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Mapping of residential consumer flexibility from electric vehicles and electric heating

Kartlegging av forbrukerfleksibilitet fra elbiler og elektrisk

oppvarming i husholdninger

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Environmental Physics and Renewable Energy

Acknowledgment

Writing a master's thesis has been a new and challenging experience for me. I have learned a lot about myself and gained tremendous respect for scientists and all the work they put into their research and publications. I have developed a true passion for this topic and can not wait to further explore this field. I feel fortunate to have had the opportunity to work with a relevant and timely topic with such intelligent people.

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Abstract

In combination with an increasing consumption, due to electrification, the green shift challenges the power grid. When regulative energy production is substituted with production from uncontrollable sources, the need for a flexible consumption increases. This can originate from shifting or decreasing household consumption.

This thesis investigates the flexibility of residential electrical vehicle (EV) charging and electric heating. In addition, this thesis aims to research the potential benefits and challenges related to smart charging and will examine how temperature and other factors affect the availability of flexibility. The two data sets that have been used provide real consumption from 1140 and 2043 households and include information regarding EV chargers and heating source respectively. The data spans from November/December 2020 through March 2021. Firstly, coincidence factors (CFs) for residential EV charging, with and without smart charging, have been quantified. The CF represents the concurrent home charging. Secondly, charging session duration and delivered energy have been calculated and used to further discuss the availability of flexibility. Lastly, the flexibility of electric heating has been examined by comparing mean consumption profiles for groups of households with and without electric heating.

The results from real charging behavior indicate that households with smart charging have a significantly higher consumption during the night. The CF for smart charging vehicles is quantified to a maximum of over 30% and 10% for smart and normal charging respectively. These results coincide with other research. EVs with smart charging will have their charging allocated to hours of low electricity price. Smart charging will cause the EV charging to synchronize, resulting in a high CF. This can possibly create issues in the low-voltage grid. The CFs have a negative correlation with temperature meaning the EVs charge more frequently in colder weather.

The analysis of charging sessions shows a mean duration of around 4.7 hours independent of being smart or normal. The mean delivered energy is calculated to around $23kWh$ for both smart and normal charging. The difference between the time the EV needs to reach the desired battery level and the time it is connected to a charger is considered to be its flexible window. The combination of the CF and charging session duration and energy can be used to further estimate the flexibility potential of EVs.

The available flexibility from space and water heating has been studied by categorizing real consumer data based on heating sources. Four groups consisting of households with electric water heating, shared water heating, electric space heating, and district space heating were established. The average normalized consumption of the groups shows a significant difference in the morning hours. This implies that

some electric heating is in use during the morning hours, consequently revealing a potential for flexibility. The groups without electric water and space heating have a lower consumption. At last, the consumption is negatively correlated with temperature meaning the potential for flexibility from electric heating is increasing with decreasing temperatures and vice versa.

Further research on CFs and charging sessions can benefit the prediction of demand from EVs. This is likely going to be important for the planning of grid investments, especially in the low voltage grid. Lastly more research on charging behavior, CFs and electric heating would likely be beneficial for prediction of flexibility volumes. This would be of interest to aggregators and TSOs.

Sammendrag

Kombinasjonen av et økt forbruk fra elektrifisering og et driv mot det grønne skiftet gir utfordringer i det elektriske kraftsystemet. Når regulerbar energi produksjon blir erstattet av produksjon fra uregulerbare energikilder, øker behovet for et fleksibelt forbruk. Denne fleksibiliteten kan komme fra flytting og reduksjon av forbruk fra husholdninger. Denne oppgaven undersøker fleksibilitet fra hjemmelading av elbiler og elektrisk oppvarming. I tillegg ønsker oppgaven å avdekke potensielle fordeler og ulemper relatert til smart lading, samt se på hvordan temperatur og andre faktorer kan påvirke tilgjengelighet av fleksibilitet. De to datasettene som har blitt brukt, inkluderte reelt forbruk fra 1140 og 2043 husholdnigner med informasjon henholdsvis fra elbilladere og om oppvarming. Datasettene strekker seg fra november/desember 2020 til og med mars 2021. Først har sammenfallsfaktoren på elbillading blitt beregnet for smart og normal lading. Sammenfallsfaktoren sier noe om hvor stor andel av el-biler som lader til samme tid. Videre er lengde og lagret energi fra ladeøktene blitt beregnet og brukes til å videre diskutere tilgjengeligheten av fleksibilitet. Til slutt er fleksibilitet fra elektrisk oppvarming undersøkt ved å sammelikne gjennomsnittlige forbruksprofiler fra grupper med og uten elektrisk oppvarming.

Resultatene fra reell ladeoppførsel viser at husholdninger med smart lading har et signifikant høyere forbruk om natten. Sammenfallsfaktorene for smart ladning viser verdier på over 30% om natten, mens normal lading har verdier over 10%. Disse resultatene sammenfaller med modellerte resultater fra Danmark både for smart og normal lading. Sammenfallsfaktoren er vist å være negativt korrelert med temperatur. Det vil si at synkende temperaturer vil føre til økte sammenfallsfaktorer. Elbiler med smart lading får ladingen deres flyttet til tider med lav strømpris. Etterhvert som flere og flere elbiler lades etter pris vil ladingen synkroniseres, noe som resulterer i høye sammenfallsfaktorer. Høye sammenfallsfaktorer kan vise seg å skape problemer for strømnettet. Analysen av ladeøkter har vist at en gjennomsnittlig lading varer omtrent 4.7 timer, uavhengig av om den er smart eller normal. Det samme gjelder for energien som er ladet, som for begge typer lading er rundt $23kWh$. Forskjellen mellom tiden elbilen trenger for å nå et ønsket batterinivå og tiden elbilen står koblet i laderen vil være det vinduet hvor elbilen kan være fleksibel. Kombinasjonen av de beregnede sammenfallsfaktorene, lengde og energi fra ladeøktene kan videre brukes til å estiemere fleksibilititets potensialet fra elbiler.

