous intraday, and balancing markets. The day-ahead market is the primary market for power trading in the Nordic region. Here, power producers, power suppliers, brokers, energy companies, and large industrial customers buy and sell large volumes of power. The participants in the day-ahead market make bids and offers between 8 AM and 12 PM, while the TSOs publish the trading capacity for each bidding area before 10 AM. Based on the received bids, offers, and trading capacity, the prices for each hour of the following day are determined.

The Nord Pool power exchange calculates the system price and the area prices. The system price is equal for the Nordic market and works as a reference price for price determination in the financial power markets. While the system price does not consider any congestion in the grid, the area prices do. In this way, area prices contribute to a balance between the purchase and sell bids from participants in the different bidding zones in the Nordic region. Norway is currently divided into five different bidding zones, as shown in table 2.1.

Table 2.1: The five bidding zones in Norway.

NO1	Oslo
NO2	Kristiansand
NO3	Trondheim
NO4	Tromsø
NO5	Bergen

The day-ahead market plays a vital role in ensuring the balance between supply and demand. However, unexpected events could occur after the auction of the day-ahead market has closed, leading to the actual production or consumption changes from the initial position in the day-ahead market. Therefore, the intraday market enables continuously trading in the period between clearance in the day-ahead market and up to one hour before the hour of operation. This is with the intention that participants are able to accomplish a balance through the trading (Energifakta Norge, 2022). Both day-ahead and intraday trading takes place on the Nord Pool exchange.

As one of its TSO tasks, Statnett runs the latter wholesale market in Norway, the balancing markets. There are other events that could disturb the balance in the power market. In these cases, Statnett utilizes the balancing markets to regulate the production or consumption depending on what is needed to maintain the instantaneous balance in the power system.

The end-user market consists of individual consumers who enter into agreements to purchase electricity from a power supplier. In the Norwegian end-user market, one-third are households, one-third are industries, and one-third are medium-sized customers like hotels and chain stores.

2.1.4 Regulations of the Electricity Grid

Due to the monopolistic nature of the power grid, the grid operations are not subject to competition. The authority regulates the power system and grants licenses for the production and transmission of energy as a monopoly control. The monopoly control is in place to ensure that the operation, utilization, and development of the grid are rational and in the best interest of society.

The grid operators are subject to direct and incentive-based policy instruments in the regulatory framework. The direct regulations are in place to ensure the necessary level of investment, maintenance, and operation in the power grid. At the same time, the revenue cap regulation is in place to incentivize the grid companies to find cost-effective ways of meeting the requirements of the authorities.

Due to the monopolistic nature of the power grid, the end-users are also tied to their local grid company. In this way, the end-users pay the cost of being connected to the grid through the DSOs.

Connection charge

The TSO and DSO require a one-time connection expense of the end-user to cover the costs of connecting the customer to the power grid. The grid company needs to present an estimate of the connection charge in advance.

Network tariffs

The network tariffs vary across the country as it is the DSO's responsibility to set its own tariffs in the designated area. However, the national authority sets the general principles for the tariff design that all DSOs must follow. As the end-user is tied to their local grid company, the network tariffs are intended to cover the costs for the respective grid-level the customer is connected to and for the overhead grid (NVE, 2018). However, the network tariffs set by the DSOs must be objective and non-discriminatory. It is designed to reflect a long-term signal of efficient utilization and development of the power grid and is allowed to differentiate on relevant conditions in the area.

The general design of the network tariff consists of two components, a fixed component and a variable component. The fixed component covers the fixed grid costs and the customer-specific costs not covered by the variable component (NVE, 2021). In addition, it is thought to provide a reasonable return on investments given efficient operation, utilization, and development of the network. The variable component is meant to reflect the costs of the end-users electricity consumption.

The taxes are not a part of the network tariff but are incorporated in the end-users total invoice. The taxes include electricity tax and value-added tax (VAT). In addition, a fee earmarked for the Energy Fund and a payment for electricity certificates are added.

Finnmark, and the municipalities of Karlsøy, Kvænangen, Kåfjord, Lyngden, Nordreisa, Skjerøy og Storfjord are exempt from the electricity tax and VAT. Moreover, Troms and Nordland are exempt from VAT.

In June 2021, the Ministry of Petroleum and Energy resolved a new regulatory requirement on how the network tariff should be redesigned. The purpose of the regulatory change is to facilitate the best possible utilization of the power grid and contribute to a reasonable distribution of the network costs between the end-users (Ministry of Petroleum and Energy, 2021a). As the use of power is expected to increase due to the electrification of society, so is the demand on the power grid also expected to increase.

Yet, with the same general design as the current network tariff model, the new network tariff model is to reward the end-users who utilize the off-peak hours of the power grid. NVE (2022), in collaboration with other relevant companies and organizations, proposes changes to motivate the end-users to shift their consumption to increase grid utilization. With the general design of the current network tariff model, the proposal wants to adjust the components by the following:

1. A minimum of 50% of the revenue should come from the variable component.
2. The variable component should be time differentiated to motivate the end-users to shift the consumption to time periods when there is more capacity in the power grid.
3. The part of the network tariff model that is not collected by the variable component should be collected by a fixed component. The fixed component should be capacity-based and motivate the end-users to even out large consumption peaks. In addition, the fixed component should not be based on the maximum consumption in a single hour.
4. The new network tariff model should be introduced in line with the above recommendations from July 1, 2022, followed by an evaluation of the new network tariff model in the autumn of 2024.

2.2 Electric Vehicles in Norway

2.2.1 The Electric Vehicle Market

Norway is the country in the world with the most EVs per citizen, which puts the Norwegian EV market in a unique situation in a global context (Lorentzen and Grøndahl, 2019). EVs are either partially or fully powered by electric power. However, only EVs solely powered by electricity are taken into consideration in the following chapters. This means that vehicles partially powered by electric energy, such as hybrid electric vehicles (HEV) and plug-in hybrid electric vehicles (PHEV), are not included.

At the end of 2021, the total number of privately owned cars was approximately 2.9 million in Norway (SSB, 2022). EVs fully powered by electricity contributed to 460734 of these registered vehicles. Accordingly, the share of EVs accounted for approximately 16% of the total Norwegian car fleet in 2021. The number of new registrations of EVs has experienced rapid growth over the last few years as figure 2.1 indicates. Figure 2.1 shows that the number of new registered EVs has increased in all counties from 2010 to 2021. Vestland (former Hordaland) is the county with the highest share of new registered electric vehicles in 2021.

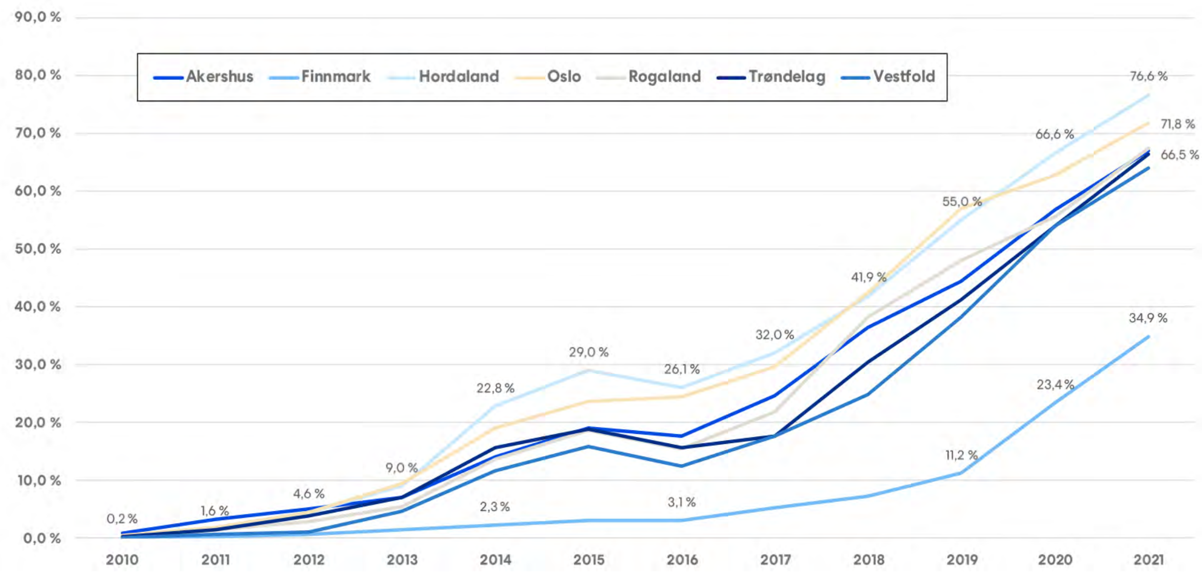

Figure 2.1: The development in the share of new registered EVs in selected counties of Norway (Ofv, 2022).

Different political measures are one of the reasons why the Norwegian EV market is unique. Different governments have gradually introduced the incentives to promote zero-emission vehicles since the early 1990s. According to Figenbaum and Kolbenstvedt (2016), exemptions from the one-off registration tax and VAT, and access to the bus lane are incentives that have had the greatest effect on the sales of EVs. In addition, exemptions of toll road charges on national roads, free or reduced-price on ferries, and free or reduced-price on public parking, are other EV advantages that are considered to have contributed to the high sales number (Ministry of Transport, 2021). The latter incentives are thought to be less substantial but can be of great importance for the individual EV buyers (Figenbaum and Kolbenstvedt, 2016).

2.2.2 Impact on the Electricity Grid

As the number of EVs is expected to continue to grow, the demand for charging will increase; thus, greater peak demand in the power grid is expected. These demand peaks will become one of the main challenges for the power grid (Ydersbond and Amundsen, 2020).

NVE expects the transmission grid to be able to resist the higher energy consumption from EVs as it will be a relatively small load compared to the total power consumption (Skotland et al., 2016). The Norwegian power grid can support a fully electrified car fleet without investing in additional capacity if charging occurs when the electricity usage is low (Bjørndalen et al., 2019). On the other hand, it may create challenges for transformers and cables in the distribution network if many people charge their vehicles simultaneously in the same area. This applies especially to areas with less capacity in the first place. Consequently, the distribution network will face the biggest challenges (Skotland et al., 2016).

Systems for smart charging and load-shifting may reduce the possible challenges of capacity due to the increasing number of EVs and the subsequent charging. Both smart charging and load-shifting illustrate scenarios where the consumers move the consumption from one period to another (Skotland et al., 2016). Additionally, incentivizing the end-users to adapt their consumption to the capacity of the electricity grid is thought to reduce the impact on the power grid. Designing the network tariff model in this matter would reduce the cost for the end-users (Bjørndalen et al., 2019).

2.2.3 Charging

Home charging

In contrast to a traditional car, where the refueling is a mechanical process, refueling an EV is a chemical process through charging. There are two methods for charging an EV at home. The EV owner can either use a home charger unit, also called a wallbox, or an ordinary socket. The Norwegian Directorate for Civil Protection (2017) recommends the usage of a wallbox as it provides better safety, charges faster, and has greater flexibility than charging with an ordinary socket. In addition, the usage of an ordinary socket is thought to increase the risk of fire.

There are two types of wallboxes, smart wallboxes and simple wallboxes. Smart wallboxes have the functions of implementing time control and power supply control. Power control involves controlling the use of electricity to even out the consumption, while time control consists in deciding when the charging will start and stop (Norsk Elbilforening, nd).

In 2018, 43% of all EV owners used a wallbox to charge their vehicle (Figenbaum and Nordbakke, 2019). According to Norsk Elbilforening (2021), 77% of all EV owners charged their EVs with a wallbox in 2021, hence the number of EV owners using a wallbox has increased substantially from 2018 to 2021 (Norsk Elbilforening, 2021). The EV owners charged their vehicle either with a 16A fuse, which delivers 3.7 kW, or a 32A fuse, which delivers between 7-22 kW. The higher the charging effect, the faster the EVs are charged. The charging effect the wallbox provides is also delimited to what the specific EV is able to receive. If the vehicle only can take 3.7 kW when charging, regardless of the effect the wallbox can provide, the EV will not be able to receive more than 3.7 kW.

The wallbox receives power from the electricity grid and converts it to the kind of current the car battery can store (The European Commission, nd). The power from the electricity grid is always alternating current (AC). However, EVs can only store power as direct current (DC) in the battery. In order to charge the battery, the power needs to be converted from AC to DC. The onboard charger inside the vehicle is responsible for the converting.

Charging habits

According to Figenbaum (2018), more than 94% of EV owners charge their vehicles at home. The charging takes place either in the garage or in their own parking lot. Moreover, 80% of the EV owners charge three times or more per week (Figenbaum and Nordbakke, 2019). This is illustrated in figure 2.2.

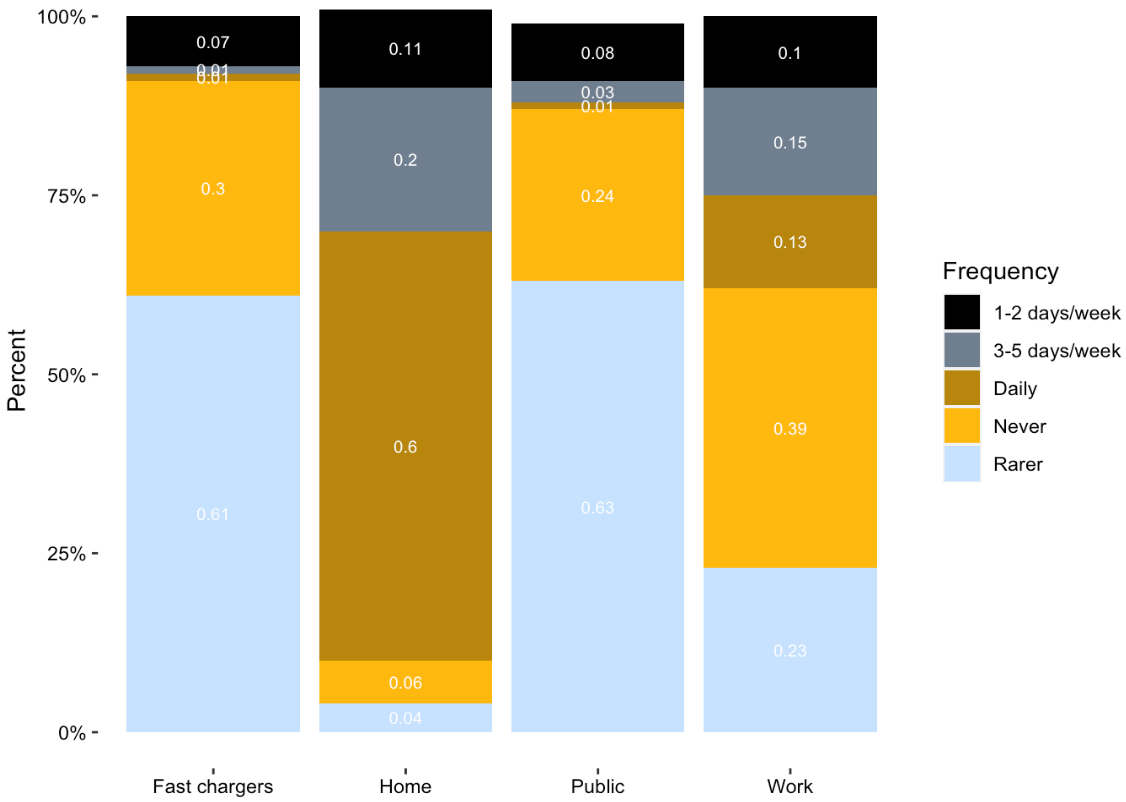

Figure 2.2: Frequency of charging the electric vehicle (Figenbaum, 2018).

As explained by Figenbaum (2018), the typical EV owner plugs the vehicle into the charger when coming home from work, starting around 4 PM. This is supported by surveys conducted by Norsk Elbilforening (2019), which reveals that more than half of today's EV owners charge their vehicle in the time period between 4 PM and 8 PM. A more recent study conducted by Norsk Elbilforening states that 53% of the EV owners charge their car at night (Sletvold, 2021). Lastly, 37% of EV owners states that they charge their car daily.

2.3 Literature Review

The interest and research in the EV industry are growing as new and existing technologies are rapidly developed. The research articles have inspired us to write our thesis on charging strategies based on the charging behavior of the typical EV owner. Many studies seek to minimize the grid load when charging the EV at home, exploit the possibility of discharging technology (V2G), or minimize costs when fast charging. Other studies concern both grid load and cost minimization, while it seems to be few studies solely concerning cost minimization for different charging behaviors. This section provides an overview of existing literature relevant to the scope of our thesis.

Wang, Infield and Gill (2021) propose a simple and effective heuristic approach for minimizing the EV charging cost of smart charging in a smart grid environment. The smart grid environment refers to an aggregator which gathers usage data from EV owners and makes daily charging schedules based on the submitted data in response to a real-time price signal. The authors first present an optimization model, where the objective function minimizes charging costs across the whole simulation period, which is set to 24 hours with a resolution of 10 minutes. Furthermore, the authors propose a heuristic method to implement the model while satisfying the constraints. The method follows the idea of filling the valleys of the price signal curve with EV charging. This is presented in two steps. The first step concerns scheduling the charging of the EV for each vehicle based on its availability and the price signal. This means that the charging time slot with the lowest price value from the price signal is selected first, and the price valley filling continues until the EV is fully charged. The next step is to identify and eliminate any voltage points that have been violated from the charging profiles. Meaning, detected voltage violations identified in the simulation runs are excluded from the charging scheduling list. The proposed model is tested on a typical domestic distribution network in the UK. Then, the authors present a dynamic optimal power flow approach to demonstrate the effectiveness of the smart charging model.

Hexeberg (2014) proposes an algorithm for smart charging and discharging procedure of EVs in which the batteries' storage capacity can be exploited to provide network services under given assumptions. When developing the algorithm, the author investigates three different charging scenarios. Firstly, a dumb charging strategy is considered, which means that all charging starts at 5 PM and continues until the battery is fully charged. Secondly, the paper considers a profit-maximization scenario, which means that the vehicle is charged when the electricity prices are low and discharged at times when the prices are high. Lastly, a power factor control scenario is considered where the car is charged, similar to the first scenario, if the voltage is above a certain level, and charging time is reduced if the voltage is below. Furthermore, Hexeberg (2014) develops and implements algorithms for all the charging scenarios. The proposed algorithm is applied to a number of EVs in Norway, corresponding to a 50% adoption of EVs. The author finds that when all the vehicles are charged according to the first scenario, it results in a major peak in demand and reduction of the voltage between 6 PM and 8 PM. Furthermore, the findings show that the second and the third scenario improved the voltage profile.