Tilgjengeligheten av fleksibilitet fra elektrisk oppvarming av rom og vann er analysert ved å kategorisere forbrukere ut ifra oppvarmingskilde. Fire grupper bestående av kunder med elektrisk oppvarming av vann, vann oppvarmet med fjernvarme, elektrisk romoppvarming og rom oppvarmet med fjernvarme ble laget. Det gjennomsnittlige normaliserte forbruket til gruppene med elektrisk oppvarming viser signifikant høyere

forbruk om morgenen sammenliknet med de uten elektrisk oppvarming. Dette antyder at det er et forbruk til oppvarming om morgenen som kan brukes som kilde til fleksibilitet. Forbruket er også inverst korrelert med temperatur hvilket vil si at potensialet for fleksibilitet også øker med minkende temperaturer og vice versa.

Videre forskning på sammenfallsfaktorer og ladeøkter kan være til nytte for estimering av fremtidig kraftbehov til elbiler. Dette vil trolig være viktig for planlegging og utbygging av strømnettet, og da spesielt i lavspent nettet. Til sist vil trolig også videre forskning på ladeøkter, sammenfallsfaktorer og elektrisk oppvarming være viktig for estimering av størrelsen på fleksible reserver. Dette vil være av interesse for aggregatorer og TSOer.

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List of Abbreviations

VRE	Variable Renewable Energy
EV	Electric Vehicle
TSO	Transmission System Operator
DSO	Distribution System Operator
CF	Coincidence Factor
IRES	Intermittent Renewable Energy Sources
BEV	Battery Electric Vehicle
PHEV	Plug-in Hybrid Electric Vehicle
EVSE	Electrical Vehicle Supply Equipment
AC	Alternating Current
DC	Direct Current
IT	Insulated Terra
TN	Terra Neutral
BMS	Battery Management System
V2G	Vehicle to Grid

List of Symbols

V	Voltage
W	Watt
A	Ampere
C	Carbon
O	Oxygen
CO_2	Carbon dioxide
Hz	Hertz

Chapter 1

Introduction

1.1 Motivation

Since the industrial revolution, the use of gas, coal, and oil has changed the society to a great extent. Fossil fuels accelerated the development of new technology like steam locomotives and cars. Despite benefiting past and present generations, burning fossil fuels releases carbon dioxide, CO_2, into the atmosphere. The CO_2 in the atmosphere works as insulation, heating up the earth consequently causing the climate to change [1]. With goals to stop this climate change, the Paris Agreement was signed in 2015. There has since been a number of climate goals worldwide aiming to prevent climate change and reduce its impacts [2, 3].

Traditionally, the power grid was constructed as a centralized system. An example is simplified in Figure 1.1. A traditional grid has large power production plants at the top and end-users at the bottom. The power production is typically harnessed by burning coal or from water flowing through a turbine. Nuclear reactors also make up a big share of the power production in many countries. Independent of the type of power production, the producers have had to meet the instantaneous power demand from the end-user at all times [4].

Several different climate goals have led to a global focus on cutting CO_2 emissions, by for example phasing out the use of coal and capturing CO_2. Another way of cutting CO_2 emissions is through electrification. Electrification is a process of substituting fossil fuels with electricity as a source of power. Electrification is already evident in the transport sector where for example cars and trains now can run on electricity instead of fossil fuels. When converting to electricity as a source of power the source of the electricity should also be CO_2 emission-free. To provide electricity produced without CO_2 emissions, many countries have already developed wind-and solar farms. Despite benefiting the environment, the increasing demand for electricity and increasing penetration of variable renewable energy (VRE) pose a challenge to traditional electric power grids [5]. As a result of this, the power grid is gradually changing.

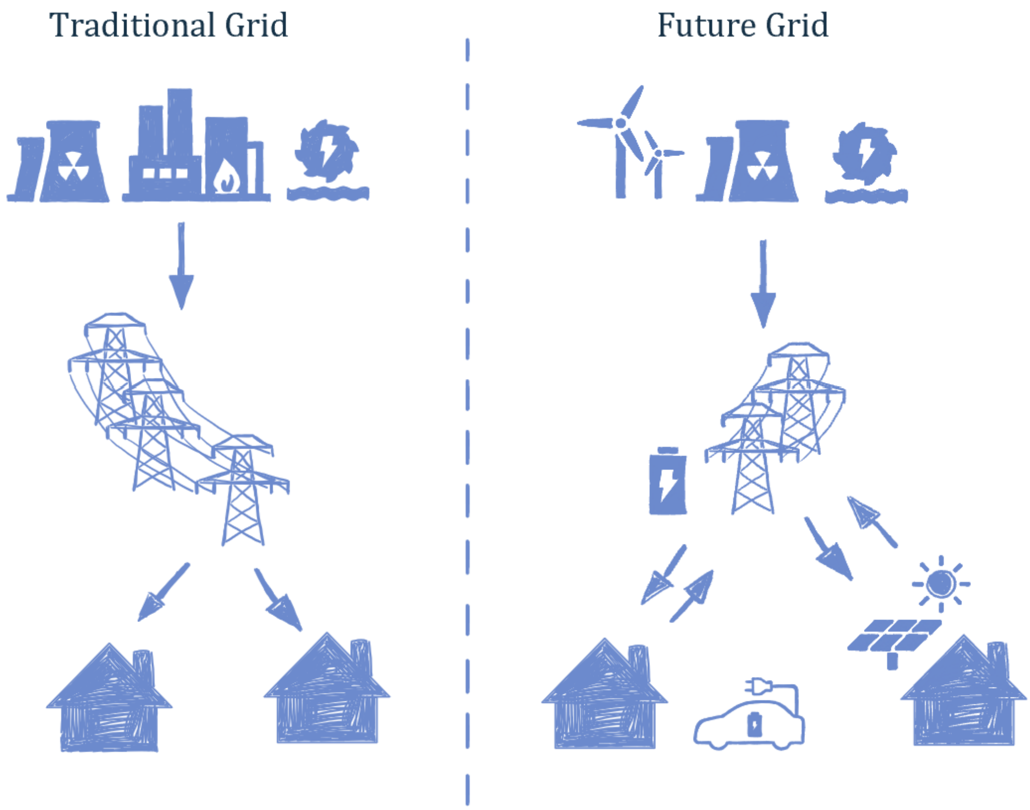

Figure 1.1: A simple example of a traditional grid (left), and future grid (right) made based on [6, 7, 8].