Kriekinge, De Cauwer, Sapountzoglou, Coosemans and Messagie (2021) present two different MPC algorithms for charge scheduling. The first objective function minimizes the grid electricity costs. This enables cost minimization for uni-directional charging, which means power flows from the grid to the vehicle. The second objective function minimizes the peak power cost and enables peak shaving and cost minimization for both uni- and bi-directional charging. Bi-directional charging is when power can flow both ways. As a result, four different charging strategies are defined. The authors test the strategies in a simulator, which uses PV forecast from the transmission system operator in Belgium and a developed deep recurrent neural network (RNN) for the load forecast. When compared to uncoordinated charging, the authors discover that all charging schedules presented are able to lower peak power. Furthermore, the authors find that bi-directional charging reduces the peak power to a lower level than before the EVs were introduced.

The paper by Wangsness and Halse (2021) studies whether uncoordinated charging of EVs might impose challenges on the local grid. The authors analyze data from 107 DSOs from 2008 to 2017 to investigate how an increase in the EV fleet affects the costs at the local grids. The proposed model is a fixed effect regression used on a panel with the given data. The objective is to investigate how the time varying variable, which is EVs, influences the time-dependent endogenous variable, which is total cost. Wangsness and Halse (2021) find that an increase in the number of EVs in the operational area of a DSO is associated with an increase in local grid costs. Additionally, the study demonstrates relatively large heterogeneity in the effect of EVs on grid costs.

Bjørndalen, Ingeberg, Brønmo, and Norheim (2019) study the effect on the grid costs if every household charges the EV at the same time. The authors present a power demand model developed by Pöyry. This is a bottom-up tool which can be used to study future hourly demand during the peak day of the year. The data is collected from three different grid companies. Moreover, the authors present three future charging behaviors: 1) charging every day in the afternoon, 2) charging when needed in the afternoon, and 3) charging at night.

The results obtained by Bjørndalen, Ingeberg, Brønmo, and Norheim (2019) illustrate that when charging at night, the peak is in the morning between 8 AM and 9 AM, which is the same result obtained when no EVs were charged. Furthermore, the load increases between 5 PM and 8 PM when charging in the afternoon when required, although the peak in the afternoon will not become larger than the peak in the morning. Lastly, the results demonstrate that the peak in the afternoon is considerably larger than the peak in the morning when charging every day in the afternoon. Next, the authors look into the investment requirements for the local distribution networks under the different charging strategies. The findings illustrate that charging at night does not require any investments while charging in the afternoon will lead to a cost increase of 7% for the local distribution company. These investments consist of network tariffs and investment contributions.

The mentioned research articles have inspired us to write our thesis. Nevertheless, we see that there is still a lack of studies on when the EV owners should charge their vehicles based on minimizing the charging cost. With this thesis, we attempt to fill the gap in the research by comparing different charging strategies in order to minimize the charging costs for EV owners. In order to exploit and compare the charging strategies, a mathematical optimization model is developed to gain insight into what charging strategies are associated with the highest and lowest annual charging cost.

3 Problem Description

The goal of this thesis is to exploit and compare different charging strategies based on charging behavior of EV owners. In order to compare the charging strategies, a mathematical optimization model is created to minimize the charging cost of the different charging schedules for the EV owners. For the purpose of minimizing cost, it is needed to formulate a charging schedule based on normal charging behavior in mathematical terms. The aim is to create the model as realistic as possible while still making some assumptions to avoid the model being too complex to implement in the decision-making for the EV owners. The model only takes into consideration vehicles that are solely powered by electricity.

3.1 Home Charging for Electric Vehicle Owners

The increasing number of EV owners with a wallbox installed at home enables them to charge the vehicle at their own preferred time. In this way, the EV owners can schedule their charging to periods when the spot prices for electricity are lower. However, some EV owners are not as price-conscious and schedule the charging when it is more convenient regardless of the price level. Two factors determine the charging costs, the amount of electricity retrieved from the grid per hour and the spot price, which varies from hour to hour. In this model, the hourly spot prices for 2021 are retrieved from Nord Pool. This means that the costs associated with the charging behaviors depend on the time periods the EV owners decided to charge the vehicles in 2021. Thus, the analysis is conducted retrospectively.

The purpose of the battery of the EV is to store energy; thus, the amount stored is a crucial parameter. EVs have a built-in battery where the power the vehicles retrieve from the grid is stored. Each car type has a different battery capacity, given in kWh. This means that the amount of power stored varies among different EVs. Thus, the amount of electricity charged is limited to the battery capacity and the state of charge. The state of charge is the level of electricity stored in the battery of the EV. The model must ensure that the state of charge does not exceed the battery capacity. Moreover, the state of charge should not fall below a certain battery capacity level for the EV owners not to experience range anxiety. Range anxiety is the fear of running out of power. The model makes sure the state of charge is always greater than or equal to the specific level of the battery capacity.

The EV owners are thought to use the vehicle for the same daily travels every day of the week. This means that longer trips are not included in the charging schedule. The daily electricity demand for the EV owners is calculated using the average daily driving distance. The model ensures the car is used for daily travels by subtracting the daily demand of kWh from the battery's state of charge. Additionally, the state of charge is connected by each hour on each day to ensure the proper state of charge levels at all times. In this way, the amount retrieved from the grid is added to the state of charge when the car is plugged into the wallbox and subtracted when the car is driving. The model takes care of this by making sure the state of charge in the current hour is equal to the state of charge in the previous hour and the amount charged in the current hour. This also applies to days, where the model ensures that the state of charge at the beginning of each day is equal to the state of charge at the end of the previous day and the amount charged on the current day.

The amount of electricity an EV can obtain from the wallbox in one hour is primarily determined by the maximum charging rate it can give. This, in turn, is dependent on the main fuse of the house. The model ensures the total amount of electricity received does not exceed the maximum kW the wallbox can give. Additionally, a charging device inside the battery of the vehicle limits how much power it can receive in one hour. The device ensures that the EV does not receive more electricity than it can handle. The model assumes that the charging rate the vehicle receives from the wallbox is the same for all vehicles.

When the EV is plugged into the charger, the amount of electricity the vehicle receives from the grid cannot be less than 0. This also applies to the state of charge of the car. The model ensures that the amount of electricity received from the grid and the state of charge is always greater than or equal to 0.

3.2 The Charging Strategies

Seven charging strategies are formulated based on the presented charging behavior and included in the model. In this part of the thesis, the charging strategies are presented.

3.2.1 Fully Flexible

The charging strategy is included as a benchmark strategy to illustrate the optimal charging schedule if the EV owner can charge the vehicle at any time during the week. The strategy is fully flexible as it can charge all hours of the day on both weekdays and weekends. However, the charging strategy is restricted to drive the EV at 3 PM every day of the week. It is assumed that this is a time period where many EV owners use their cars for daily trips. As a result, the EV owners cannot charge the vehicles during this hour due to the driving.

3.2.2 Forced Afternoon

The forced afternoon charging strategy is based on one of the most common charging behaviors of EV owners, where the vehicle is plugged into the wallbox right after work every weekday. Hence, the EV is charged regardless of the state of charge of the battery. Right after work is assumed to be at 4 PM, which means the EV owners start to charge the vehicle during peak hours of electricity. The model restricts the strategy to have a fully charged battery at the end of each charging period. The charging period is 4 PM to 8 PM Monday through Friday. In addition, the car is thought to be driven at 3 PM every day of the week which is outside the charging period.

3.2.3 Flexible Afternoon

The flexible afternoon charging strategy is also based on one of the most common charging behaviors, where the EV owners still charge the vehicle right after work from 4 PM to 8 PM. However, the EV owners can plug the vehicle into the wallbox when necessary to charge the battery. In the model, it is assumed to be necessary never to have less than 20% of the battery capacity available. This is due to range anxiety. In addition, it is assumed that it is necessary to charge the battery to be capable of making the daily trips on the following days. The EVs are thought to be driven at 3 PM every day of the week, which is outside the charging period. The charging strategy still restricts the EV owners to only be able to charge Monday through Friday, and not outside the charging period of 4 PM to 8 PM nor on the weekends.

3.2.4 Forced Night

Forced night charging illustrates a charging schedule where the EV owners utilize the off-peak hours of electricity. The EV owners are forced to charge the vehicle every night on weekdays. Hence, the EV owners are restricted to fully charge the vehicle at the end of the charging period. The charging period starts at 12 AM and ends at 7 AM, and ranges from the night of Sunday to Monday until the night of Thursday to Friday. Accordingly, EVs are not allowed to be charged during the weekend. Additionally, the vehicles are thought to be driven at 3 PM every day of the week, which is outside the charging period.

3.2.5 Flexible Night

In the flexible night charging strategy, the EV owners still utilize the off-peak hours of electricity during the night. The model illustrates EV owners who can plug the car into the wallbox from 12 AM until 7 AM when it is necessary to charge the battery. It is assumed to be necessary never to have less than 20% of the battery capacity available due to range anxiety. In addition, it is assumed to be necessary to have sufficient battery stored to drive the daily trips the following days. The EV owners can only charge the vehicle during the weekdays and not on the weekends. The charging periods range from the night of Sunday to Monday until the night of Thursday to Friday. Additionally, the EVs are thought to be driven at 3 PM every day of the week, which is outside the charging period.

3.2.6 Forced Weekend

The forced weekend charging strategy illustrates the scenario when the EV owners fully charge the battery during the weekends. The EV owners can charge the vehicle at any time during the weekend. Therefore, the charging period starts at 12 AM on Saturday and lasts until 11 PM on Sunday. The model forces the EV to be fully charged at 11 PM on Sunday as the EV owners charge the battery full every weekend. However, the strategy is restricted to use the vehicle for daily trips every day of the week at 3 PM. Meaning, the charging schedule cannot charge the EV at this hour.

3.2.7 Flexible Weekend

The flexible weekend charging strategy restricts the EV owners to only charge during the weekends. The charging period starts at 12 AM on Saturday and lasts until 11 PM on Sunday. However, in this weekend charging strategy, the EV does not need to be fully charged at the end of the charging period and charges only when it is necessary. It is assumed to be necessary never to have less than 20% of the battery capacity available due to range anxiety. In addition, it is assumed to be necessary to have sufficient battery stored to drive the daily trips in the following weeks. The charging strategy is flexible in which the EV owners can charge the vehicle at any time during the weekends except when it is used for daily trips at 3 PM.

3.2.8 Summary of the Strategies

Table 3.1: Summary of the all the charging strategies presented.

Name	Charging period	Driving
Fully flexible	12 AM to 11 PM	3 PM
Forced afternoon	4 PM to 8 PM	3 PM
Flexible afternoon	4 PM to 8 PM	3 PM
Forced night	12 AM to 7 AM	3 PM
Flexible night	12 AM to 7 AM	3 PM
Forced weekend	12 AM to 11 PM	3 PM
Flexible weekend	12 AM to 11 PM	3 PM

4 Optimization Model

This chapter will provide a short introduction to mathematical programming before the optimization model is presented. The optimization model is formulated using mathematical programming techniques and includes sets, parameters, decision variables, objective function, and constraints.

4.1 Mathematical Programming

Mathematical programming is one of the most widely used models in the field of operational research and management science (Williams, 2013). Operational research is an approach to find optimal solutions to a range of problems to assist in decision-making, such as the optimal use of limited resources. A common characteristic of mathematical programming is that it involves optimization. The optimization model is formulated mathematically with decision variables, objective function, and constraints (Lundgren et al., 2010). The decision variables vary and can be controlled or affected by the decision-maker, while the objective function depends on the decision variables and is either maximized or minimized. Moreover, the optimal values of the decision variables are restricted by a set of constraints.

There exists a large variety of mathematical programming models. Some examples are linear programming, non-linear programming, and integer programming. The linear programming model is the most widely used and is especially important as many problems can be modeled as linear programs (Fourer et al., 2003).

4.1.1 Linear Programming

In a linear programming (LP) model all the costs, requirements, and other quantities of interest are expressed in terms that is strictly proportionate to the levels of activities, or sums of such terms. The objective is a linear function and the constraints are linear equations and inequalities (Fourer et al., 2003). An LP problem can be written in general form as

$$\begin{aligned} \min \quad & z = \sum_{j=1}^{n} c_j x_j \\ s.t. \quad & \sum_{j=1}^{n} a_{ij} x_j \ \leq \ b_i, \qquad i = 1, .., m \\ & \qquad\quad x_j \ \geq \ 0, \qquad j = 1, .., n \end{aligned}$$

Here, c_{j} is the coefficient for variable x_{j} in the objective function, while a_{ij} is the coefficient for variable x_{j} in the first constraint. b_{i} is the coefficient of the right-hand side in the same constraint (Lundgren et al., 2010).

Mathematical programming models can be solved by using computer software. In this thesis, we use AMPL to formulate the model and CPLEX as a solver to obtain the optimal solution. In the next part, the optimization model will be presented in mathematical terms.

4.2 Optimization Model

4.2.1 Sets

T = Set of all time periods

D = Set of all days

First, the sets in the model are defined. The sets include a set of time periods and a set of days. The set containing the time periods includes all the hours in a day, while the set of days represents all days in a year.

4.2.2 Parameters

$p_{\mathrm{t,d}}$	Spot price of electricity in time period t on day d
e	Variable cost of the network tariff dependent on the power consumption
r	Charging rate
C	Maximum battery capacity of the EV
c	Minimum battery capacity of the EV
$\bar{d}$	Average daily demand of kWh used for daily trips
$Y_{t,d}$	1 the charging strategy allows for charging at time t and day d, 0 otherwise
$Z_{t,d}$	1 if the EV is driving at time t and day d, 0 otherwise

The charging strategies are influenced by a set of parameters, including spot prices, variable costs, charging rate, maximum and minimum battery capacity, average daily demand for electricity and two binary parameters. Some of the parameters are defined by the car-specific characteristics of the EV in the model, such as maximum battery capacity, minimum battery capacity, and the calculated average daily demand for electricity.

The spot prices and the variable cost are given in NOK. Moreover, the charging rate in kWh is the amount of electricity retrieved from the grid to charge the battery of the vehicle. The maximum battery capacity represents the maximum amount of electricity the battery of the EV can store. The minimum battery capacity is set to have at least a state of charge of 20% of the maximum battery capacity. The average daily demand is the amount of kWh required to drive the daily trips every day of the week.

The model includes two binary parameters to specify when the different charging strategies are set to have the opportunity to charge and drive.

4.2.3 Decision Variables

$x_{t,d}$	Amount of electricity retrieved from the grid at time period t on day d
$SOC_{t,d}$	State of charge of the EV's battery at time period t on day d

The first decision variable includes the amount of electricity retrieved from the grid to charge the EV each time period of each day. Moreover, the second decision variable includes the state of charge of the battery each time period of each day. Both variables are continuous and measured in kWh.

4.2.4 Objective Function

The objective function aims to minimize the charging cost:

$$min \sum_{t \in T,\, d \in D} p_{t,d} \cdot x_{t,d} + \sum_{t \in T,\, d \in D} e \cdot x_{t,d} \tag{4.1}$$

4.2.5 Constraints

In this section, the constraints for the charging strategies are presented. The general presentation of the model is formulated mathematically before the model is described in detail. Lastly, the different charging strategies are presented and potential constraints are added to the general model.

4.2.5.1 General Presentation of the Model

$$SOC_{t,d} \;=\; C, \qquad t = 0,\; d = 1 \tag{4.2}$$

$$SOC_{t,d} \;=\; SOC_{t-1,d} \;+\; x_{t,d} \cdot Y_{t,d} \;-\bar{d} \cdot Z_{t,d}, \qquad \forall\, t \in T : t > 0,\; d \in D \tag{4.3}$$

$$SOC_{0,d} \ = \ SOC_{23,d-1} \ + \ x_{0,d}, \qquad \forall\, d \in D : d > 1 \tag{4.4}$$

$$SOC_{t,d} \ \leq C, \qquad \forall\, t \in T,\ d \in D \tag{4.5}$$

$$SOC_{t,d} \ \geq c, \qquad \forall\, t \in T,\ d \in D \tag{4.6}$$

$$x_{t,d} \leq r, \qquad \forall\, t \in T,\ d \in D \tag{4.7}$$

$$x_{t,d} \geq 0, \qquad \forall\, t \in T,\ d \in D \tag{4.8}$$

$$SOC_{t,d} \geq 0, \qquad \forall\, t \in T,\ d \in D \tag{4.9}$$

The initial state of charge is defined by constraint 4.2. The constraint ensures that the EV starts with the total battery capacity at the beginning of the modeling period. This is defined as the first hour of the first day.

Constraint 4.3 ensures balance between the state of charge of each time period. The balance is defined by the state of charge in the previous time period, the amount charged in the current time period, and the amount consumed for daily trips in the current time period. The time periods are connected, so the state of charge at the current time period is equal to the state of charge in the previous time period. In addition, if the strategy allows for charging, then the amount charged in the current time period is added to the state of charge. If the charging strategy is required to drive, the amount consumed for daily trips is subtracted from the state of charge. The two binary parameters $Y_{t,d}$ and $Z_{t,d}$ ensure these concerns.

Constraint 4.4 ensures balance between the state of charge of each day. The balance is defined by the state of charge at 11 PM on the previous day and the amount charged at 12 AM on the current day. In this way, the constraint connects the state of charge between the 365 days of the model.

Constraint 4.5 makes sure the state of charge of the EV do not exceed the battery capacity of the specific vehicle. Furthermore, constraint 4.6 ensures the state of charge of the EV never go below a level of 20% of the battery capacity. This means that the EV owner demands that the state of charge is above the range anxiety level.

The amount of electricity retrieved from the grid cannot exceed the charging rate. This is ensured by constraint 4.7, which limits the EV not to retrieve more electricity than the standard wallbox can give. The vehicle cannot receive more because the wallbox cannot deliver more effect.

Constraints 4.8 and 4.9 are non-negativity constraints. The constraints ensure that the amount of electricity retrieved from the grid and the battery's state of charge is greater than or equal to 0.

The formulated model is similar to the literature presented in the literature review in chapter 2. Nevertheless, the model has some dissimilarities compared to the literature. Hexeberg (2014) describes a similar objective function but maximizes the revenue for the EV owners by including the ability to discharge the EV. Hence, the solution finds the optimal objective where the amount of energy sold to the grid is subtracted by the amount bought from the grid. In our thesis, the formulated model includes all hours in a day and all days in a year, while Hexeberg (2014) formulates the model for a single 24-hour period. Furthermore, Wang, Infield, and Gill (2021) minimize charging cost for the EV owners in a smart grid environment. Based on a real-time price signal, the model schedules the charging for when the price signal curve decreases. The authors formulated the model to schedule the charging in advance as a smart charging method, while our thesis presents a retrospective analysis of the known spot prices of electricity for 2021.

4.2.5.2 Fully Flexible

Fully flexible charging strategy includes all the constraints presented in the general presentation of the model. The charging strategy is restricted to drive at 3 PM every day of the week. Therefore, $Z_{t,d} = 1$ at time period 15 in constraint 4.3. As the charging strategy is fully flexible, the model is allowed to charge every hour of every day except when the car is driving. Thus, the parameter $Y_{t,d} = 1$ for all time periods except when t is 15 and for all d in days.

4.2.5.3 Forced Afternoon

The charging strategy includes all the constraints presented in the general presentation of the model. Forced afternoon charging strategy is forced to charge every weekday after work. This means $Y_{t,d} = 1$ when the time period is 16, ..., 20 in weekdays in constraint 4.3. In the same constraint, $Z_{t,d} = 1$ at time period 15 every day of the week, including the weekends. Consequently, the EV owner cannot charge the vehicle at this hour as it is driving. Although the strategy is limited to only charge during the weekdays, the EV is still used for daily trips on the weekends. Hence, the constraint makes sure the state of charge on Mondays is equal to the state of charge at the end of Fridays subtracted by the amount consumed for daily trips on Saturdays and Sundays.

In order for the strategy to charge every day after work, constraint 4.10 is added to the model. The constraint ensures the battery is fully charged at the end of the charging period, which in this case is at 8 PM. As the charging strategy only includes charging on the weekdays, the state of charge on the weekends is not affected by the constraint.

$$SOC_{t,d} \; = \; C, \qquad \forall \, d \in D, \; t = 20 \tag{4.10}$$

4.2.5.4 Flexible Afternoon

The charging strategy includes all the constraints presented in the general presentation of the model. Flexible afternoon strategy charges the EV when necessary on the weekdays. In constraint 4.3, $Y_{t,d} = 1$ when the time period is 16, ..., 20 in weekdays. $Z_{t,d} = 1$ at time period 15 every day of the week. Consequently, the EV owner cannot charge the vehicle at this hour as it is driving. The EV is also used for daily trips on the weekends, although the strategy is limited to charge Mondays through Fridays. Thus, the state of charge on Mondays is equal to the state of charge at the end of Fridays subtracted by the amount consumed for daily trips on Saturdays and Sundays.

4.2.5.5 Forced Night

The charging strategy includes all the constraints presented in the general presentation of the model. Forced night strategy is forced to charge every weekday at night. This means $Y_{t,d} = 1$ when the time period is 00, ..., 07 in weekdays in constraint 4.3. The time periods range from the night of Sundays to Mondays until the night of Thursdays to Fridays. In the same constraint, $Z_{t,d} = 1$ at time period 15 every day of the week as it is driving. Although the strategy is limited to only charge at night during the weekdays, the EV is still used for daily trips on the weekends. Hence, the state of charge when the charging period begins at 12 AM on Mondays is equal to the state of charge at the end of Fridays subtracted by the amount consumed for daily trips on Fridays, Saturdays, and Sundays.

In order to force the strategy to charge every weekday at night, constraint 4.11 is added to the model. The constraint ensures the battery is fully charged at the end of the charging period, which in this case is at 7 AM. As the strategy only includes charging on the weekdays, the state of charge on the weekends is not affected by the constraint.

$$SOC_{t,d} \; = \; C, \qquad \forall \, d \in D, \; t = 07 \tag{4.11}$$

4.2.5.6 Flexible Night

The charging strategy includes all the constraints presented in the general presentation of the model. Flexible night strategy charges when necessary at night on the weekdays. In constraint 4.3, $Y_{t,d} = 1$ when the time period is 00, ..., 07 in weekdays. The time periods range from the night of Sundays to Mondays until the night of Thursdays to Fridays. In addition, $Z_{t,d} = 1$ at time period 15 every day of the week as it is used for driving. The EV is also used for daily trips on the weekends, although the strategy is limited to charge during the weekdays. Hence, the state of charge when the charging period begins at 12

AM on Mondays is equal to the state of charge at the end of Fridays subtracted by the amount consumed for daily trips on Fridays, Saturdays, and Sundays.

4.2.5.7 Forced Weekend

The charging strategy includes all the constraints presented in the general presentation of the model. Forced weekend strategy is forced to charge on the weekends. Therefore, $Y_{t,d} = 1$ at any time period t in the weekend. The charging period starts at 12 AM on Saturdays and ends at 11 PM on Sundays. The charging strategy is restricted to drive at 3 PM both Saturdays and Sundays. Therefore, $Z_{t,d} = 1$ at time period 15 in constraint 4.3. The EV is also used for daily trips on the weekdays, although the charging strategy is limited to charge during the weekends. Hence, the state of charge when the charging period begins at 12 AM on Saturdays is equal to the state of charge at the end of Sundays subtracted by the amount consumed for daily trips on the weekdays.

In order to force the EV to be fully charged at 11 PM on Sundays, constraint 4.12 is added. As the strategy only includes charging on the weekends, the state of charge on the weekdays is not affected by the constraint.

$$SOC_{t,d} \; = \; C \qquad \forall \, d \in D, \; t = 23 \tag{4.12}$$

4.2.5.8 Flexible Weekend

The charging strategy includes all the constraints presented in the general presentation of the model. Flexible weekend strategy charges the EV when necessary on the weekends. In constraint 4.3, $Y_{t,d} = 1$ at any time period t on the weekends. The weekends start at 12 AM on Saturdays and end at 11 PM on Sundays. Additionally, $Z_{t,d} = 1$ at time period 15 on Saturdays and Sundays, as the model restricts the EV to drive at 3 PM on both days. Although the strategy is limited to charge during the weekends, the EV is also used for daily trips on the weekdays. Hence, the state of charge when the charging period begins at 12 AM on Saturdays is equal to the state of charge at the end of Sundays subtracted by the amount consumed for daily trips on the weekdays.

5 Data Description

This chapter presents and describes the data sources used in the optimization model. The model optimizes each charging strategy individually and relies on input data retrieved from various sources. To be regarded as valid input data in the model, the data retrieved needed different methods of processing and computation. Therefore, this chapter is split into two parts: computation of the data and implementation of the data. Lastly, the assumptions made regarding input values are discussed.

5.1 Computation of the Data

For all the charging strategies, the annual charging cost is defined by the amount of kWh retrieved from the grid and the corresponding spot price when the charging takes place. The data on electricity prices and car-specific characteristics needed computation and are presented in the following section.

5.1.1 Electricity Prices

The hourly day-ahead prices are retrieved from Nord Pool, where the data set initially was given in NOK/MWh for all the bidding areas in Norway. In the raw data, each row represents the hourly spot price starting on January 1, 2021, at 12 AM and ending on December 31, 2021, at 11 PM. Each observation applies to one hour, e.g., from 12 AM to 1 AM, which yields a total of 43800 observations when including all the bidding areas in Norway.

The raw data of spot prices were transformed to better fit the model. Firstly, only the spot prices of Bergen (NO5) were derived from the raw data. As presented in chapter 2, Vestland (former Hordaland) had the highest number of new registered EVs in 2021. In this matter, the total number of observations was reduced to 8760. The data for 2021 consists of three columns, including all the dates, hours in each day and the corresponding spot prices for NO5.

For the purpose of calculating the annual cost when retrieving electricity measured in kWh from the grid, the electricity prices are converted from NOK/MWh to NOK/kWh.

This was applied to the raw data by dividing the spot prices by 1000. In addition, the day-ahead prices on Nord Pool are wholesale prices and exclude fees, charges, or taxes applied to the electricity prices at a national level. Therefore, the VAT of 25% is added to the spot prices.

The computation of the electricity prices was done in Excel. In addition, the data on the spot prices were transformed to a format that better suits parameters in AMPL. The columns of the dates, hours and corresponding spot prices are split into multiple columns horizontally to have each column representing one day and each row representing one hour for the whole year. The hours were converted to a single-hour format, although the interpretation of the hour remains the same. The same transformation was applied to the dates as AMPL would struggle to interpret the formulated model in short date format. Therefore, the dates were converted into a single number format for all 365 days in 2021. Table 5.1 illustrates the transformed spot prices when including the taxes for bidding zone NO5 on the first seven days of 2021.

Table 5.1: Data structure for spot prices the first seven days of 2021.

	1	2	3	4	5	6	7
0	0.32574	0.33409	0.32991	0.32195	0.36279	0.39049	0.55878
1	0.31790	0.32521	0.32104	0.31399	0.35809	0.37595	0.53050
2	0.31308	0.32300	0.31151	0.31176	0.35326	0.36798	0.50833
3	0.30968	0.32195	0.30773	0.31373	0.35404	0.36626	0.51598
...	...	...	...	...	...	...	...
...	...	...	...	...	...	...	...
22	0.34519	0.35054	0.34180	0.40408	0.41823	0.50660	0.75023
23	0.33475	0.33866	0.32535	0.35708	0.38105	0.42544	0.65670

5.1.2 The Norwegian Electric Vehicle Fleet

OFV provided us with data on the ten most sold EVs in 2021. The data on the selected EV models consists of the brand name, the model name, the driving range in km by New European Driving Cycle standard (NEDC) and Worldwide Harmonized Light Vehicles Test Procedure standard (WLTP), and the total number of the registered vehicles with the corresponding range per 31.12.2021. By September 2018, all car manufacturers were required by EU law to test the EVs' range by the WLTP standard (European Automobile Manufacturers Association, nd). Therefore, only the information on the EVs with range given in WLTP was considered.

The same EV models are registered with multiple driving ranges and number of registrations. Therefore, the EV models were grouped in Excel and the minimum and maximum range of the selected EVs were identified. Lastly, the total number of registrations of each EV model with the different ranges was computed. In table 5.2, the five most popular EVs by different car manufacturers per 31.12.2021 is shown.

Table 5.2: The five most registered EVs per 31.12.2021.

Brand name	Model	Min range	Max range	Number of registrations
Tesla	Model 3	409	640	96700
Nissan	Leaf	117	389	79135
Volkswagen	ID.4	336	517	71541
Skoda	Enyaq	355	673	64822
Audi	E-tron	231	485	54862

5.2 Implementation of the Data

In order to implement the optimization model, we have made some assumptions about the car-specific characteristics and how the electricity is retrieved from the grid. An EV with similar characteristics as Tesla Model 3 is included in the model as this was the most registered EV per 31.12.2021. This section will outline and justify the different input values of the model.

5.2.1 Battery Capacity and Driving Range

Based on the data obtained from OFV, most registrations of Tesla Model 3 have a battery capacity of 75 kWh and a driving range of 560 km. Therefore, these characteristics are used as input values in our model.

Table 5.2 shows how the driving range varies between the EV models and how the driving range varies within the same EV model. In order to use the model for EVs with other car-specific characteristics, the two critical input values of battery capacity and driving range are adjusted in a later scenario analysis. The scenario analysis intends to investigate how an increase of 100 km in driving range will affect the variable cost of each charging strategy. Therefore, different values of battery capacity and driving range are chosen to represent other EV models. The table 5.3 displays the range and corresponding battery capacity of the selected EV models.

Table 5.3: Overview of the selected driving range and battery capacity.

Range	Battery capacity
200 km	35 kWh
300 km	45 kWh
400 km	55 kWh
500 km	65 kWh
600 km	75 kWh

The shortest range is set to 200 km and represents a short-range EV, while the EV with the longest range of 600 km represents a long-range EV. The long-range EV with range of 600 km has approximately similar characteristics as the imitated Tesla Model 3 in the initial model. As the scenario analysis intends to investigate how an increase of 100 km in driving range will affect the charging cost of the charging strategies, the driving range increases by 100 km at each time. Moreover, the battery capacity also needs to increase in a similar proportion as more battery capacity leads to a longer range.

5.2.2 Average Driving Distance

Data on average driving distance for passenger cars is retrieved from the Norwegian National Travel Survey 2018/2019 (Grue et al., 2021). In 2018/2019, the average total daily driving distance was 43.2 km for passenger cars. There have not been conducted any more recent surveys due to the impact on travel behavior after Covid-19. As the pandemic and the following infection control measures restricted the daily travel activity, it is thought to have reduced the average driving distance in 2021. Therefore, the average driving distance of 2018/2019 is used in the model to represent what is considered normal travel activity.

Based on the survey, the daily trips mainly consist of travels to work, school, shopping, and other errands, and travels for leisure activities. As the data retrieved only includes daily trips, other longer trips are not included in the model. Consequently, we assume that the average daily driving distance is applied to all days of the week. It is thought that the afternoon and night charging strategies are not affected by the specific hour of driving. The fully flexible and weekend charging strategies are not limited to charge at specific hours of the day, and the EV owners have more flexibility. Therefore, we assume the EVs are used for daily trips between 3 PM and 4 PM. As a consequence, the EVs cannot be charged during the assumed hours of daily trips.

The amount of kWh an EV consumes at each trip is affected by internal and external factors, whereas these factors affect the EV models differently. Highly variable factors such as weather conditions, outside temperature, road conditions, driving conditions, and car-specific variations in consumption of battery are not taken into consideration in the model. As a result, the average daily demand for kWh to use for daily trips, $\bar{d}$, is calculated by the following equation for all EVs included in the thesis:

$$\frac{Battery\ capacity}{Driving\ range} \cdot average\ daily\ driving\ distance$$

Based on the data obtained from OFV, an EV similar to Tesla Model 3 has a driving range of 560 km and battery capacity of 75 kWh. By only taking these input values into consideration, the EV consumes $75/560 = 0.1339$ kWh/km. The average daily demand for kWh will then be $0.1339 \cdot 43.2 \ = 5.79$ kWh. The same calculation is applied to the EVs with different battery capacities and driving ranges which are implemented in the scenario analysis. Table 5.4 summarizes all the EVs.

Table 5.4: Driving range, battery capacity and average daily demand to use for daily trips for all EVs.

Range (km)	Battery capacity (kWh)	Average daily demand (kWh)
200	35	7.56
300	45	6.48
400	55	5.94
500	65	5.62
560	75	5.79
600	75	5.40

5.2.3 Charging Rate

In Norway, the 230V IT-system is the most common power distribution system in the low-voltage segment of the distribution grid (Oslo Economics, 2019). Therefore, we assume this IT-system is installed in our model. In addition, the main fuse in a house determines the amount of electricity coming into the home and controls how fast the EV can be charged. A wallbox with a 16A fuse will be able to charge an EV overnight to have a range of 125-150 km, while a wallbox with a 32A fuse are able to charge twice as much (Bjørndalen et al., 2019). Given that the average daily driving distance is 43.2 km, we assume that an average household has a 16A fuse, as they do not need a 32A fuse. Thus, the model is based on a 230V IT-system with a 16A fuse.

The EV owners can either use a wallbox or an ordinary socket when charging the EV at home. However, the Norwegian Directorate for Civil Protection (2017) recommends the usage of a wallbox as it provides better safety, charges faster, and has greater flexibility than charging with an ordinary socket. In addition, 77% of the EV owners used a wallbox to charge their EVs in 2021 (Norsk Elbilforening, 2021). The EV owners are thought to charge the EV with a 16A fuse, hence the wallbox delivers 3.7 kW.

Consequently, the charging rate in the model will have an effect of maximum 3.7 kW. Although some EVs theoretically can receive more than 3.7 kW, it will not be possible for the vehicle to receive more as the wallbox cannot deliver more effect with a 16A fuse. Hence, we assume the charging rate of 3.7 kW to be constant regardless of any other internal or external factors. The battery wear is ignored as we assume that the charging effect will not alter over time. Additionally, it is disregarded that the charging speed may decrease as the battery fills.

5.2.4 State of Charge

The state of charge is the level of battery charged relative to the battery capacity. Hence, the state of charge cannot exceed the battery capacity of the EV. The initial state of charge is set to be 100% of the battery capacity for all the charging strategies. This is applied in order for the strategies to start at the same initial state of charge at the beginning of the charging period of 2021. As the state of charge cannot exceed the battery capacity of the vehicle, the maximum state of charge is also set equal to the battery capacity of the EV. Additionally, forced afternoon, forced night, and forced weekend are thought to fully charge the battery at the end of the charging period. Therefore, these charging strategies restrict the state of charge to be equal to the battery capacity at the end of the given charging period.

It is desirable that the state of charge does not fall below a certain level of the battery capacity for the EV owners not to experience range anxiety. In order to avoid the fear of running out of power while driving the EV, the model implements a minimum state of charge of 20% of the battery capacity. By this, the model ensures that the state of charge always is greater than or equal to the certain level of the battery capacity.

5.2.5 Network Tariffs

In western Norway, BKK is the DSO responsible for the distribution of the electricity to the end-users. For this reason, the network tariff model implemented in the model is based on the prices of 2021 retrieved from their website. The current network tariff model is implemented as it was defined for customers at the beginning of 2021. In addition, data on the prices of the new network tariff model was retrieved to implement the new prices in a scenario analysis. NVE (2022), in collaboration with other relevant companies and organizations, created a common proposal on the design of the model. BKK signed the proposal and has published how the new network tariff model will affect the private customers on their website. As the retrieved data on the new network tariff are thought to be in line with the proposal of NVE, this is used as a basis in the scenario analysis.

The current network tariff model consists of two fixed parts: a variable cost depending on the consumption and a fixed cost. In 2021, private customers experienced the same variable cost depending on the consumption of 0.4261 NOK/kWh throughout the year and an annual fixed cost of 2050 NOK (BKK, nd). To describe a realistic invoice for the end-user, the electricity tax, VAT, and the fee earmarked for the Energy Fund are included in the variable cost.

The new network tariff model to be implemented on July 1, 2022, still consists of the two parts. However, the new network tariff model intends to facilitate the best possible utilization of the power grid and contribute to a reasonable distribution of the network costs between the end-users. In line with the recommendations, the variable component is still dependent on consumption. Still, it is time differentiated to motivate the end-user to shift its consumption to hours where there is more grid capacity. Moreover, the fixed cost depends on the consumption to motivate the end-user to even out the demand peaks.

The new variable cost depends on how much energy is consumed and when it is consumed. The price per kWh at night (10 PM to 6 AM) and on the weekends is lower than the price per kWh during the day. Table 5.5 provides an overview of the variable costs in the new network tariff model for customers of BKK (BKK Nett, 2022).

Table 5.5: New variable costs in the network tariff model.

Time	Variable cost
Day	0.4990 NOK/kWh
Night/Weekend	0.3990 NOK/kWh

The new fixed cost will differ depending on how much electricity the end-user consumes and motivate to spread the consumption. Table 5.6 illustrates the new fixed costs associated to the power consumption (BKK Nett, 2022). BKK splits the fixed cost into six different steps, whereas each step is associated with a certain level of electricity consumption. The average consumption of the three hours (on three different days) with the highest consumption in the previous month will determine which step the end-user is associated with. To illustrate, if the customer consumes on average 4 kW in the three hours where the most electricity is consumed, then the fixed cost for the customer is set to step 2, equivalent to 206 NOK that month.

Table 5.6: New fixed costs in the network tariff model.