After the introduction of more VRE and new technology, the grid is becoming more decentralized with zero-emission power production from renewable sources such as wind and solar at several levels in the grid [8]. VRE sources are weather dependent, subsequently creating challenges for maintaining the balance between production and consumption [9]. When energy production can not be controlled, a flexible consumption is increasingly important in order to ensure security of supply [10, 11].

In addition to the challenges posed by VRE, the increasing electric consumption and electrification also puts the power grid under pressure [12]. A large part of this consumption comes from households. As much as 30% of Norway's total electricity consumption originates from households. In 2021 Norway's total consumption was $139.5TWh$, which means that the households alone consumed over $40TWh$ [13].

EVs and especially residential electric heating compose a great share of Norwegian household consumption [13]. Electrification catalyzed the demand for electric personal transport. During the last 10 years, the fleet of EVs in Norway has increased exponentially, now adding up to almost 600 000 units [14]. Electric heating is already common in most Norwegian households, often subsidized by wood burning [15].

In the future power grid, the consumer is also changing. Consumers are now able to produce and supply electricity to the grid. These consumers are called prosumers, and they create a two-way flow of electricity. In the traditional grid the electricity only flows from the producers to the consumers. New technology is also important for the future grid. By the beginning of 2019 all households in Norway were equipped with smart electric meters (AMS) [16]. These meters make it possible to closely monitor household consumption. The technology of remote control and scheduling of appliances and loads make it possible to control household consumption. An increasing consumption and fluctuating electricity production have resulted in increasingly volatile prices [10]. This has already given consumers incentives to monitor and exploit their flexibility to lower their electricity expenses.

The demand for power is also increasing. When multiple loads are connected at the same time they demand an instantaneous power from the grid. The grid is dimensioned for the maximum peak power demanded [17]. Outside the hours of peak demand, the grid operates below its capacity, not exploiting its potential. When the maximum power demand increases the grid needs to be expanded at the society's expense. By strategically moving or decreasing flexible consumption away from the existing peaks the grid is utilized more sustainably [18]. When the instantaneous power demand increases it could potentially overload the grid. For example, if consumers cook dinner, wash clothes and charge their EV at the same time. This create a consumption peak for the household. With Norway's high proportion of EVs, coinciding charging could cause even higher peaks, which poses a new power demand issue for the grid [19]. On the other hand, the charging of an EV could be a large flexible load. By exploiting the EVs' flexibility these power demand peaks could be decreased [20].

As established, the changing power grid faces problems with balancing, overloading, security of supply and volatile prices due to more VRE sources and a increasing demand due to electrification. Power grid flexibility is already considered to be a part of the solution. According to Sidqi et al., "household flexibility potential is defined as the capacity to increase, decrease or shift the consumption of domestic appliances over time" [21]. Different research postulates that utilizing household flexibility will facilitate more renewable power production by providing balancing reserves [10, 22], limit price volatility [10], reduce congestion in transmission networks [22] and ideally reduce households electricity bill [23]. Consequently being an important part of the future grid and making it a much-discussed topic [24].

Flexible loads can be managed indirectly when consumers voluntarily change consumption as a response to price, or directly when consumers or third parties disconnect loads [15]. Both indirect and direct load management has shown results of reduced consumption in peak hours [25, 26]. Several researchers have already explored household flexibility by looking at consumption characteristics and factors that affect the size and time of consumption [27, 28, 29]. D'Hulst et al. installed smart appliances (including hot water buffers and EV's) in 186 households in Belgium to quantify the flexibility [30]. Sidqi et al. quantified flexibility from space and water heating and found a correlation with temperature [21]. Bollerslev et al. modeled coincidence factors from EV user data which can be seen as an indication of when and how many EVs charge at the same time [31]. Unterluggauer et al. have also modeled CFs in Denmark but for different charging strategies [19].

Looking at the Norwegian case, a high penetration of EVs and electric heating offers a potential for household flexibility. This flexibility is needed to avoid overloading the grid in times of peak consumption and facilitate production from uncontrollable renewable sources [20]. However, researchers have still not used real consumer data to map the charging behavior for both smart and normal charging. These results could be beneficial for the quantification of flexibility from EVs and reveal the effects of smart charging in the grid. Furthermore, the difference in consumption for households with different heating systems has also not been investigated by comparing actual consumer data from households with different heating. The data has been provided by Statnett, which is participating in this study.

1.2 Thesis objective

Norway and many other countries share the common goal of electrification as a means of cutting emissions. To reach this goal as sustainably as possible, good utilization of the grid and the power sources is important. In addition, the security of supply needs to be maintained, and power grid flexibility is a part of the solution.

This thesis aims to explore the availability of grid flexibility, mainly from EVs but also electric heating in Norway. Studying charging patterns and data from EVs can contribute to reaching the goal of efficient utilization of the grid by actively controlling charging and thereby exploiting the EVs' flexibility. By understanding the time of use of electric heating, it can contribute as a source of flexibility. For this purpose, two sets of consumer data have been provided by Statnett. The data sets contain hourly consumption in kWh from 3183 households, in different parts of Norway. One data set range from November through March and the other from December through March.

The following research questions have been studied in this thesis:

- **What is the coincidence factor (CF) of residential EV charging, and how is it affected by smart charging?** Establishing what share of the fleet of EVs charge at the same time is a valuable step toward quantifying the flexibility potential. Being able to separate normal charging and smart charging could also provide valuable information about the impact of smart charging on the grid.

- **How does the CF change across time?** The CF will naturally change over the course of a day, week, and year. Finding patterns and relationships between CF, time, and temperature is an important step towards predicting the size of the flexibility. With a cold climate, like Norway, the correlation with temperature would be of great importance.

- **What are the duration and energy delivered in a charging session?** The potential of flexibility from EVs depends on the time of connection to the charger compared to the time needed to reach the desired battery level. The EV will some times be connected for a longer period of time than the minimum time needed for charging. The potential of flexibility would be the difference between those two periods. Calculating the charging session duration and delivered energy could say something about the size of flexibility from an average charging session.

- **How does electric heating affect a household's consumption?** Exploring the effect of electric heating on the consumption profile of a household could pinpoint the time and size of the flexibility potential. Lastly, the correlation between consumption and temperature is also calculated. The need for heating is expected to vary with temperature, thus, the temperature would naturally affect the availability of flexibility.

1.2.1 Limitation

The data used for the analysis is aggregated consumption, with the exception being data from the EV charger. This means that data provided is the total consumption from heating, light, cooking etc. The consumption for electrical heating is consequently not separated from the rest of the consumption, making it hard to study the flexibility potential from electric heating. Exploring the flexibility potential of heat sources is subsequently done by looking at patterns and the size of total consumption for different groups of households. Another limitation for the research is the duration of the data. As mentioned, the data sets used for the thesis range from November through March. Not having data for the warmer half of the year limits the insight from this period.

1.3 Thesis outline

The Introduction has covered the motivation for studying flexibility in the electric power grid. In addition, it has explained what the thesis aim to study. Subsequently, the content of the chapters are described:

- **Chapter 2** elaborates the theory of the electric power grid with a description of the challenges in the grid. Some information about the Norwegian grid system is also provided. Next up, the concept of grid flexibility and why it is important is explained. The sources of flexibility investigated in the thesis are looked into in greater detail. At the end of the chapter, methods for utilizing flexibility are presented.

- **Chapter 3** starts with a presentation of the data sets used in the thesis. To give an overview of how the different results have been found, a diagram of the method is provided. A detailed description is given for certain computations and decisions.

- **Chapter 4** presents all results in the same order as the research questions were asked. The results will be discussed and compared with previous research. The discussion covers thoughts about benefits and challenges for both the present and the future. A discussion of the method also takes place in Chapter 4.

- **Chapter 5** finishes the thesis with a conclusion covering the research questions and thoughts about further work.

Chapter 2

Theory

2.1 The electric power grid

In simple words, the electric power grid is a system of power transmission technologies connecting producers and consumers of electricity. A simplified sketch is presented in Figure 2.1. The power grid is controlled by a transmission system operator (TSO) and distribution system operators (DSOs). The TSO controls the parts of the transmission grid with high capacities and voltages over $132kV$. Together, different DSOs control the regional and distribution grid with voltages between $230V$ and $132kV$. The end users are mostly connected to the distribution grid, while large industries and electricity producers are connected to the transmission grid. The regional grid connects the transmission grid to the distribution grid [32, 33].

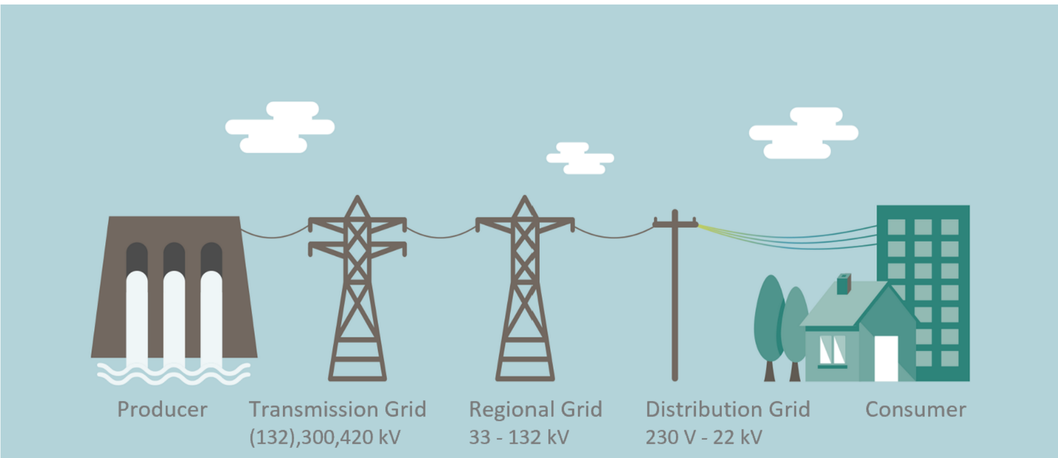

Figure 2.1: Simplified model of the Norwegian power grid used with permission from [32] with additional information from [33].

2.1.1 Grid balance

Production and consumption of electricity must be in balance at all times [34]. To keep this balance, the system operators continuously monitor and control production and consumption throughout the year. In times when consumption is expected to be low, the cheapest electricity is bought resulting in a low price for the consumers. This would encourage consumption. On the other hand, if there is expected to be a lot of consumption, the more expensive electricity is needed [35]. This cause the price to increase which motivate people to decrease their consumption. The prices are always set one day in advance. From the time the price is set to the next day both the actual production and consumption can differ from what was expected. The grid will then experience imbalances, and the system operator can pay to increase or decrease production or to have consumption turned on or off [34]. This will be discussed in greater detail in Section 2.1.3. Grid balancing is necessary to ensure electricity security and quality for everyone. In Norway, which is part of the synchronous Nordic area, the frequency of the grid is $50Hz$ when the grid is in balance. If the power grid experiences large imbalances, it will cause the frequency to change, leading to disturbances for consumers or in the worst case blackouts [34, 35]. The Norwegian TSO, Statnett, is therefore bound by law to keep the frequency within $50Hz \pm 2\%$ [36].