Step	kW	Monthly fixed cost	Annually fixed cost
1	0-2	124 NOK	1500 NOK
2	2-5	206 NOK	2475 NOK
3	5-10	305 NOK	4200 NOK
4	10-15	494 NOK	5925 NOK
5	15-20	638 NOK	7650 NOK
6	20-23	781 NOK	9375 NOK

As described by BKK Nett (2022), 50% of the private customers will never be above step 2 at any time during the year. In addition, 90% will never consume more than 10 kW on average in the three hours where the most electricity is consumed. Although the new network tariff model is thought to differentiate the fixed cost per month, we assume that all EV owners have a consumption equivalent to step 2 throughout the year and experience a similar fixed cost.

In order to compare the different charging strategies, the fixed cost is not included in the objective function as we have assumed that the fixed cost is equal for all EV owners.

5.2.6 How We Formulated the Model

In this thesis, we use AMPL to formulate the mathematical problem and CPLEX as a solver to obtain the optimal solution. AMPL is a modeling language that can be used to develop and apply mathematical problems (Fourer et al., 2003). Firstly, we formulated the model in mathematical terms. The data described in this chapter were implemented in a data file in AMPL. An excerpt of the formulated data file is shown in appendix A2. Then, the formulated model in mathematical terms was implemented in a model file in AMPL. In appendix A3, A4, and A5, excerpts of the model files of fully flexible, forced afternoon, and flexible night charging strategies are included for illustration.

5.2.7 Summary of Assumptions

A summary of the data inputs for the initial model is given in table 5.7.

Table 5.7: Summary of data input.

Description	Value
Battery capacity	75 kWh
Driving range	560 km
Average daily demand	5.79 kWh
Charging rate	3.7 kW
Initial SOC	100%
Max SOC	100%
Min SOC	20%

6 Results

In the analysis, the optimization model is used to compare the seven charging strategies described in the previous chapters. The analysis will present, compare and discuss the results obtained by the model for the different charging strategies. Lastly, a scenario analysis is performed to investigate how the objective of the charging strategies would be affected if 1) the new network tariff model is implemented, and 2) the battery capacity and possible driving range are adjusted.

6.1 Analysis of the Charging Strategies

6.1.1 Presentation of Results

The first part of the analysis will present the optimal solution for each charging strategy designed in this thesis. The models are run in AMPL using the CPLEX solver.

6.1.1.1 Fully Flexible

The optimal objective function is 2090.31, which represents the cost of fully flexible charging in 2021. By including the fixed cost of the network tariff model, the total annual cost of the strategy is 4140.31 NOK. The result is presented in table 6.1.

Table 6.1: Results for fully flexible charging.

Variable cost	2090.31 NOK/year
Fixed cost	2050.00 NOK/year
Total cost	4140.31 NOK/year

Fully flexible is theoretically the optimal charging strategy the EV owners can take. This is because the EV owners can charge the vehicle at any time during the day or night of the week when the prices are relatively lower. However, the strategy is limited by the daily driving at 3 PM, when the vehicle is unavailable for charging.

6.1.1.2 Forced Afternoon

The optimal objective function is 2584.01, which represents the cost of forced afternoon charging in 2021. The charging strategy yields a total annual cost for the EV owners of 4634.01 NOK when including the fixed cost of the network tariff model. The result is summarised in table 6.2.

Table 6.2: Results for forced afternoon charging.

Variable cost	2584.01 NOK/year
Fixed cost	2050.00 NOK/year
Total cost	4634.01 NOK/year

The EV owners experience the highest charging cost of all the strategies presented when charging the vehicle right after work. The charging period of the strategy starts every weekday at 4 PM and lasts until 8 PM. This means the EV owners charge the vehicle during peak hours of electricity.

6.1.1.3 Flexible Afternoon

The optimal objective function is 2187.93, which represents the cost of flexible afternoon charging in 2021. Including the fixed cost of the network tariff model, the total annual cost for the EV owners is 4237.93 NOK. This is presented in table 6.3.

Table 6.3: Results for flexible afternoon charging.

Variable cost	2187.93 NOK/year
Fixed cost	2050.00 NOK/year
Total cost	4237.93 NOK/year

The strategy still charges the vehicles during peak hours of electricity. However, the EV owners are not restricted to charge the vehicle every weekday. The optimal solution shows that the EV owners charge on average 3.26 days a week. As it is a retrospective analysis, the optimization model can schedule the charging for when the spot prices are relatively lower. The optimal solution suggests to charge more during certain weeks and less when the spot prices are relatively higher. Thus, the model has the flexibility to charge five days in one week and zero days the following week.

6.1.1.4 Forced Night

The optimal objective function is 2234.15, which represents the cost of forced night charging in 2021. By including the fixed cost of the network tariff model, the total annual cost for the EV owners is 4284.15 NOK. The result is presented in table 6.4.

Table 6.4: Results for forced night charging.

Variable cost	2234.15 NOK/year
Fixed cost	2050.00 NOK/year
Total cost	4284.15 NOK/year

The charging period of the strategy starts every weekday at 12 AM and lasts until 7 AM. This means the EV owners utilize the off-peak hours of electricity when charging at night.

6.1.1.5 Flexible Night

The optimal objective function is 1935.36, which represents the cost of flexible night charging in 2021. By including the fixed cost of the network tariff model, the total annual cost for the EV owners is 3985.36 NOK. The result is presented in table 6.5.

Table 6.5: Results for flexible night charging.

Variable cost	1935.36 NOK/year
Fixed cost	2050.00 NOK/year
Total cost	3985.36 NOK/year

The strategy still charges the vehicles during off-peak hours of electricity. The EV owners achieve the lowest annual cost of the seven charging strategies presented with this charging strategy. The optimal solution shows that the EV owners charge on average 2.55 nights a week. As it is a retrospective analysis, the optimal solution schedules the charging for when the spot prices are relatively lower at night. Thus, the model has the flexibility to charge more nights in one week and fewer nights the following week.

6.1.1.6 Forced Weekend

The optimal objective function is 2389.01, which represents the cost of forced weekend charging in 2021. By including the fixed cost of the network tariff model, the total annual cost for the EV owners is 4439.01 NOK. The result is presented in table 6.6.

Table 6.6: Results for forced weekend charging.

Variable cost	2389.01 NOK/year
Fixed cost	2050.00 NOK/year
Total cost	4439.01 NOK/year

The EV owners utilize the off-peak hours by only charging on the weekends. With this strategy, the EV owners can start charging at any time from 12 AM on Saturdays until 11 PM on Sundays. However, the EVs are used for daily trips at 3 PM. The strategy is forced to obtain full battery capacity at the end of Sundays and therefore charges on average 1.86 days a week. This implies that the vehicles are charged almost every Saturday and Sunday in 2021.

6.1.1.7 Flexible Weekend

The optimal objective function is 2161.82, which represents the cost of flexible weekend charging in 2021. By including the fixed cost of the network tariff model, the total annual cost for the EV owners is 4211.82 NOK. The result is presented in table 6.7.

Table 6.7: Results for flexible weekend charging.

Variable cost	2161.82 NOK/year
Fixed cost	2050.00 NOK/year
Total cost	4211.82 NOK/year

The EV owners utilize the off-peak hours of electricity as the charging is restricted to the weekends. The charging period starts at 12 AM on Saturdays and ends at 11 PM on Sundays. However, the EVs are used for daily trips at 3 PM. In this strategy, the model is not forced to fully charge the battery but has the flexibility to charge when it is needed. Hence, the optimal solution charges on average 1.65 days a week.

6.1.2 Comparison of the Charging Strategies

In this part, the charging strategies are compared to each other based on the results obtained by the optimization model. Figure 6.1 illustrates the variable cost and total kWh charged for each charging strategy in 2021.

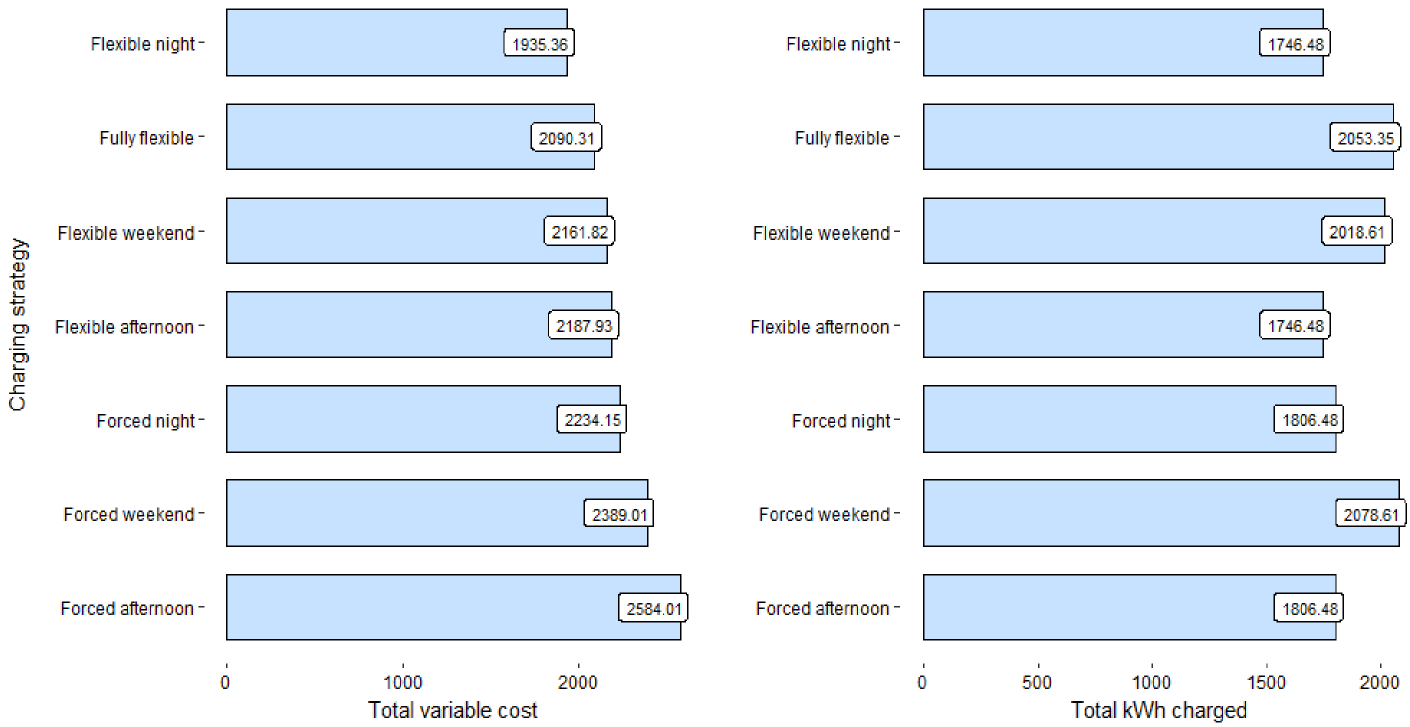

Figure 6.1: Total variable cost and total kWh charged of charging strategies. The plots are in ascending order associated with the variable cost of the strategies.

Of all the charging strategies presented, flexible night charging is the cheapest strategy in 2021. Furthermore, the most common charging behavior, forced afternoon charging, is the most expensive strategy. The strategies range from an annual variable cost of 1935.36 NOK to 2584.01 NOK. This means the forced afternoon strategy is approximately 34% more costly compared to the least costly strategy.

Forced afternoon and forced night charge in total the same amount of kWh in 2021, as seen in figure 6.1. The strategies charge more than what is regarded as necessary as the strategies are forced to have full battery capacity at the end of the charging period. Both strategies decide to charge more on Mondays compared to the rest of the weekdays where the strategies charge the same amount each day. This is shown in figure 6.2. Although the charging strategies charge the same total amount, forced afternoon is approximately 16% more costly than forced night. This indicates that charging at night time is cheaper than charging after work.

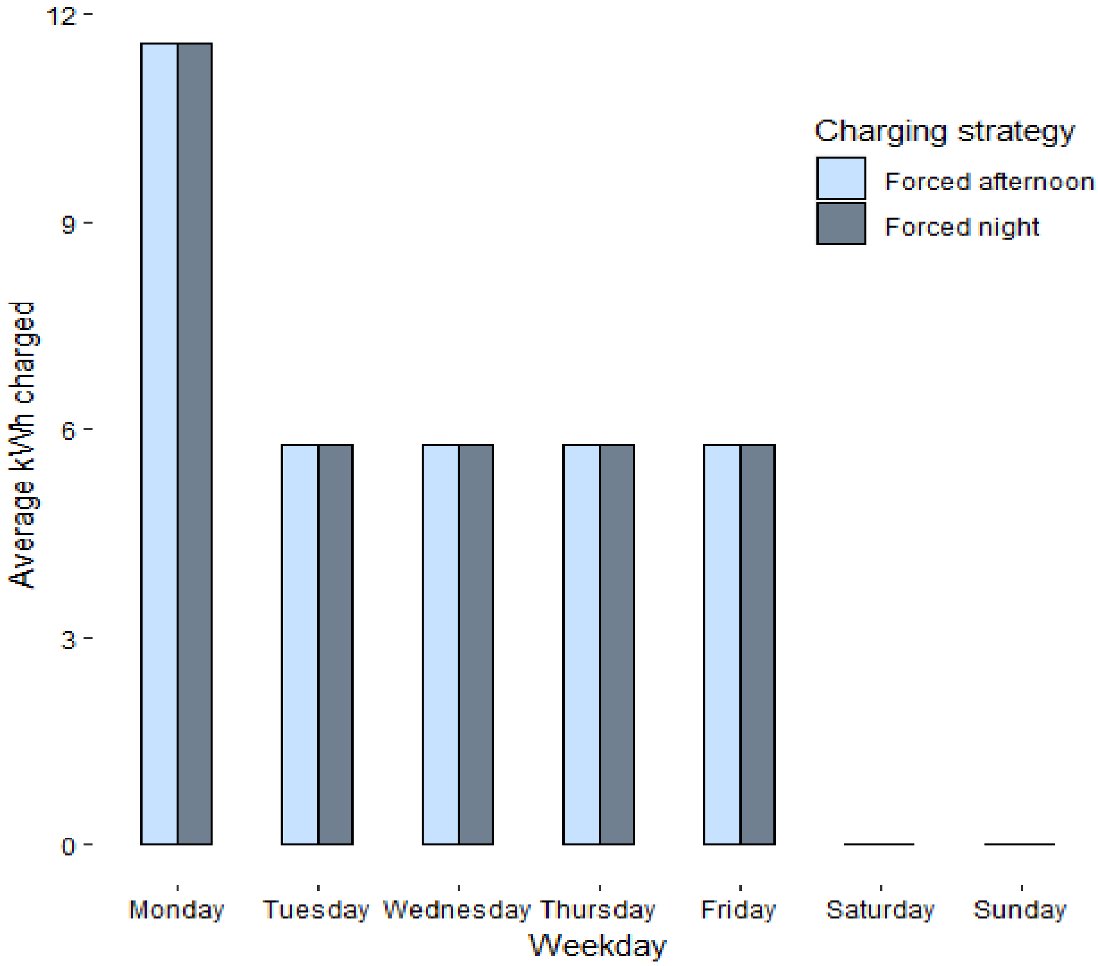

Figure 6.2: Average kWh charged in a week for forced afternoon and forced night strategies.

Flexible strategies and flexible night are less costly than the forced strategies as the flexible strategies charge less. These flexible strategies charge the same total amount of kWh in 2021, as seen in figure 6.1. The results show the flexible night strategy charges on average 2.55 nights in a week while the flexible afternoon strategy charges on average 3.26 days a week. This difference might be a result of the night charging period consisting of more hours than the afternoon charging period. In this way, flexible night strategy is able to charge more in one night than the flexible afternoon strategy is able to charge after work.

In addition, flexible afternoon spreads the charging to specific hours on different days when the prices are relatively lower. This is shown in the model as the afternoon strategy charge the most at 4 PM and 8 PM. Although the charging strategies charge the same total amount, flexible night is the cheapest of the two strategies. Flexible afternoon is approximately 13% more costly compared to the flexible night strategy. This indicates that charging at night is cheaper than charging after work.

Figure 6.1 illustrates that the weekend strategies charge more kWh than the charging strategies for afternoon and night. This might be a consequence of having fewer available charging days during the weeks. As previously presented, flexible afternoon and flexible night charge on average 3.26 days a week and 2.55 nights a week, respectively. This is more days than the weekend strategies have available in each charging period of one week. Even though the weekend charging strategies charge more, these strategies are less costly than forced afternoon charging. This can be explained by the flexibility the weekend strategies have to charge outside peak hours of electricity. This is shown by the optimal solutions of the weekend strategies which charge more from 12 AM to 7 AM than from 8 AM to 11 PM. Despite charging more at night time, forced weekend charging is still more costly than forced night charging. In addition, flexible weekend charging is approximately 12% more costly than flexible night charging. This implies that it is cheaper to charge the EVs at night during the week rather than on the weekends.

Forced weekend is approximately 11% more costly than flexible weekend. As the flexible weekend charging is not forced to fully charge the battery at the end of Sundays, the strategy is the cheapest of the two weekend strategies. The EV owners have more flexibility when it comes to the total amount charged and the opportunity to fully charge the battery if it foresees that the spot prices are relatively lower compared to the following weekends. Hence, the strategy can store and prepare in order to have a sufficient amount of battery for the daily trips to come.

Initially, the fully flexible strategy was thought to be the cheapest charging strategy as the model has the flexibility to charge whenever. In this benchmark strategy, the model schedules the charging for when the spot prices are relatively lower. The optimal solution charges more during the night than during the day. This indicates that charging at night is cheaper than during the daytime. However, when comparing the strategies, flexible night is cheaper than fully flexible. This is because fully flexible charges in total more kWh in 2021. The larger amount of charging can be explained by the scheduled daily trips in the models. In the flexible night strategy, the daily trips are scheduled outside the charging period of 12 AM to 7 AM. This is not the case in the benchmark strategy, where the scheduled daily trips at 3 PM might affect how the model schedules the total amount charged. The optimal solution of the benchmark strategy shows that the model charges a sufficient amount at 4 PM throughout the year. This implies that the model might want to increase the state of charge right after the daily trips, which could explain the difference in the total amount charged. Another explanation might be that the charging period in flexible night strategy is more limited than the charging period of the benchmark strategy. Although the period when charging at night is more limited, it could potentially consist of spot prices that are relatively lower than the overall charging period for the fully flexible strategy.

The analysis shows that the difference in annual variable cost between the charging strategies varies to some extent. It is possible to discuss what is considered to be a sufficient difference in the annual variable cost. The least costly strategy in 2021 turned out to be flexible night, while the most costly strategy was forced afternoon. These strategies range from an annual variable cost of 1935.36 NOK to 2584.01 NOK, which is a cost increase of approximately 34%. For some EV owners, this difference might be regarded as sufficient. This could be the case if the household has more than one EV that needs to be charged as this will increase the total charging costs. However, other EV owners might not be as price-conscious and schedule the charging when it is more convenient regardless of the price level. Hence, the difference in charging cost might not be regarded as sufficient.