VRE or Intermittent Renewable Energy Sources (IRES) are both names used for renewable energy sources that are recognized as uncontrollable. Firstly, production from these sources can be hard to predict. This creates a problem for the grid balancing [5]. Secondly, controllable electricity production, for example from coal power plants, ceases as a result of the green transition. The result is that VREs make up a greater share of the total electricity production. With decreasing possibilities for regulating the production, the need for energy storage and control of consumption is increasingly important [5]. In Norway, hydro power plants with reservoirs of water serve as a controllable source of renewable energy. Provided that the water reservoir is filled, simply changing the water flow controls the power production. Despite the large controllable reserves in Norway, the VRE production in the rest of Europe still results in an increased need for flexibility [37].

As briefly mentioned in the introduction, the grid is dimensioned for the absolute highest power demand. The transformers and power cables have a maximum transmission capacity. This capacity needs to handle the demand from consumers at the time of highest demand. For the rest of the time the capacity is not fully utilized [38]. The consequence is that an increase of consumption in the peak hour could result in the need for expanding or upgrading the grid, despite most of the grid having unused potential. Having a flexible consumption during those hours enhances the utilization of the grid, possibly avoiding increasing peaks and costs for the society [38]. Household consumption profiles and peaks will be revisited in a later section.

2.1.2 The Norwegian electricity system at consumer level

Norwegian houses can be supplied with $230V$ or $400V$ depending on the type of grid in their area. The IT-grids (Insulated-Terra) are the most widespread, supplying households with $230V$. For IT-grids the neutral point of the distribution transformer is isolated from the earth [39]. The TN-grids (Terra-Neutral) the neutral point is connected all the way to the end user. The consumer can either be supplied with $230V$ or $400V$ from the TN-grids. Thus, an EV charging at home and other appliances would then be supplied with $230V$ (IT-grid) or $400V$ (TN-grid) [39]. As data from Tibber shows, the most common application in Norway is a three-phase $16A$ (IT-grid) residential charger that can charge $6.37kW$. While gradually converting to the TN-grid the same charging power ($16A$ three-phase) will increase to $11.08kW$. The different charging powers for EVs will be presented in greater detail in section 2.2.2.

2.1.3 Electricity pricing

The Norwegian power grid extends through a long country with large variations in population density and weather. Norway's power production, mostly hydropower, is to a great extent located in the north and west. The population on the other hand is mostly located in the south. The power grid does not have enough capacity to balance out the zones with a surplus and deficit of electricity [40]. As a result, the price zones have been created. The different prices are a direct signal of electricity surplus or shortage aiming to help even out the imbalances [41]. In areas with excess electricity generation, prices are often lower to facilitate consumption and industry. In zones of shortage, prices would typically be higher to restrict consumption [41].

The price zones in Norway are shown on the map in Figure 2.2. In Norway, the northern and western areas typically have a lot of hydropower and a smaller population, while on the other hand, the south-east (NO1) has a bigger population and little power production. This leads to cheaper electricity in the north and west compared to the southeast [40].

As established, electricity prices differ between zones as a result of the expected power balance in each zone and the transmission capacity to the neighboring zones [40]. This price is determined by the power market. When customers consume electricity, their bill mainly consist of the price for the actual energy consumption, called the spot price, and for the connection to the grid, called the distribution grid tariff [38]. In addition, the electricity bill includes electricity taxes and fees, and the power

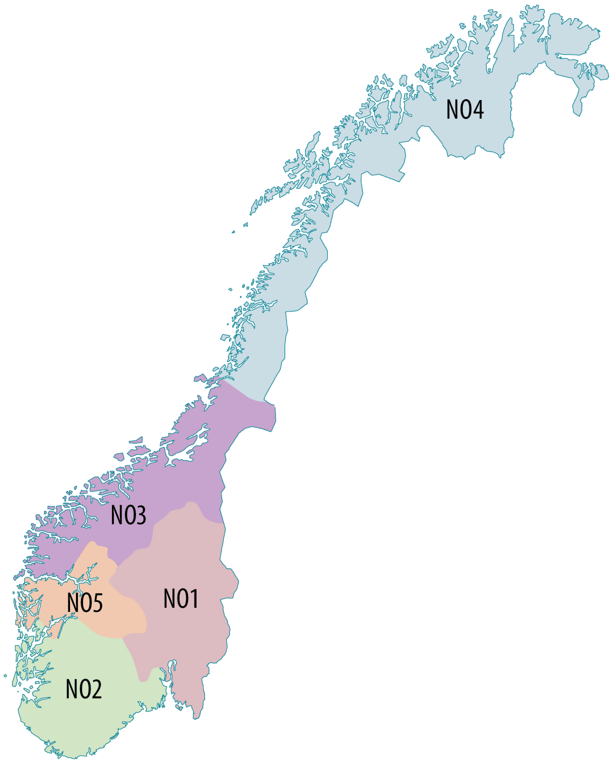

Figure 2.2: Map of the Norwegian price areas reprinted with permission [40].

supplier surcharge. How the spot price is determined will be explained in the next section "The Power Market".

The grid tariff is divided into two parts, the capacity and the energy links. The price of the customers' capacity link is determined by the average of the three hours with the highest consumption in the previous month [38]. These three values must be of three different days. The result is that the more power the customer demand from the grid at a time, the higher the capacity link is. The energy link is determined by the time of consumption and the amount of energy the customer consumes. For example, it is often the cheapest way to consume electricity at night [38].

This electricity pricing incentivizes the customer to keep their peak demand low to avoid a high capacity link. The solution for the customer will be to shift and even out the consumption over time. Consequently, the demand peaks will decrease, and potentially decrease the need for reinforcing the grid [38]. This is an example of indirect load control, which was explained in the Introduction.

2.1.4 The power market

In Norway, electricity trading is market based. The market is split into an end-user market and a wholesale market. In the end-user market, the consumer chooses a power supplier to buy their electricity from [34]. In the wholesale market, European electricity producers and suppliers can trade electricity with each other. This European market is called SDAC (Single Day-Ahead Coupling) [42]. The wholesale market consists is divided into three. One of those markets is the balancing market [43], which will be explained in greater detail in the next section. The other two are the day-ahead market and the intra-day market. In the day-ahead market the power supplier offers electricity production, and together with the expected demand, the spot price for the next day is determined in every zone. However, the actual consumption and delivered production might differ from what was predicted when the price was set the day before. In that case, the intra-day market is used to trade electricity continuously [43, 35].

The spot price determined in the day ahead market represents the expected situation of grid. In the morning and afternoon when consumption is usually high [38], the more expensive energy production might be needed to meet the demand. This would cause the spot price to increase. On the other hand, the spot price during the night will typically be low because only the cheapest energy production would be needed [43]. Consequently would the cost of different power production also affect the spot price.

The Balancing market and reserves

In the balancing market the TSO can buy flexibility to ensure instantaneous balance between production and consumption in hours of unexpected disturbances [34]. Flexibility can come from increasing or decreasing both production and consumption. The balancing market is divided into four main groups of reserves [44], see figure Figure 2.3. Within each of the four reserves, bids of increasing or decreasing production or consumption are offered. The bids must meet the specific requirements for each reserve. The Fast Frequency Reserve (FFR) is the first group of reserves to be activated when bigger imbalances occur. The FFR is activated to prevent the frequency from dropping below $49Hz$ [45]. The reserves in the FFR need to have an activation time within 0.7-1.3 seconds and stay active for 5-30 seconds. The Frequency Containment Reserves (FCR), also called primary reserves, need to be activated within 30 seconds as an automatic response to a change in frequency [46]. This group of reserves have a minimum duration of 15 minutes. The last group of reserves to be activated is the automatic and manual Frequency Restoration Reserve, aFRR, and mFRR respectively. The minimum volume size of bids in the aFRR market is $1MW$,

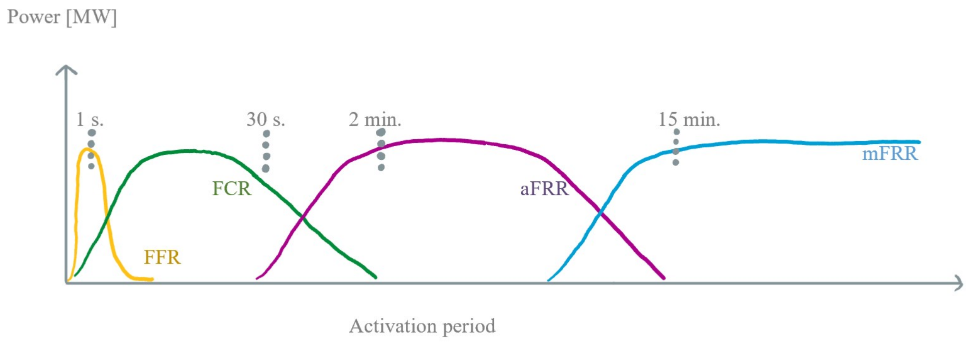

Figure 2.3: Model of the four flexibility reserves FFR, FCR, aFRR and mFRR, with their activation period based on [35].

and the response time is two minutes. The aFRR is automatically activated and aims to bring the system back into balance. When aFRR is activated, the frequency return to normal levels and the FCR ceases[47]. The mFRR can be activated when there is an additional need to handle imbalances or congestions in the grid [48]. The minimum volume of the bids in the mFRR is $5MW$ in NO1 and NO3, and $10MW$ in NO2, NO5 and NO4. The reserves in the aFRR and mFRR need to be activated for as long as the bid period lasts. As figure Figure 2.3 shows, the reserves have a span from 1 second to 15 minutes activation period. The reserves with shorter activation period are active for a shorter amount of time, while the reserves with longer activation period are activated for longer periods. Having enough flexible resources in all of these reserves is crucial for the TSO's ability to keep the grid in balance. This emphasizes the need for more research on flexibility that meets the requirements in the different reserves.

For aggregators the strict requirements of the bids can be hard to meet. The volume size, response time and duration determine in what reserve the aggregated flexibility can be offered. To be able to exploit more of the available flexibility these requirements might need to be changed. For example, in a pilot project where aggregators offered consumer flexibility into the mFRR market the minimum bid size was lowered. This pilot will be further discussed in section 2.2.4 [49].

2.2 Consumer flexibility

As stated in the introduction, flexibility is the potential to change consumption over time [21]. For instance, flexibility can be activated by temporarily pausing an industrial process, or, as this thesis investigates, controlling when customers charge their EVs and use their electric heating systems.

2.2.1 Household flexibility

Degefa et al. defines household flexibility as a load that can "change its consumption profile without significant change in efficiency or convenience" [50]. Household flexibility is the flexibility achieved by moving or reducing the consumption of appliances and loads in a household. This will be elaborated later in this section. Most households share a common consumption profile built up by different loads.

Figure 2.4 represents a typical household consumption profile. The consumption is low during the night and at typical work hours, with two peaks, one in the morning and one in the afternoon. This profile is as mentioned the aggregation of consumption for space and water heating, cooking, light, washing appliances, entertainment and more. According to Elvia, a Norwegian DSO, in an average Norwegian household, 60% of the consumption comes from space heating, 15-20% from water heating, 15% from electrical appliances and 10% from light [51]. This distribution applies to the total yearly production. During the coldest months more electricity is used for heating and light than it would during summer. After the introduction of the EV, the consumption profile changes. Consumption increases in hours of charging, usually beginning in the afternoon or early at night and continuing into the night as the orange dotted line in Figure 2.4 shows.