6.2 Scenario Analysis

In the following part, we will investigate how the optimal solution is affected if different input values in the model are changed. The scenario analysis is divided into two scenarios. Scenario 1 illustrates the implementation of the new network tariff model, while scenario 2 changes the battery capacity and driving range for the EV in the model. Both scenarios are implemented based on the spot prices of 2021.

6.2.1 Scenario 1: New Network Tariff Model

In the first scenario, the presented model is run with the proposed new network tariff model, as explained in previous chapters. The model is run as if the new network tariff was applied in 2021. In the following section, the cost effect of the new network tariff on the charging strategies is analyzed. The cost effect is shown as a percentage change of the objectives based on the current network tariff. The results are presented in table 6.8.

Table 6.8: Results of variable cost for the charging strategies.

Charging strategy	New network tariff (NOK/year)	$\Delta\%$
Fully flexible	2041.87	−2.66
Forced afternoon	2715.70	+5.10
Flexible afternoon	2315.25	+5.82
Forced night	2186.20	−2.15
Flexible night	1891.24	−2.28
Forced weekend	2332.68	−2.36
Flexible weekend	2107.12	−2.53

If the new network tariff model had been implemented in 2021, the results show the same order of the charging strategies associated with the costs as the current network tariff model. Meaning, forced afternoon is still the most costly, and flexible night is still the least costly of all the charging strategies presented.

The new network tariff differentiates the variable cost by if the consumption takes place during the day and night or weekend. Compared to the variable cost of 0.4261 NOK/kWh in the current network tariff model, the new cost for consumption during the night is set lower, and for consumption during the day is set higher. As a result, the scenario analysis suggests that the objectives for all the charging strategies, except the afternoon strategies, would have decreased if the new model had been implemented. Table 6.8 shows that the variable cost of the strategies utilizing the off-peak hours of electricity would have decreased while the variable costs for the afternoon strategies would have increased. Forced afternoon and flexible afternoon would have experienced an increase of 5.10% and 5.82%, respectively. The charging strategies which utilize the off-peak hours are fully flexible, forced night, flexible night, forced weekend, and flexible weekend. These strategies would have experienced a decrease due to the variable cost of consumption at night and weekends being lower than the variable cost of consumption during the day. As shown in table 6.8, the weekend strategies would have experienced a decrease of 2.36% and 2.53% in charging costs compared to the current network tariff model. Moreover, the night strategies would have experienced a decrease of 2.15% and 2.28%.

The new network tariff model aims to incentivize consumers to shift their consumption to hours where the grid has more capacity by reducing the variable cost at these time periods. By only looking at the variable cost, the afternoon strategies would have experienced an increase when charging at hours where the grid capacity is lower. This indeed could work as an incentive for EV owners to shift their consumption as the difference between the most and least costly charging strategies becomes more considerable.

In addition to differentiating the variable cost, the new network tariff model also intends to motivate the consumers to even out peak demand on the electricity grid by differentiating the fixed cost. Therefore, the actual total annual cost the EV owners would have experienced is also affected by the fixed cost. The total annual costs, including the fixed costs, are illustrated in table 6.9.

Table 6.9: Results of total cost for the charging strategies.

Charging strategy	Total cost (NOK/year)
Fully flexible	4516.87
Forced afternoon	5190.70
Flexible afternoon	4790.25
Forced night	4661.20
Flexible night	4366.24
Forced weekend	4807.68
Flexible weekend	4582.12

As shown in table 6.9, the total annual cost for all the charging strategies would have increased. The model implemented assumes that the EV owners consume electricity for charging and other consumption equivalent to step 2. Therefore, the fixed cost is 425 NOK $(2475 - 2050)$ more expensive than the fixed cost in the current network tariff model.

As all the EV owners are assumed to have the same electricity consumption, the fixed cost will be equal for all the strategies. Thus, the scenario analysis does not show the real effect of the differentiation in the fixed cost. As a result, the variable cost is the only part of the annual cost that varies between the strategies in the model.

The model does not illustrate the different outcomes if EV owners consume more or less electricity than consumption equivalent to step 2. The incentive for load-shifting might be stronger when the EV owners have relatively large electricity consumption peaks as the load-shifting may lead to a lower total consumption. This implies a lower fixed cost and, therefore, a lower total annual cost. In this case, the lower fixed cost in the new network tariff model might be an incentive for load-shifting.

6.2.2 Scenario 2: Changes in Battery Capacity and Driving Range

The EV studied in the preceding sections has car-specific characteristics similar to a Tesla Model 3. However, not all EVs represented in the Norwegian car fleet have the same characteristics as the Tesla Model 3. In the second scenario analysis, the input values of driving range and battery capacity are adjusted to investigate the cost effect on the charging strategies. Table 6.10 illustrates the adjustments of the car-specific characteristics.

Table 6.10: Overview of driving range, battery capacity and average daily demand

Range (km)	Battery capacity (kWh)	Average daily demand (kWh)
200	35	7.56
300	45	6.48
400	55	5.94
500	65	5.62
600	75	5.40

The input values of the driving range are given in km, the battery capacity are given in kWh, and the average daily demand is the calculated usage of kWh on daily trips. Further sections will name the different EVs by only the driving range and not all the corresponding characteristics.

The scenario analysis intends to investigate how an increase of 100 km in driving range will affect the variable costs in each charging strategy. As the driving range increases by 100 km each time, the battery capacity also needs to increase as more battery capacity leads to a longer range. An EV with a range of 600 km is considered to have approximately similar car-specific characteristics as a Tesla Model 3.

Fully flexible

Solving the optimization model with the adjusted driving range and battery capacity results in a change in the annual variable cost of charging. The fully flexible strategy with the new input values yields the objectives shown in table 6.11. The cost reduction is associated with a 100 km range increase.

Table 6.11: Results for fully flexible charging.

Driving range	Cost (NOK/year)	Cost reduction (Δ%)
200 km	3005.22	0
300 km	2526.66	−15.92
400 km	2223.87	−11.98
500 km	2085.51	−6.22
600 km	1924.72	−7.71

For the EVs presented, EVs with a 200 km range experience the highest cost associated with the fully flexible strategy. The optimal solution suggests that the EVs need to charge on average 4.39 days a week, which is more than all the other vehicles in the scenario. The EVs need to maintain a state of charge above 20% at all times and consume the most kWh per daily trip. This gives the owners of an EV with a range of 200 km less flexibility to store electricity for the daily trips in the following weeks; thus, the car is charged more on average per week.

When the range increases by 100 km, the model suggests that the EV owners need to charge the vehicle on average 4.09 days a week. This is similar to the average presented for the EVs of 200 km range, however, the annual variable cost decreases by 15.92%. Thus, EVs with 300 km range will experience a lower annual charging cost by charging almost the same number of days a week as EVs with a shorter driving range.

As the range increases to 400 km and 500 km, the model suggests the EVs to charge on average 3.2 days a week and 3.18 days a week, respectively. When the range increases from 300 km to 400 km, the annual cost is reduced by 11.98%. When the range increases from 400 km to 500 km, the cost reduction is not as significant as shown in table 6.11. This might be a result of the EVs with 400 km and 500 km range charge on average almost the exact same number of days. The annual charging cost compared to 300 km is lower because the EVs have more flexibility and charge one day less.

Consequently, EVs with 600 km range are the most flexible of the presented vehicles. The optimal solution finds that the EVs charge on average 2.82 days a week. Since the analysis is retrospective, the model can plan to charge when the spot prices are relatively lower and use the electricity stored in the battery when the prices are relatively higher. However, the cost reduction when increasing the range from 500 km to 600 km is not as significant as increasing from 200 km to 300 km, which experienced the greatest cost reduction.

As figure 6.3 shows all the EVs with different driving ranges follow the same charging curve. The curves imply that all the EVs charge on average the most amount of kWh at 3 AM, followed by a sufficient amount at 2 PM, 4 PM and 11 PM, throughout the year. This indicates that the spot prices are relatively lower at these hours.

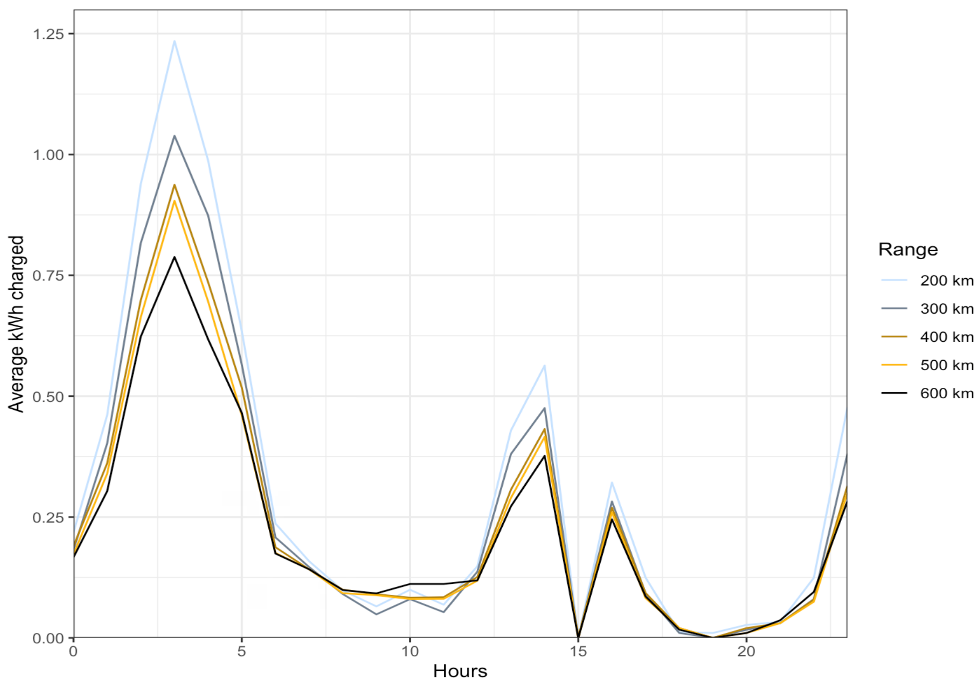

Figure 6.3: Average kWh charged per hour for fully flexible in 2021.

Forced afternoon

Solving the optimization model with the adjusted driving range and battery capacity results in a change in the annual variable cost of charging. Forced afternoon charging with the new input values yields the objectives shown in table 6.12. The cost reduction is associated with a 100 km range increase.

Table 6.12: Results for forced afternoon charging.

Driving range	Cost (NOK/year)	Cost reduction (Δ%)
200 km	3414.57	0
300 km	2906.95	-14.87
400 km	2654.21	-8.69
500 km	2504.44	-5.64
600 km	2402.62	-4.07

Of all the different driving ranges presented, the EVs with 200 km range have the highest annual charging cost for this strategy. This can be a consequence of an EV with a 200 km range needing to charge more kWh every day as it consumes more kWh for daily trips. As the range increases, the EVs do not need to charge as much since the consumption for daily trips is less. Every time the range increases by 100 km, the annual variable cost decreases. Therefore, the cost reduction is based on the amount kWh retrieved from the grid. The largest cost reduction of 14.87% is seen when the range increases from 200 km to 300 km.

Forced afternoon charging is the most expensive charging strategy for all the EVs in the scenario analysis. The strategy restricts all the EVs to charge every weekday, but the amount charged differs between the EVs. Since the charging strategy is forced to charge every weekday, the model chooses to charge when the spot prices are relatively lower. As seen in figure 6.4, the model suggests that all the EVs charge on average the most at 4 PM and 8 PM and the least at 6 PM throughout the year. In addition, all the EVs charge the most on Mondays and less on Tuesdays to Fridays. This might be an indication that the spot prices on Mondays and at 4 PM and 8 PM are relatively lower compared to the other days and hours in the charging period. However, it can also be an indication of the model wanting to increase the state of charge as soon as it is allowed to charge after the weekend.

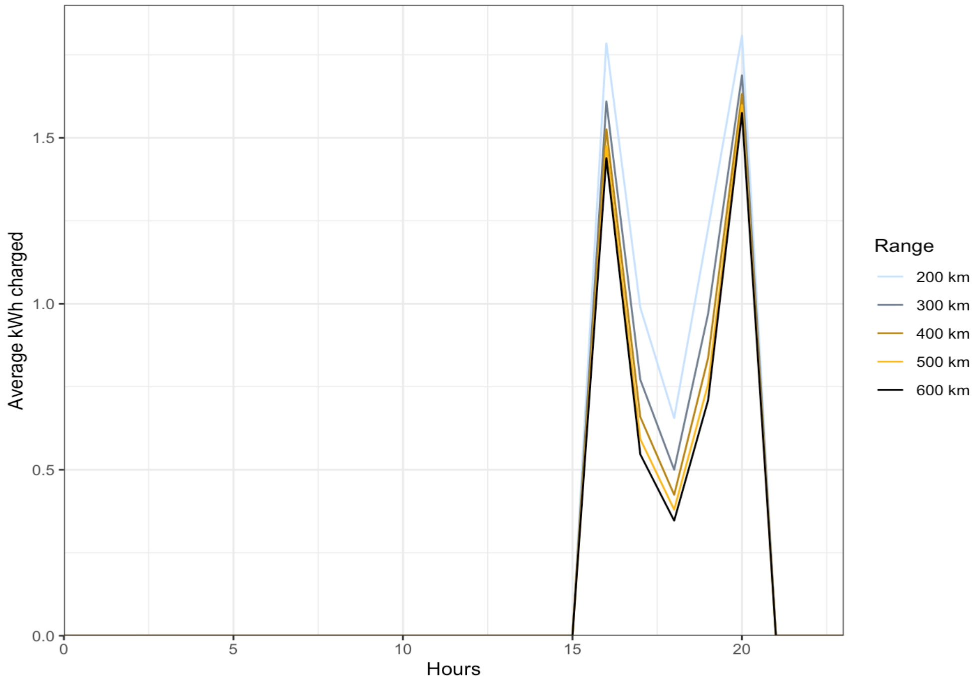

Figure 6.4: Average kWh charged per hour for forced afternoon in 2021.

Flexible afternoon

Solving the optimization model with the adjusted driving range and battery capacity results in a change in the annual variable cost of charging. Flexible afternoon charging with the new input values yields the objectives shown in table 6.13. The cost reduction is associated with a 100 km range increase.

Table 6.13: Results for flexible afternoon charging.

Driving range	Cost (NOK/year)	Cost reduction (Δ%)
200 km	3064.28	0
300 km	2587.05	−15.57
400 km	2303.31	−10.97
500 km	2166.01	−5.96
600 km	2022.84	−6.61

For the EVs presented in the scenario analysis, the vehicles with a 200 km range experience the highest charging cost with the flexible afternoon strategy. The optimal solution shows that the EVs with this characteristic charge on average 4.2 days a week. This is more than all the other EVs charge on average in the scenario, which might explain the higher charging cost for the EVs with 200 km range. The EV owners do not have the flexibility to the same extent to store electricity and prepare for the following weeks.

When the range increases by 100 km, the model suggests that the EV owners charge the vehicle on average 3.85 days a week. As the flexibility increases when the range increases, the EVs with a range of 300 km experience a cost reduction of 15.57% compared to the EVs with 200 km range. Furthermore, the EVs need to be charged 3.55 days a week and 3.45 days a week when the range increases to 400 km and 500 km, respectively. As the EVs with 400 km and 500 km range charge on average almost the exact same number of days, the cost reduction is not as significant as between 300 km and 400 km, as shown in table 6.13. The annual charging cost compared to 300 km is lower because the EVs have more flexibility and charge less.

Accordingly, the flexibility increases when the range increases to 600 km. The optimal solution suggests that the EVs charge on average 3.09 days a week. As a retrospective analysis is conducted, the model is able to plan the charging to hours where the spot prices are relatively lower and use the electricity stored when the spot prices are relatively higher. However, the cost reduction when increasing the range from 500 km to 600 km is not as significant as increasing from 200 km to 300 km, which experienced the greatest cost reduction.

As figure 6.5 shows, all the EVs with different driving ranges follow the same charging curve, and is similar to the charging curve of forced afternoon. The curves imply that all the EVs charge on average the most amount of kWh at 4 PM and 8 PM, throughout the year. This indicates that the spot prices are relatively lower at these hours.

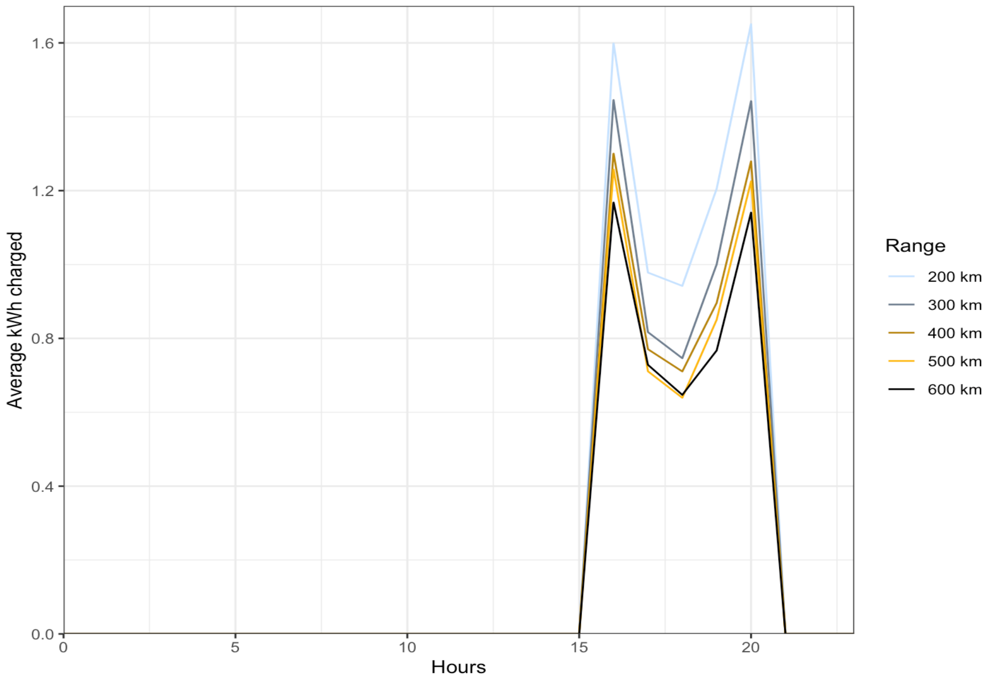

Figure 6.5: Average kWh charged per hour for flexible afternoon in 2021.

Forced night

Solving the optimization model with the adjusted driving range and battery capacity results in a change in the annual variable cost of charging. The forced night charging with the new input values yields the objectives shown in table 6.14. The cost reduction is associated with a 100 km range increase.

Table 6.14: Results for forced night charging.