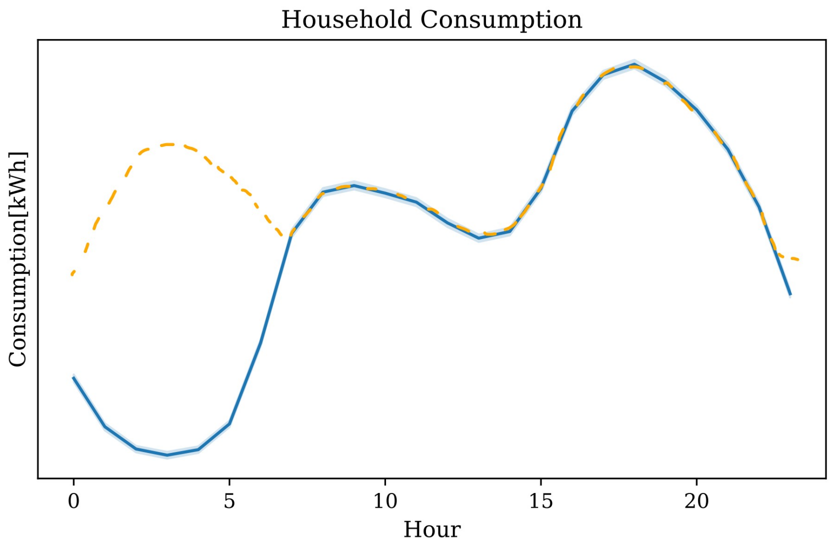

Figure 2.4: Example of two household consumption profiles without (blue) and with (orange) an EV.

All types of loads can be considered flexible in the sense that they can be turned off. Nevertheless, some loads are more suitable for flexibility purposes than others. Larger loads that are convenient to control are usually of the most interest. In Table 2.1, a collection of examples is listed. The type of load is marked with a ✓ if it is covered in the thesis.

Table 2.1: List of some household loads with potential as a source of flexibility.

Load	Included in thesis
Electric vehicles	✓
Solar cells	×
Ventilation	×
Batteries	×
Electric water boiler	✓
Electric space heating	✓
Electric space cooling	×
Dryers	×
Washing machines	×
Dishwashers	×

Due to the limited use of solar cells, ventilation, cooling systems and batteries in Norwegian households, they are not included in this research. However, solar cells and batteries are increasingly popular and will be relevant for future research. Smaller appliances such as dishwashers, washing machines, and dryers are also considered flexible loads, but with a smaller potential [30], and are consequently not included. EVs and electric heating are both common and large loads, thus these will be the primary focus of this thesis.

The charging of an EV and electric heating are loads that can be turned on and off at any time, different from a washing machine that stays on for a set amount of time when started. This allows for constant availability when the load is connected. When using electric heating and charging EVs as a flexible resource the comfort and convenience for the user should be prioritized [30, 21]. Having a fully charged car in the morning or keeping a comfortable indoor temperature is a requirement for most customers. This requirement restricts the availability, but might be a criterion for consumers.

As established, if consumers want to exploit their flexibility, they can shift or reduce their consumption [52]. Figure 2.5 shows an example of a non-flexible consumption curve and a flexible consumption curve. Load shifting is the result of a customer moving their electricity consumption. Two examples could be to charge the

EV at night instead of in the afternoon or schedule the dishwasher to start in the middle of the day. Peak shaving occurs when a consumer reduces consumption in typical peak hours. The total energy remains unchanged, thus the reduction of energy in peak hours is distributed outside the peak [52]. A household could also lower its peaks by reducing its energy demand. This is not demonstrated in Figure 2.5.

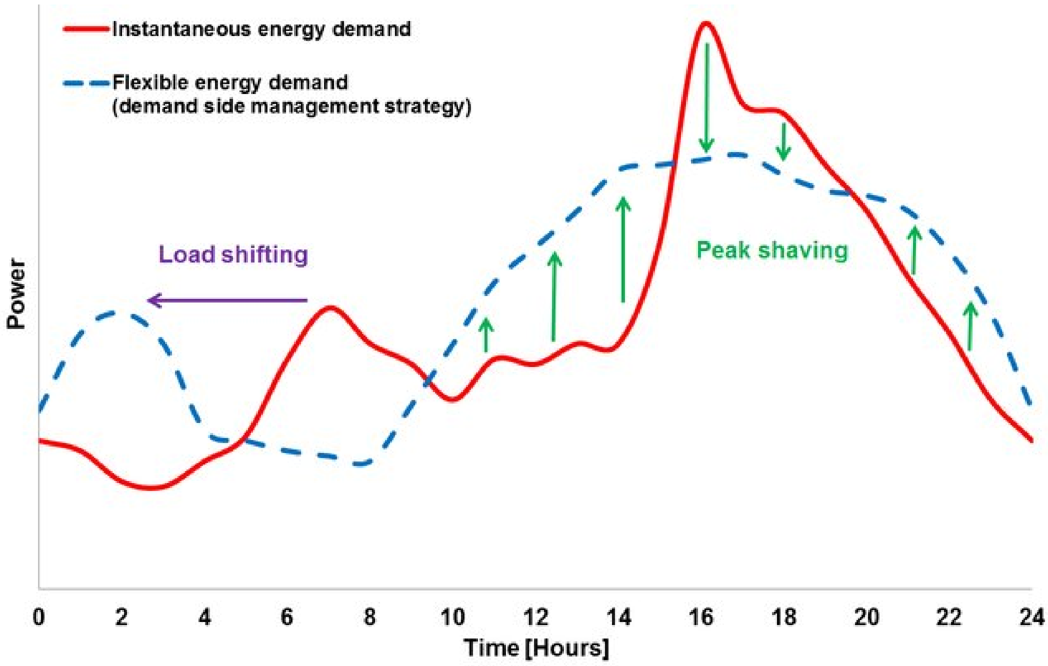

Figure 2.5: An example of a normal consumption curve (red) and a consumption curve with flexible consumption (blue). Reprinted from [52].

2.2.2 The electric vehicle

The absolute first EV was made in 1832, but it was not until 2010 Nissan launched the LEAF marking the beginning of a rapidly growing EV market [53]. Despite generally using the term EV, it is worth mentioning that the term often covers both battery electric vehicles (BEVs) and plug-in hybrids (PHEVs). The BEV is the type of electric vehicle studied in this thesis. Since 2013, the range and battery sizes have increased and a number of new EV models from different brands have been launched. Table 2.2 shows a selection of different models. The year of launch, battery size, and driving range are included.