Driving range	Cost (NOK/year)	Cost reduction (Δ%)
200 km	2925.66	0
300 km	2503.43	−14.43
400 km	2292.69	−8.42
500 km	2167.81	−5.55
600 km	2082.20	−3.95

The EVs with 200 km range have the highest annual charging cost of all the vehicles with different driving ranges presented for this strategy. This can be explained by the EVs with 200 km range need to charge a greater amount of kWh for daily trips compared to the other vehicles. When the range increases, the model implies that the EVs do not need to charge as much as they use less kWh per daily trip. Hence, every time the range increases by 100 km, the annual charging cost decreases. Therefore, the cost reduction is based on the amount kWh charged. The largest cost reduction of 14.43% is seen when the range increases from 200 km to 300 km.

The forced night strategy restricts all the EVs to charge every night on the weekdays, but the amount charged differs between the EVs. As the charging strategy is forced to charge every night, the model chooses to charge when the spot prices are relatively lower during the night. The model suggests that all the EVs charge on average the most at 3 AM and the least at 7 AM throughout the year, as seen in figure 6.6. In addition, all the EVs charge the most on Mondays and less on Tuesdays to Fridays. This indicates that the spot prices are relatively lower on Mondays at 3 AM compared to the other days and hours in the charging period. It might also indicate that the model wants to increase the state of charge as soon as it is allowed to charge the first day after the weekend.

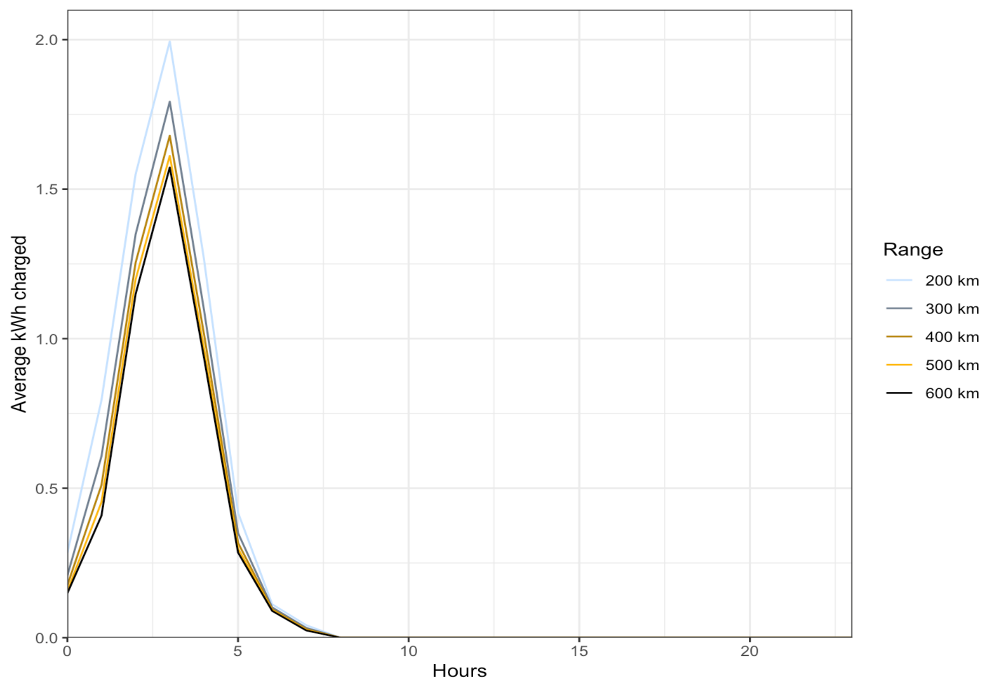

Figure 6.6: Average kWh charged per hour for forced night in 2021.

Flexible night

Solving the optimization model with the adjusted driving range and battery capacity results in a change in the annual variable cost of charging. The flexible night strategy with the new input values yields the objectives shown in table 6.15. The cost reduction is associated with a 100 km range increase.

Table 6.15: Results for flexible night charging.

Driving range	Cost (NOK/year)	Cost reduction (Δ%)
200km	2718.64	0
300km	2294.43	-15.60
400km	2041.35	-11.03
500km	1917.44	-6.07
600km	1786.07	-6.85

Flexible night is the least costly charging strategy for all the EVs in the scenario analysis. The optimal solution finds that EVs with 200 km range charge the vehicle on average 3.59 days a week, which is more than all the other EVs in the analysis. As a result, the charging strategy is the most expensive for EVs with a 200 km range. The EV owners experience a higher charging cost as the EVs are less flexible to store and prepare for the following weeks.

When the range increases to 300 km, the model suggests that the EV owners charge the vehicle on average 3.26 days a week. With the flexibility to store and charge when the spot prices are relatively lower, the EVs with a range of 300 km experience a cost reduction of 15.60%. Furthermore, the EVs need to charge on average 2.82 days a week and 2.74 days a week when the range increases to 400 km and 500 km range, respectively. As the EVs with 400 km and 500 km range charge on average almost the exact same number of days, the cost reduction is not as significant as between 300 km and 400 km, as shown in table 6.15. The annual charging cost compared to 300 km is lower because the EVs have more flexibility and charge less.

Consequently, the flexibility increases when the range increases to 600 km. The optimal solution finds that the EVs charge on average 2.44 days in a week. The model is able to decide to charge during hours when the spot prices are relatively lower and use power stored when the spot prices are relatively higher. However, the cost reduction when increasing the range from 500 km to 600 km is not as significant as increasing from 200 km to 300 km, which experienced the greatest cost reduction.

As figure 6.7 shows, all the EVs with different driving ranges follow the same charging curve, and is similar to the charging curve of forced night. The curves imply that all the EVs on average charge the most amount of kWh at 3 AM throughout the year. This indicates that the spot prices are relatively lower at this hour.

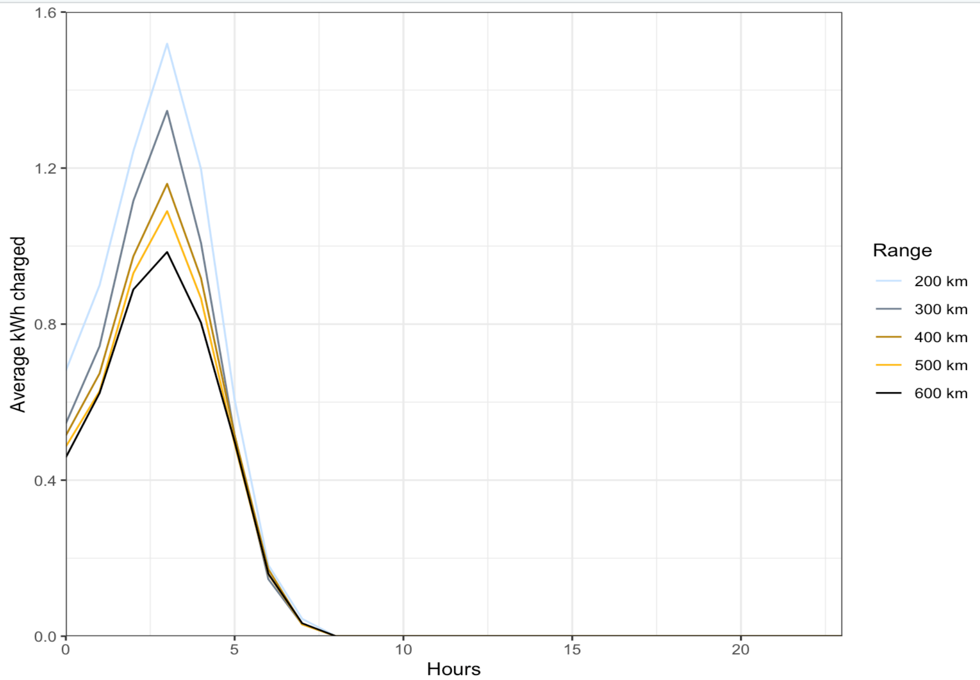

Figure 6.7: Average kWh charged per hour for flexible night in 2021.

Forced weekend

Solving the optimization model with the adjusted driving range and battery capacity results in a change in the annual variable cost of charging. The forced weekend charging with the new input values yields the objectives shown in table 6.16. The cost reduction is associated with a 100 km range increase.

Table 6.16: Results for forced weekend charging.

Driving range	Cost (NOK/year)	Cost reduction (Δ%)
200km	–	–
300km	2705.13	0
400km	2454.11	−10.23
500km	2315.45	−5.65
600km	2220.65	−4.09

Forced weekend restricts all the EVs to charge the battery full at the end of every weekend, but the amount charged differs between the EVs. Moreover, the charging strategy is not possible for EVs with range of 200 km as the constraint 4.3 cannot hold in the presented model. This constraint ensures balance between the state of charge of each time period. In this case, these EVs do not have the capacity to charge the amount required during the weekend to handle the energy consumption of the daily trips in the following weeks. Therefore, the balance of state of charge between each time period is violated. To investigate when all the constraints hold, the first feasible solution is obtained when increasing the driving range to 300 km, as shown in table 6.16.

As forced weekend charging is not possible for EVs with 200 km range, EVs with range of 300 km have the most expensive charging cost in this strategy. The EVs experience the highest charging cost as the vehicles use more kWh for daily trips compared to the other vehicles. When the range increases, the model implies that the EVs do not need to charge as much as the use of kWh per daily trip is less. Hence, every time the range increases by 100 km, the annual charging cost decreases. Therefore, the cost reduction is based on the amount of kWh charged. The largest cost reduction of 10.23% is seen when the range increases from 300 km to 400 km.

Throughout the year, all the feasible solutions charge on average the most at 4 AM and the least at 7 PM in the optimal solution, as illustrated in figure 6.8. This indicates that the spot prices are relatively lower on average at 4 AM compared to all the other hours in the charging period. Moreover, the optimal solution suggests that EVs with 300 km range charge on average 1.98 days on the weekends. This means the EVs have to charge almost every day of the weekend to store the amount required for the daily trips in the following weeks. As the range increases to 400 km, 500 km, and 600 km, the EVs need to charge on average more than 1.82 days on the weekends. This means that they need to charge somewhat less compared to the EVs with shorter range. Hence, the EVs become slightly more flexible as the driving range and the battery capacity increase.

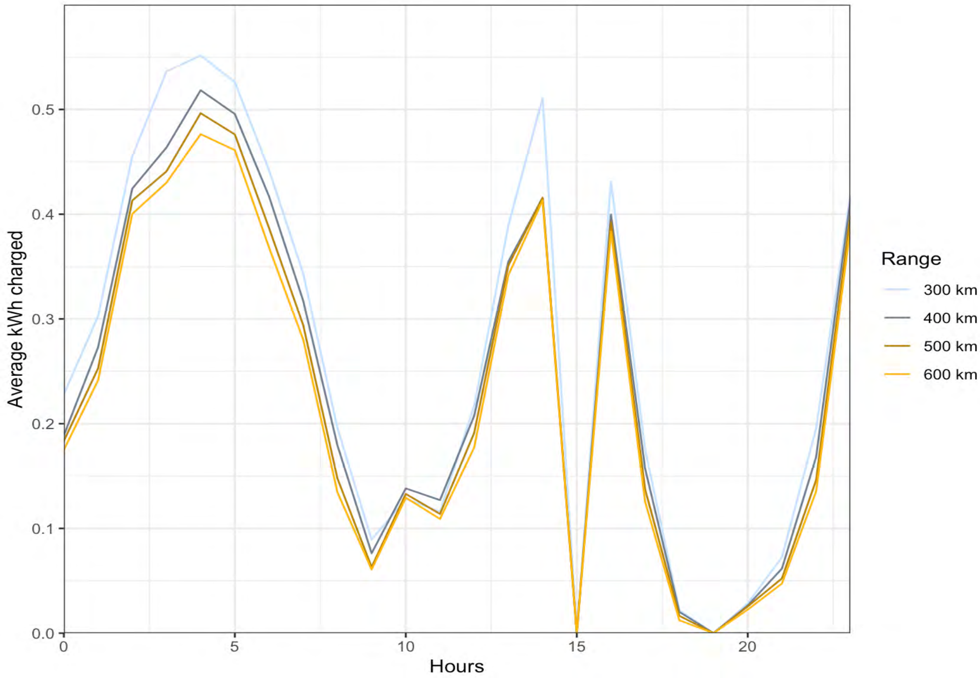

Figure 6.8: Average kWh charged per hour for forced weekend in 2021.

Flexible weekend

Solving the optimization model with the adjusted driving range and battery capacity results in a change in the annual variable cost of charging. The flexible weekend charging with the new input values yields the objectives shown in table 6.17. The cost reduction is associated with a 100 km range increase.

Table 6.17: Results for flexible weekend charging.

Driving range	Cost (NOK/year)	Cost reduction (Δ%)
200km	–	–
300km	2617.97	0
400km	2295.98	−12.30
500km	2153.12	−6.22
600km	1990.26	−7.56

The flexible weekend strategy is not possible for EVs with a range of 200 km as the constraint which ensures balance between the state of charge of each time period cannot hold. In the model, the EVs do not have the capacity to charge the amount required in two days to handle the energy consumption of the following weeks. The first feasible solution is obtained by increasing the range to 300 km.

Whereas flexible weekend charging is not possible for EVs with 200 km range, EVs with 300 km range experience the most expensive charging cost in the strategy presented. Compared to the other vehicles, the EVs use more kWh for daily trips and therefore experience the highest charging cost. When the range increases, the optimal solutions imply that the EVs use less kWh per daily trip and charge less. Thus, the annual charging cost decreases when the range increases. Therefore, the cost reduction is based on the amount of kWh charged. The largest cost reduction of 12.30% is seen when the range increases from 300 km to 400 km.

As illustrated in figure 6.9, the feasible solutions charge on average the most at 4 AM and nothing at 7 PM throughout the year. This indicates that the spot prices of electricity are relatively lower at 4 AM than all the other hours in the charging period. Furthermore, the optimal solution shows that EVs with a range of 300 km charge on average 1.98 days on the weekend. Meaning, EVs with 300 km range need to charge approximately every day of the weekend regardless of which of the two weekend charging strategies are being used. When the range of the EVs increase to 400 km, 500 km, and 600 km, the EVs need to charge on average more than 1.59 days on the weekends. Compared to the EVs with shorter range, these vehicles have more flexibility to store electricity and therefore charge less.

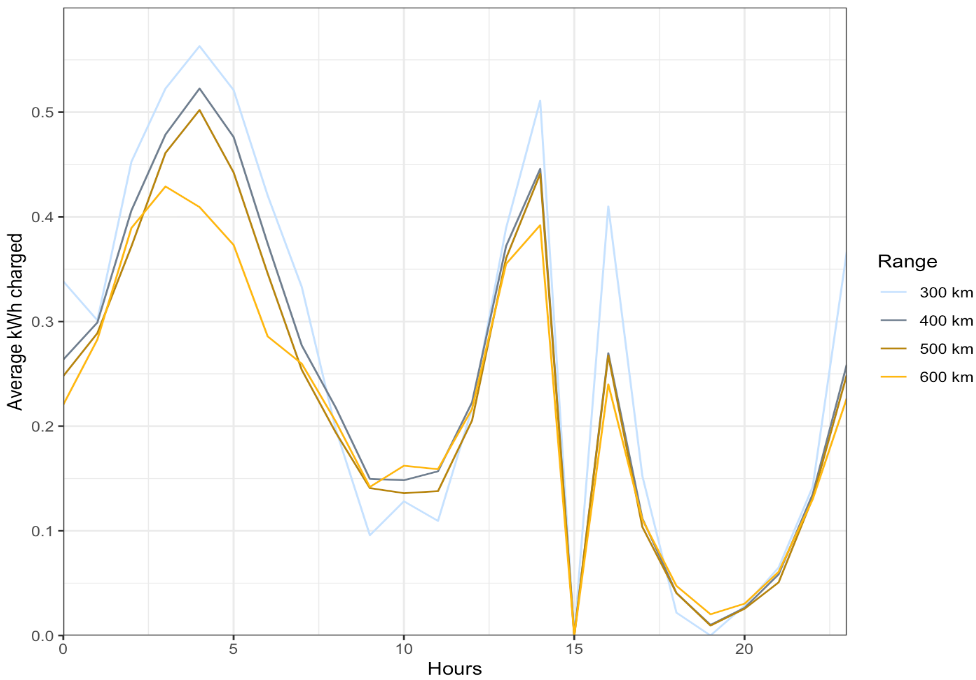

Figure 6.9: Average kWh charged per hour for flexible weekend in 2021.

6.3 Summary of the Analysis

In this analysis, we studied the presented charging strategies consisting of different time periods based on common charging behavior of EV owners in Norway. The initial EV of the model has car-specific characteristics similar to the most sold EV in 2021, Tesla Model 3. The aim of the general analysis is to exploit and compare the strategies by minimizing the annual charging cost of the different strategies.

The results of the optimization model suggest that flexible night charging would have been the least costly of all the strategies presented. We found that the variable cost of this strategy would equal 1935.36 NOK. Furthermore, forced afternoon charging would have been the most costly and the cost would equal 2584.01 NOK. This is a cost increase of approximately 34%. Moreover, the model finds that fully flexible, forced weekend, and flexible weekend choose to charge the most during the night. This implies that charging at night reduces the charging cost as the optimization model aims to minimize the annual cost.

When the new network tariff model was implemented in the general model, we found that the forced afternoon strategy would still be the most costly. In addition, flexible night charging would still be the least costly strategy. The charging strategies thought to utilize the grid capacity, meaning fully flexible, both night charging strategies and both weekend charging strategies, would have experienced a decrease in the variable cost. Furthermore, the model finds that the forced and flexible afternoon strategies would have experienced an increase in the variable cost. When including the fixed cost of the new network tariff model, we found that all the charging strategies would have experienced an increase in the total annual cost.

As the driving range and battery capacity were adjusted in the last scenario analysis, the model found that the forced afternoon charging and flexible night charging for all the EVs still would be the most costly and least costly of the strategies. Furthermore, the model found that EVs with shorter range would experience a higher charging cost in all the charging strategies. The greatest cost reduction is shown for all EVs in all the charging strategies when increasing the range from 200 km to 300 km. The analysis shows that an increase in the range gives the EV owners more flexibility and can charge when the spot prices are relatively lower. Hence, these vehicles have lower charging costs for all the charging strategies in the scenario. Lastly, the EVs with 200 km range cannot charge only during the weekends given the restrictions in the model.

7 Discussion

In the previous chapter, we presented the findings of our model. In this chapter, the limitations of the data and model and the validity of the results will be discussed. Lastly, future work related to the research in this thesis is proposed and discussed.

7.1 Limitations and Validity of Results

The model and the input data in this thesis are subject to assumptions which are likely to affect or limit the results. The results obtained are valid only for the input parameters of the specific EVs used in the model. Hence, the validity of the results depends on the assumptions made when formulating the model and deciding on the input values for the data. First, the limitations of the formulated charging strategies are discussed before the assumptions on important parameters are justified below.

The charging strategies formulated are intended to illustrate normal charging behavior for EV owners. Still, some assumptions were included to avoid making the model too complex to implement in the decision-making. However, some of the assumptions might be difficult to implement in real life. Firstly, fully flexible strategy was formulated to represent the optimal charging schedule since the EV owners can charge at any time except when driving. In reality, this charging strategy might be difficult for an EV owner to implement as it involves sporadically charging. It is reasonable to assume that the vehicle is unavailable for charging some hours of the day. Still, the charging strategy was included as a benchmark strategy to represent the charging cost of the optimal schedule. However, the solution suggested that the flexible night strategy resulted in a lower charging cost. The fully flexible strategy charges in total more kWh than what is regarded as necessary, hence the proposed optimal charging strategy is more costly.

Further, the flexible afternoon and the flexible night strategy might also be difficult for the EV owners to implement in real life. In the model, the charging strategies are to minimize the charging cost based on the spot prices of 2021. Hence, the flexible strategies charge at hours where the spot prices are relatively low to obtain a state of charge above 20% and to cover the daily trips. Consequently, the optimal solutions charge when necessary and do not follow a pattern for the EV owners to easily implement. It might be especially difficult for EV owners to implement at night without a smart charging device.

In this thesis, the charging of an EV is a central process. When the EVs are connected to the wallbox, the charging rate is a crucial parameter for the EVs to be able to charge. The charging rate limits the amount of electricity retrieved from the grid. In the presented model, we assumed that all EV owners have a 16A fuse and are able to charge the EVs with a constant charging rate of 3.7 kW by using a wallbox. In reality, the charging effect the wallbox can deliver varies between households as the type of wallbox and main fuse installed varies. Additionally, different EVs are capable of receiving different amounts of charging rate. Although some EVs theoretically are capable of receiving more than 3.7 kW, it will not be possible for these vehicles to receive more as the wallbox cannot deliver more effect with a 16A fuse. In this case, the wallbox is the limitation of the charging rate. However, EVs can also limit the charging rate as some EVs are not capable of receiving a larger amount of kW regardless of the fuse the wallbox is connected to.

In addition, the charging rate is assumed to be unaffected by internal and external factors that may affect the charging rate. In reality, the chemical process of charging is affected by factors such as battery temperature and outside temperature. In Norway, the temperature varies between the regions, seasons, and time of the day. The chemical process slows down as the temperature decreases, hence the charging rate is not likely to be constant throughout the day and year.

The thesis assumed that the EVs are allowed to charge until the state of charge is 100%. We argue that this is a reasonable assumption as the EV owners are likely to demand the battery to be fully charged at the end of the charging period. However, the vast majority of EVs charge slower after reaching a state of charge of 80% (NAF, 2022). As the charging process is thought to slow down after this state of charge, many EV owners are likely to stop the charging process before reaching the full battery capacity. In addition, the model assumed the EV owners want to maintain a state of charge of 20% at all times. This is thought to be a reasonable assumption as the EV owners are likely to not want to reach a level of 0% of the battery capacity. Therefore, the EV owners are thought to experience range anxiety at some point prior to this level.

Furthermore, another crucial parameter is the average daily demand for kWh for daily trips. As explained in chapter 5, the parameter is determined by the battery capacity, driving range, and the average daily driving distance. In the model, the driving range by the manufacturer of the EV is used as input data. However, these measures might not necessarily be the actual driving range. Other factors which may affect the driving range are therefore not considered in the model. In reality, seasonal variation in outside temperature, different road conditions, and driving speed are factors that can affect the actual driving range.

As the average daily demand for kWh is also determined by the average daily driving distance, this is an important data input. Based on the findings of the National Travel Survey of 2018/2019 (Grue et al., 2021), the average daily driving distance is 43.2 km. Considering Covid-19 impacted the travel behavior, the daily driving distance assumed may not be representative of the average daily driving distance in 2021. Still, we argue that the average driving distance of 2018/2019 should be interpreted as valid as it reflects what is considered normal travel activity.

The hourly spot prices for electricity are another crucial parameter for determining the charging cost of the charging strategies. This thesis was conducted as a retrospective study and is only representative for the given county and year. In this model, the results obtained are only valid for the county of Vestland in 2021 as the hourly spot prices and the cost of the network tariff model are retrieved for bidding zone NO5 in 2021. Spot prices vary greatly between different countries, regions, seasons, and hours. Thus, the charging costs of the charging strategies are highly dependent on the patterns in the spot prices.

The results obtained from the analysis are regarded as valid only for the specific EVs presented and under the assumptions made for the input parameters. The aim of the thesis was to exploit and compare different charging strategies by creating an optimization model. The analysis illustrates the comparison of the charging cost of the seven charging strategies. The model also gives insight into the most and least costly charging strategy. Lastly, as we saw from the scenario analysis, the optimization model can be used to estimate the change in charging cost if the new network tariff model had been implemented in 2021, and how adjustments made to the battery capacity and driving range lead to differences in charging costs.

7.2 Further Work

In the process of writing this thesis, we found many interesting topics within the field of EV charging and the electricity grid, which we could not include in the thesis. In this section, we will present proposals for further research related to the presented topic, which could be taken into consideration.

As this thesis is a retrospective research based on the spot prices for electricity in 2021, it would be of interest to investigate future spot prices. A further study could forecast future prices to investigate the presented charging strategies based on the future spot prices. As the number of EVs in Norway increases, this analysis could be of special interest for the new and existing EV owners. Since Norway is in a unique position as regards the EV fleet, this could be interesting to apply to other regions and countries as well. Especially since the spot prices of Norway are considered to not be as volatile compared to other countries in Europe.

Secondly, it is also of interest to research the effect of the charging strategies on the power grid. The research can investigate if there are some of the presented charging strategies that impacts the grid more compared to other strategies. As the number of EVs is expected to continue to increase in the future, a greater peak demand in the power grid is also expected, especially if EV owners charge the EVs at the same time periods of the day. These demand peaks will become one of the main challenges for the stability of the power grid.

Lastly, as the EV market is growing rapidly and the technology is developing quickly, it might be of interest to investigate how V2G-technology could be included in the model and how it would affect the charging cost of the charging strategies in the future. This may also be included in the model presented in this thesis to illustrate how the V2G-technology would affect the charging strategies in a retrospective manner. Additionally, the EVs in the future are likely to have longer driving ranges as the technology evolves quickly. Thus, it would be of interest to include EVs with longer driving range and more battery capacity compared to the ones presented in this thesis.

8 Conclusion

In this thesis, we have formulated and implemented an optimization model to imitate seven different charging strategies for EV owners based on charging behavior. In order to achieve this, a linear programming model was constructed to minimize the annual charging cost for the EV owners. The purpose of the analysis was to exploit and compare the different charging strategies to investigate how the different charging behaviors would have performed based on the spot prices of electricity in 2021. In addition, two different scenario analyses were performed to investigate how adjustments in the input values would affect the objectives of the charging strategies by 1) the new network tariff model is implemented, and 2) the battery capacity and possible driving range changes.

The results obtained by the formulated model showed that the charging strategies obtained an annual charging cost ranging from 1935.36 NOK to 2584.01 NOK, which is a cost increase of approximately 34%. The strategy of flexible night charging was found to be the least costly of the charging strategies. Furthermore, forced afternoon charging would have obtained the highest charging cost. The results also showed that the charging strategies not restricted to charge during certain charging periods choose to charge the most during the night. This implies that charging at night reduces charging cost as the optimization model minimizes the annual charging cost.

When the new network tariff model was implemented to the model, the most and least costly charging strategies remained the same. However, the results indicated that all the charging strategies thought to utilize the grid capacity would have experienced a decrease in the charging cost compared to the cost obtained in the current network tariff model. However, the same effect is not applied to the charging strategies charging in the afternoon. Forced afternoon and flexible afternoon strategies would have experienced an increase of 5.10% and 5.82% in variable costs, respectively, compared to the objective with the current network tariff model.

In order to illustrate the annual total cost of charging the EVs, the fixed cost was included in the analysis. When including the fixed cost of the new network tariff model, the results show that all the charging strategies would have experienced an increase in the total annual cost. Both variable cost and fixed cost are intended to motivate the the consumers to shift their consumption to off-peak hours. As the afternoon strategies experience an increase in both variable and fixed cost, this might be an incentive to shift the consumption to off-peak hours.

As the driving range and battery capacity were adjusted in the last scenario, the results showed that EVs with shorter range would experience a higher charging cost in all the charging strategies. The scenario analysis intends to investigate the cost effect of increasing the range by 100 km, whereas the results show the greatest cost reduction when increasing the range from 200 km to 300 km for all EVs in all the strategies. The analysis shows that an increase in the range gives the EV owners more flexibility and can charge when the spot prices of electricity are relatively lower. Hence, these vehicles have lower charging costs for all the strategies in the scenario. Lastly, the EVs with 200 km range cannot charge only during the weekends given the restrictions in the model.

References

Bjørndalen, J., Ingeberg, K., Norheim, B., and Brønmo, G. (2019). Kostnader i strømnettet - gevinster ved koordinert lading av elbiler. Retrieved from https://publikasjoner.nve.no/eksternrapport/2019/eksternrapport2019_51.pdf.

BKK (n.d.). Priser og betaling. Retrieved February 10, 2022, from https://nett.bkk.no/kundeservice?categoryId=271ab4eb-d361-4c8e-b55f-bbea47b61868.

BKK Nett (2022). Slik blir den nye nettleiemodellen. Retrieved May 25, 2022,from https://kommunikasjon.ntb.no/pressemelding/slik-blir-den-nye-nettleiemodellen?publisherId=17848001releaseId=17934068.

Dsb (2017). Elbil-lading og sikkerhet. Retrieved from https://www.dsb.no/lover/elektriske-anlegg-og-elektrisk-utstyr/tema/elbil—lading-og-sikkerhet/elbiler-lading-og-brannfare.

Energi Norge (2022). Felles anbefalinger til ny modell for nettleie. Retrieved from https://www.energinorge.no/contentassets/0c75ce4f42b54f528eb97cd7ebd3f1d7/220317—-felles-posisjoner-ny-nettleie—med-signaturer.pdf.

Energifakta Norge (2019). Strømnettet. Retrieved March 10, 2022, from https://energifaktanorge.no/norsk-energiforsyning/kraftnett/.

Energifakta Norge (2021). Kraftproduksjon. Retrieved March 11, 2022, from https://energifaktanorge.no/norsk-energiforsyning/kraftforsyningen/.

Energifakta Norge (2022). Kraftmarkedet. Retrieved March 10, 2022, from https://energifaktanorge.no/en/norsk-energiforsyning/kraftmarkedet/.

European Automobile Manufacturers Association (n.d.). Getting ready for wltp. Retrieved from https://www.wltpfacts.eu/wp-content/uploads/2017/04/WLTP_Leaflet_FA_web.pdf.

Figenbaum, E. (2018). Electromobility status in norway. Retrieved from https://www.toi.no/getfile.php?mmfileid=47474.

Figenbaum, E. and Kolbenstvedt, M. (2016). Learning from norwegian battery electric and plug-in hybrid vehicle users. Retrieved from https://www.toi.no/getfile.php?mmfileid=43161.

Figenbaum, E. and Nordbakke, S. (2019). Battery electric vehicle user experiences in norway's maturing market. Retrieved from https://www.toi.no/getfile.php?mmfileid=50956.

Fourer, R., Gay, D. M., and Kernighan, B. W. (2003). *AMPL: A Modeling Language for Mathematical Programming*. Duxbury Press / Brooks/Cole Publishing Company, 2 edition.

Grue, B., Landa-Mata, I., and Flotve, B. L. (2021). Den nasjonale reisevaneundersøkelsen 2018/2019. Retrieved from https://www.toi.no/getfile.php?mmfileid=71405.

Hexeberg, F. L. (2014). Strategies for smart charging of electric vehicles. Master's thesis, Norwegian University of Science and Technology.

Kriekinge, G., and Cauwer, C., and Sapountzoglou, N., and Coosemans, T., and Messagie, M. (2021). Peak shaving and cost minimization using model predictive control for uni- and bi-directional charging of electric vehicles. *Energy reports*, 7:8760–8771.

Lorentzen, E. and Grøndahl, S. (2019). Notat til drivkraft norge om elbilister og hurtiglademarkedet. Retrieved from https://www.drivkraftnorge.no/siteassets/bilder/elbil–lading/notat-fra-elbilforeningen-om-elbilister-og-hurtiglademarkedet.pdf.

Lundgren, J., Rönnqvist, M., and Värbrand, P. (2010). *Optimization*. Studentlitteratur AB, Lund, 1:1 edition.

Ministry of Petroleum and Energy (2021a). Effektbaserte tariffer legger til rette for bedre utnyttelse av strømnettet – nå skal smart strømbruk belønnes. Retrieved March 10, 2022, from https://www.regjeringen.no/no/dokumentarkiv/regjeringen-solberg/aktuelt-regjeringen-solberg/oed/nyheter/2021/nettariffer/id2860406/.

Ministry of Petroleum and Energy (2021b). Strømforsyning og strømnettet. Retrieved April 20, 2022, from https://www.regjeringen.no/no/tema/energi/stromnettet/stromforsyning-og-stromnettet/id2353792/.

Ministry of Transport (2021). Norge er elektrisk. Retrieved March 7, 2022, from https://www.regjeringen.no/no/tema/transport-og-kommunikasjon/veg_og_vegtrafikk/faktaartikler-vei-og-ts/norge-er-elektrisk/id2677481/.

NAF (2022). 80 prosent elbil-batteri er det nye «full tank». Retrieved March 12, 2022, from https://kommunikasjon.ntb.no/pressemelding/80-prosent-elbil-batteri-er-det-nye-full-tank?publisherId=2126680releaseId=17926905.

Norsk Elbilforening (2019). Ladeklart norge 2025. Retrieved from https://elbil.no/wp-content/uploads/2019/03/Ladeklart-Norge-2025.pdf.

Norsk Elbilforening (2021). Elbilisten: Stadig flere har ladeboks hjemme. Retrieved April 3, 2022, from https://elbil.no/elbilisten-stadig-flere-har-ladeboks2-hjemme/.

Norsk Elbilforening (n.d). Lade med hjemmeladeboks. Retrieved from https://elbil.no/lade/lade-elbilen-hjemme/lade-med-hjemmeladeboks/.

NVE (2018). The norwegian power system. grid connection and licensing. Retrieved from https://publikasjoner.nve.no/faktaark/2018/faktaark2018_03.pdf.

NVE (2021). Nettleie. Retrieved April 23, 2022, from https://www.nve.no/reguleringsmyndigheten/kunde/nett/nettleie/.

Ofv (2022). Bilåret 2021. tall og trender. Retrieved from https://s3-eu-west-1.amazonaws.com/opplysningsraadet-for-veitrafikk/pdf/Frokostmøter-Foredrag/Bilåret-2021-tall-og-trender.pdf.

Oslo Economics (2019). Nettkundenes nytte av en oppgradering av lavspenningsnettet. Retrieved from https://publikasjoner.nve.no/eksternrapport/2019/eksternrapport2019_07.pdf.

Skotland, C. H., Eggum, E., and Spilde, D. (2016). Hva betyr elbiler for strømnettet? Retrieved from https://www.nve.no/Media/4720/elbil_strømnett_rapport.pdf.

Sletvold, S. (2021). Ladeklart norge 2025. Retrieved April 3, 2022, from https://elbil.no/slik-lader-du-smart-hjemme/.

SSB (2022). Bilparken. Retrieved February 15, 2022, from https://www.ssb.no/transport-og-reiseliv/landtransport/statistikk/bilparken.

The European Commission (n.d.). Alternating current Direct current. Retrieved March 8, 2022, from https://ec.europa.eu/health/scientific$_{c}ommittees/opinions_{l}ayman/en/electromagnetic-fields/glossary/abc/alternating-current.htm$.

Wang, Y., and Infield, D., and Gill, S. (2021). Smart charging for electric vehicles to minimise charging cost. *Journal of Power and Energy*, 231(6):526–534.

Wangsness, P. B., and Halse, A. H. (2021). The impact of electric vehicle density on local grid costs: Empirical evidence from norway. *Energy journal*, 42(5).

Williams, H. (2013). *Model Building in Mathematical Programming*. John Wiley Sons Inc, 5 edition.

Ydersbond, I. M. and Amundsen, A. H. (2020). Hurtiglading og langkjøring med elbil i innlands-norge. Retrieved from https://www.toi.no/getfile.php?mmfileid=53332.

Appendix

A1 Optimization Model

minimize

$$\sum_{t\in T,\ d\in D} p_{t,d} \cdot x_{t,d} \ + \sum_{t\in T,\ d\in D} e \cdot x_{t,d}$$

subject to

$$SOC_{t,d} \ = \ C, \qquad t = 0,\ d = 1$$

$$SOC_{t,d} \ = \ SOC_{t-1,d} \ + \ x_{t,d} \cdot Y_{t,d} \ - \bar{d} \cdot Z_{t,d}, \qquad \forall\, t \in T : t > 0,\ d \in D$$

$$SOC_{0,d} \ = \ SOC_{23,d-1} \ + \ x_{0,d}, \qquad \forall\, d \in D : d > 1$$

$$SOC_{t,d} \ \leq C, \qquad \forall\, t \in T,\ d \in D$$

$$SOC_{t,d} \ \geq c, \qquad \forall\, t \in T,\ d \in D$$

$$x_{t,d} \leq r, \qquad \forall\, t \in T,\ d \in D$$

$$x_{t,d} \geq 0, \qquad \forall\, t \in T,\ d \in D$$

$$SOC_{t,d} \geq 0, \qquad \forall\, t \in T,\ d \in D$$

A2 AMPL Data File

```
set T := 00, 01, 02, 03, 04, 05, 06, 07, 08, 09, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23;
set D := 1  2   3   4   5   6   7   8   9   10  11  12  13  14  15  16  17  18  19  20  21  22  23  24  25  26  27  28  29  30  31  32  33  34


param p :=
[*,*]:  1   2   3   4   5   6   7   8   9   10  11  12  13  14  15  16  17  18  19  20  21  22  23  24  25  26  27  28  29  30  31  32  33  34
00 0.32574  0.33409 0.32991 0.32195 0.36279 0.39049 0.55878 0.63913 0.61321 0.50236 0.52513 0.33848 0.42813 0.48150 0.63169 0.68490 0.60353 0.5
01 0.31790  0.32521 0.32104 0.31399 0.35809 0.37595 0.53050 0.61410 0.60626 0.46524 0.51206 0.32904 0.42035 0.47646 0.61248 0.66631 0.58185 0.5
02 0.31308  0.32300 0.31151 0.31176 0.35326 0.36798 0.50833 0.59336 0.59904 0.44429 0.48865 0.32256 0.40934 0.47736 0.59609 0.64349 0.58405 0.5
03 0.30968  0.32195 0.30773 0.31373 0.35404 0.36626 0.51598 0.57690 0.61438 0.43808 0.45825 0.32670 0.39975 0.50913 0.58423 0.62504 0.58393 0.5
04 0.30981  0.32274 0.30668 0.32091 0.36253 0.36863 0.53543 0.59220 0.61915 0.43769 0.48231 0.36229 0.41064 0.54424 0.59919 0.62039 0.57614 0.5
05 0.31411  0.32535 0.31138 0.33736 0.38888 0.37963 0.59069 0.65234 0.61566 0.44248 0.53560 0.45325 0.47713 0.58529 0.64316 0.61085 0.57549 0.6
06 0.31908  0.33449 0.31399 0.36830 0.46675 0.40214 0.68563 0.77301 0.62198 0.44015 0.55331 0.51936 0.54271 0.70973 0.81211 0.61923 0.58860 0.6
07 0.32548  0.34193 0.32378 0.40276 0.60776 0.46524 0.87941 1.00294 0.67225 0.48645 0.65110 0.70529 0.59896 1.05000 1.02995 0.66348 0.60366 0.9
08 0.32509  0.34859 0.32600 0.64234 0.78270 0.51288 1.09511 1.34201 0.74893 0.50559 0.74048 0.78460 0.72768 1.17470 1.24635 0.76075 0.61534 1.0
09 0.32730  0.35106 0.33488 0.65304 0.78426 0.54823 1.08771 1.39723 0.83360 0.52719 0.64179 0.71111 0.61841 1.15236 1.26080 0.82513 0.62001 0.9
10 0.33461  0.36164 0.33945 0.72329 0.79809 0.60308 1.06930 1.39100 0.84559 0.57116 0.61528 0.73104 0.59923 1.15701 1.16961 0.79713 0.71076 0.9
11 0.33840  0.36674 0.34036 0.73804 0.81479 0.59260 1.11535 1.35134 0.84920 0.58643 0.57738 0.71603 0.56799 1.17534 1.12164 0.80151 0.75399 0.8
12 0.34114  0.36346 0.33775 0.67981 0.80201 0.60490 1.09874 1.29496 0.83734 0.57893 0.56043 0.64824 0.53429 1.14565 1.02208 0.68760 0.66454 0.7
13 0.34689  0.36346 0.33723 0.73804 0.81258 0.61983 1.06735 1.23481 0.78038 0.57349 0.55111 0.62171 0.51899 1.12435 0.98841 0.63329 0.68570 0.7
14 0.35641  0.36439 0.33971 0.75710 0.80735 0.67166 1.01975 1.20176 0.74931 0.58785 0.54388 0.62158 0.51160 1.08408 0.99486 0.63174 0.64845 0.7
15 0.37353  0.36660 0.34598 0.75214 0.81544 0.71866 1.05801 1.23676 0.74931 0.60363 0.54724 0.67295 0.53364 1.03219 0.99280 0.65341 0.69428 0.7
16 0.38319  0.37665 0.36621 0.78425 0.83828 0.76448 1.16320 1.23133 0.78399 0.65601 0.55979 0.79004 0.59508 1.07685 1.05755 0.76269 0.78670 0.7
17 0.38253  0.37770 0.37248 0.85149 0.84871 0.78450 1.29590 1.42574 0.88760 0.71073 0.58178 0.82964 0.71925 1.29953 1.28324 0.83868 0.87044 0.7
18 0.37626  0.37248 0.36778 0.77799 0.61585 0.72874 1.09758 1.29548 0.89818 0.68990 0.55526 0.78150 0.70655 1.16385 1.26415 0.85660 0.93470 0.7
19 0.36883  0.37221 0.36451 0.54220 0.58455 0.65779 1.00899 1.03845 0.84765 0.63881 0.51361 0.65276 0.62346 1.13210 1.22534 0.82255 0.83058 0.6
20 0.35668  0.35746 0.35981 0.49194 0.53198 0.52153 0.83959 0.79686 0.64350 0.60053 0.47998 0.54071 0.61103 0.96274 0.99564 0.70773 0.81071 0.6
21 0.35224  0.35198 0.35303 0.45460 0.51659 0.52270 0.75684 0.77029 0.61799 0.57544 0.44286 0.52674 0.52989 0.80990 0.86641 0.68348 0.72128 0.5
22 0.34519  0.35054 0.34180 0.40408 0.41823 0.50660 0.75023 0.72869 0.56025 0.51826 0.42954 0.48844 0.51874 0.77220 0.80760 0.66980 0.67675 0.5
23 0.33475  0.33866 0.32535 0.35708 0.38105 0.42544 0.65670 0.65429 0.47223 0.46408 0.36551 0.44794 0.49294 0.71773 0.69256 0.62143 0.60885 0.4

param r :=
3.7
;

param C :=
75
;

param t1 :=
0.2
;

param d1 :=
5.79
;
```

Figure A2.1: Excerpt of the data file in AMPL.

A3 AMPL Model File for Fully Flexible

```
set T;              #Set of time (00, ..., 23)
set D;              #Set of days (1, ..., 365)

param C;            #Battery capacity
param r;            #Charging rate
param p{T, D};      #Spot prices
param c;            #20%
param d1;           #Amount kWh consumed each trip
param e := 0.4261;  #Variable cost of the network tariff model

var x {T, D} >= 0;                      #Amount of electricity received from the grid
var SOC{T, D} >= 0;                     #State of charge (SOC) of the battery of the EV

minimize cost:                          #Minimizes charging costs for the EV owner
    sum{t in T, d in D}p[t,d]*x[t,d]
    + e * sum{t in T, d in D}x[t,d];


subject to

non_neg{t in T, d in D}:                #Amount kWh charged cannot be less than 0
    x[t,d] >= 0;

max_cr{t in T, d in D}:                 #The amount of electricity retrieved from the grid cannot exceed the charging rate
    x[t,d] <= r;

initial_SOC:                            #Initial state of charge at t=16 and d=1 equals the battery capacity
    SOC[0,1] = C;

soc_t1{d in D,t in 16..23}:             #Ensures balance between SOC in the charging period each day
    SOC[t,d] = SOC[t-1,d] + x[t,d];

soc_t2{d in D, t in 00..14: t>0}:       #Ensures balance between SOC in the charging period
    SOC[t,d] = SOC[t-1,d] + x[t,d];

soc_d{d in D: d>1}:                     #Ensures balance between SOC each day
    SOC[0,d] = SOC[23,d-1] + x[0,d];

drive{d in D}:                          #Ensures daily trip at 3 PM
    SOC[15,d] = SOC[14,d] - d1;

soc_max{d in D, t in T}:                #Ensures SOC of the EV does not exceeds the battery capacity of the EV
    SOC[t,d] <= C;

soc_min{d in D, t in T}:                #Ensures SOC of the EV never goes below a certain level each day
    SOC[t,d] >= t1*C;
```

Figure A3.1: AMPL model file for the fully flexible strategy.

A4 AMPL Model File for Forced Afternoon

```
set T;               #Set of time (00, ..., 23)
set D;               #Set of days (1, ..., 365)

param C;             #Battery capacity
param r;             #Charging rate
param p{T, D};       #Spot prices
param c;             #20%
param d1;            #Amount kWh consumed each trip
param e := 0.4261;   #Variable cost of the network tariff model

var x {T, D} >= 0;                          #Amount of electricity received from the grid
var SOC{T, D} >= 0;                         #State of charge (SOC) of the battery of the EV

minimize cost:                              #Minimizes charging costs for the EV owner
    sum{t in T, d in D}p[t,d]*x[t,d]
    + e * sum{t in T, d in D}x[t,d];

subject to

non_neg{t in T, d in D}:                    #Amount kWh charged cannot be less than 0
    x[t,d] >= 0;

max_cr{t in T, d in D}:                     #The amount of electricity retrieved from the grid cannot exceed the charging rate
    x[t,d] <= r;

initial_SOC:                                #Initial state of charge at t=16 and d=1 equals the battery capacity
    SOC[16,1] = C;

soc_t1{d in 1..365 by 7,t in 16..20: t>0}:  #Ensures balance between SOC in the charging period each Friday
    SOC[t,d] = SOC[t-1,d] + x[t,d];

soc_t2{d in 4..365 by 7,t in 16..20: t>0}:  #Ensures balance between SOC in the charging period each Monday
    SOC[t,d] = SOC[t-1,d] + x[t,d];

soc_t3{d in 5..365 by 7,t in 16..20: t>0}:  #Ensures balance between SOC in the charging period each Tuesday
    SOC[t,d] = SOC[t-1,d] + x[t,d];

soc_t4{d in 6..365 by 7,t in 16..20: t>0}:  #Ensures balance between SOC in the charging period each Wednesday
    SOC[t,d] = SOC[t-1,d] + x[t,d];

soc_t5{d in 7..365 by 7,t in 16..20: t>0}:  #Ensures balance between SOC in the charging period each Thursday
    SOC[t,d] = SOC[t-1,d] + x[t,d];

soc_d1{d in 1..365 by 7: d>2}:              #Ensures balance between SOC each day for Friday
    SOC[16,d] = SOC[20,d-1] - d1 + x[16,d];

soc_d2{d in 4..365 by 7: d>2}:              #Ensures balance between SOC each day for Monday
    SOC[16,d] = SOC[20,d-1] - d1 + x[16,d];

soc_d3{d in 5..365 by 7: d>2}:              #Ensures balance between SOC each day for Tuesday
    SOC[16,d] = SOC[20,d-1] - d1 + x[16,d];

soc_d4{d in 6..365 by 7: d>2}:              #Ensures balance between SOC each day for Wednesday
    SOC[16,d] = SOC[20,d-1] - d1 + x[16,d];

soc_d5{d in 7..365 by 7: d>2}:              #Ensures balance between SOC each day for Thursday
    SOC[16,d] = SOC[20,d-1] - d1 + x[16,d];

drive_weekend{d in 4..365 by 7: d>3}:       #Ensures balance between SOC after the weekend
    SOC[16,d] = SOC[20,d-3] + x[16,d] - 2*d1;

soc_max{d in D, t in T}:                    #Ensures SOC of the EV does not exceeds the battery capacity of the EV
    SOC[t,d] <= C;

soc_min1{t in 16..20, d in 1..365 by 7}:    #Ensures SOC of the EV never goes below a certain level each Friday
    SOC[t,d] >= c*C;

soc_min2{t in 16..20, d in 4..365 by 7}:    #Ensures SOC of the EV never goes below a certain level each Monday
    SOC[t,d] >= c*C;

soc_min3{t in 16..20, d in 5..365 by 7}:    #Ensures SOC of the EV never goes below a certain level each Tuesday
    SOC[t,d] >= c*C;

soc_min4{t in 16..20, d in 6..365 by 7}:    #Ensures SOC of the EV never goes below a certain level each Wednesday
    SOC[t,d] >= c*C;

soc_minC5{t in 16..20, d in 7..365 by 7}:   #Ensures SOC of the EV never goes below a certain level each Thursday
    SOC[t,d] >= c*C;

fully_charged1{d in 1..365 by 7}:           #Ensures SOC equals battery capacity at the end of each Friday
    SOC[20,d] = C;

fully_charged2{d in 4..365 by 7}:           #Ensures SOC equals battery capacity at the end of each Monday
    SOC[20,d] = C;

fully_charged3{d in 5..365 by 7}:           #Ensures SOC equals battery capacity at the end of each Tuesday
    SOC[20,d] = C;

fully_charged4{d in 6..365 by 7}:           #Ensures SOC equals battery capacity at the end of each Wednesday
    SOC[20,d] = C;

fully_charged5{d in 7..365 by 7}:           #Ensures SOC equals battery capacity at the end of each Thursday
    SOC[20,d] = C;
```

Figure A4.1: AMPL model file for the forced afternoon strategy.

A5 AMPL Model File for Flexible Night

```
set T;               #Set of time (00, ..., 23)
set D;               #Set of days (1, ..., 365)

param C;             #Battery capacity
param r;             #Charging rate
param p{T, D};       #Spot prices
param c;             #20%
param d1;            #Amount kWh consumed each trip
param e := 0.4261;   #Variable cost of the network tariff model

var x {T, D} >= 0;                        #Amount of electricity received from the grid
var SOC{T, D} >= 0;                       #State of charge (SOC) of the battery of the EV

minimize cost:                            #Minimizes charging costs for the EV owner
    sum{t in T, d in D}p[t,d]*x[t,d]
    + e * sum{t in T, d in D}x[t,d];

subject to
non_neg{t in T, d in D}:                  #Amount kWh charged cannot be less than 0
    x[t,d] >= 0;

max_cr{t in T, d in D}:                   #The amount of electricity retrieved from the grid cannot exceed the charging rate
    x[t,d] <= r;

initial_SOC:                              #Initial state of charge at t=16 and d=1 equals the battery capacity
    SOC[00,1] = C;

soc_t1{d in 1..365 by 7,t in 00..07: t>0}:  #Ensures balance between SOC in the charging period each Friday
    SOC[t,d] = SOC[t-1,d] + x[t,d];

soc_t2{d in 4..365 by 7,t in 00..07: t>0}:  #Ensures balance between SOC in the charging period each Monday
    SOC[t,d] = SOC[t-1,d] + x[t,d];

soc_t3{d in 5..365 by 7,t in 00..07: t>0}:  #Ensures balance between SOC in the charging period each Tuesday
    SOC[t,d] = SOC[t-1,d] + x[t,d];

soc_t4{d in 6..365 by 7,t in 00..07: t>0}:  #Ensures balance between SOC in the charging period each Wednesday
    SOC[t,d] = SOC[t-1,d] + x[t,d];

soc_t15{d in 7..365 by 7,t in 00..07: t>0}: #Ensures balance between SOC in the charging period each Thursday
    SOC[t,d] = SOC[t-1,d] + x[t,d];

soc_d1{d in 1..365 by 7: d>2}:            #Ensures balance between SOC each day for Friday
    SOC[00,d] = SOC[07,d-1] - d1 + x[00,d];

soc_d2{d in 4..365 by 7: d>2}:            #Ensures balance between SOC each day for Monday
    SOC[00,d] = SOC[07,d-1] - d1 + x[00,d];

soc_d3{d in 5..365 by 7: d>2}:            #Ensures balance between SOC each day for Tuesday
    SOC[00,d] = SOC[07,d-1] - d1 + x[00,d];

soc_d4{d in 6..365 by 7: d>2}:            #Ensures balance between SOC each day for Wednesday
    SOC[00,d] = SOC[07,d-1] - d1 + x[00,d];

soc_d5{d in 7..365 by 7: d>2}:            #Ensures balance between SOC each day for Thursday
    SOC[00,d] = SOC[07,d-1] - d1 + x[00,d];

drive_weekend{d in 4..365 by 7: d>3}:        #Ensures balance between SOC after the weekend
    SOC[00,d] = SOC[07,d-3] + x[00,d] - 2*d1;

soc_max1{d in 1..365 by 7, t in 00..07}:     #Ensures SOC of the EV does not exceed the battery capacity each Friday
    SOC[t,d] <= C;

soc_max2{d in 4..365 by 7, t in 00..07}:     #Ensures SOC of the EV does not exceed the battery capacity each Monday
    SOC[t,d] <= C;

soc_max3{d in 5..365 by 7, t in 00..07}:     #Ensures SOC of the EV does not exceed the battery capacity each Tuesday
    SOC[t,d] <= C;

soc_max4{d in 6..365 by 7, t in 00..07}:     #Ensures SOC of the EV does not exceed the battery capacity each Wednesday
    SOC[t,d] <= C;

soc_max5{d in 7..365 by 7, t in 00..07}:     #Ensures SOC of the EV does not exceed the battery capacity each Thursday
    SOC[t,d] <= C;

soc_min1{t in 00..07, d in 1..365 by 7}:     #Ensures SOC of the EV never goes below a certain level each Friday
    SOC[t,d] >= c*C;

soc_min2{t in 00..07, d in 4..365 by 7}:     #Ensures SOC of the EV never goes below a certain level each Monday
    SOC[t,d] >= c*C;

soc_min3{t in 00..07, d in 5..365 by 7}:     #Ensures SOC of the EV never goes below a certain level each Tuesday
    SOC[t,d] >= c*C;

soc_min4{t in 00..07, d in 6..365 by 7}:     #Ensures SOC of the EV never goes below a certain level each Wednesday
    SOC[t,d] >= c*C;

soc_min5{t in 00..07, d in 7..365 by 7}:     #Ensures SOC of the EV never goes below a certain level each Thursday
    SOC[t,d] >= c*C;
```

Figure A5.1: AMPL model file for the flexible night strategy.

A6 Output Values for Fully Flexible

Table A6.1: Excerpt of output values for $x_{t,d}$ in fully flexible strategy. Illustrates the given output value obtained for January 2021.

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0,48	3,7	3,7	3,7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	3,7	2,09	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	3,7	2,09	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0,95	3,7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3,7
12	3,7	3,7	3,7	3,7	3,7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
20	0	0	3,7	3,7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3,7
21	3,7	3,7	3,7	3,7	3,7	3,7	3,7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3,7	3,7
22	3,7	3,7	3,7	3,7	3,7	3,7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3,37	3,7	3,7
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2,09	3,7
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
28	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
30	0	0	0	3,7	3,7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
31	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

A7 Output Values for Forced Afternoon

Table A7.1: Excerpt of output values for $x_{t,d}$ in forced afternoon strategy. Illustrates the given output value obtained for January 2021.

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,48	0	3,7	3,7	3,7	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2,09	3,7	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2,09	3,7	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2,09	3,7	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2,09	3,7	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0,48	0	3,7	3,7	3,7	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2,09	3,7	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3,7	0	0	0	2,09	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2,09	0	0	0	3,7	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2,09	0	0	0	3,7	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3,7	0	0,48	3,7	3,7	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2,09	3,7	0	0	0
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2,09	3,7	0	0	0
21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2,09	3,7	0	0	0
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2,09	3,7	0	0	0
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3,7	0	0,48	3,7	3,7	0	0	0
26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2,09	3,7	0	0	0
27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2,09	3,7	0	0	0
28	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2,09	0	0	0	3,7	0	0	0
29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2,09	0	0	0	3,7	0	0	0
30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
31	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

A8 Output Values for Flexible Night

Table A8.1: Excerpt of output values for $x_{t,d}$ in flexible night strategy. Illustrates the given output value obtained for January 2021.

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	3,7	3,7	3,7	0,48	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	3,7	2,09	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	2,09	3,7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	3,7	3,7	3,7	3,7	3,7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
20	0	3,7	3,7	3,7	3,36	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
21	3,7	3,7	3,7	3,7	3,7	3,7	3,7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
22	3,7	3,7	3,7	3,7	3,7	3,7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
28	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
29	0	0	0	3,7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
31	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0