Table 2.2: A list of a small selection of electric vehicle models with the yea they were launched, they battery size and their driving range. Data collected from [54].

Year	EV	Useable Capacity $[kWh]$	(Real) Driving range $[km]$
2010	Nissan LEAF	22	125
2012	Tesla Model S 60	62	345
2013	BMW i3 60 Ah	18.8	115
2014	Volkswagen e-Golf	20.5	130
2017	Kia Soul	30	170
2018	BMW i3 120 Ah	37.9	235
2019	Audi e-tron 55 Quattro	86.5	365
2019	Tesla S Long Range	95	525
2020	Nissan LEAF e+	59	345
2021	Kia EV6 Long Range 2WD	74	410

The table shows that the size of the battery and the driving range are increasing. Looking at the LEAF, Nissan increased the size of the battery by almost 260% over the course of 10 years. The Tesla Model S has almost doubled its battery and increased its range by more than 100km from 2012 until 2019 [54]. This table just shows a small selection of the available EV models and provides some insight into the evolution and characteristics of some EVs.

As presented in Figure 2.6, the number of electric vehicles in Norway has increased exponentially. This is a result of incentives introduced by the Norwegian government already in the 1990s [55].

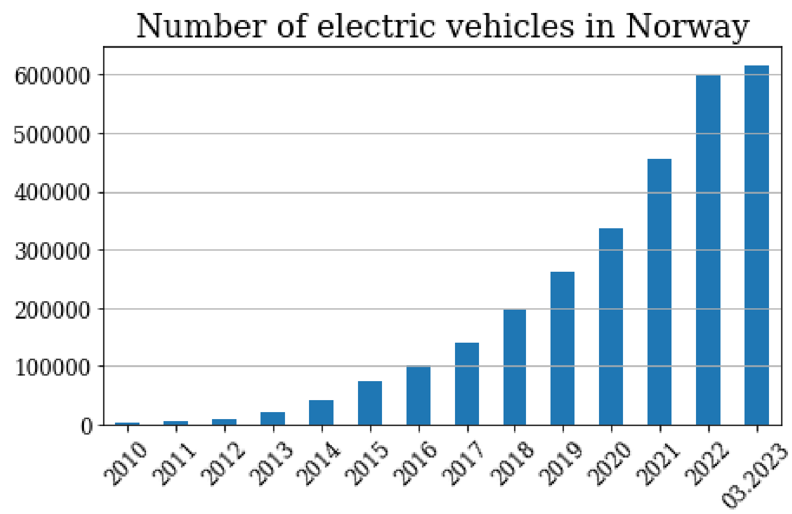

Figure 2.6: A plot of number of EVs in Norway from 2010 until March 2023 based on [14].

Among other benefits, the EV was exempt from taxes and fees related to purchase, tolls / road fees, parking fees, and the EV was allowed into the bus and taxi lane. This has led Norway to become the country with the most EVs per capita [56, 55]. In addition, low electricity prices have also motivated people to purchase an EV.

Components of an electric vehicle

To understand the characteristics of the EV, a visual representation of its main components is included in Figure 2.7.

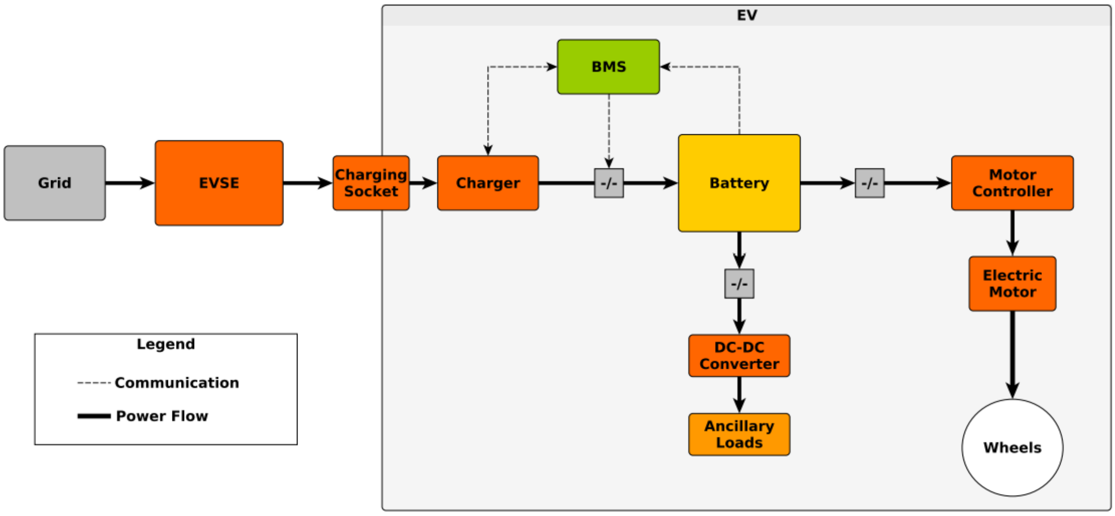

Figure 2.7: Reprinted illustration of the components of the BEV. The green square is a controller, the red-orange squares are power electronic components. The yellow square is the battery and the gray square (except the grid) is safety breakers. Reprinted from [57].

The light grey large square represents the EV itself, with the components inside. The charging socket connects the EV to the Electric Vehicle Supply Equipment (EVSE) [57]. The EVSE is the box on the wall often mistaken as the charger. This box is what connects the electric vehicle to the rest of the grid. The grid feeds the alternating current (AC) to the EVSE. The thick black lines between the squares represent the flow of power, while the gray dashed line represents the communication between the components [57]. Some of the components are explained in greater detail below [58].

- The EVSE communicates with the charger that is located inside the EV. It controls the current supplied to the EV and checks that the charger is safely connected before initializing the flow of power. For the safety of the EV, the EVSE can also stop the charging if necessary [57].

- The charger receives AC current and converts it to direct current (DC) which is then supplied to the battery. The charger also communicates with the battery management system (BMS).
- The BMS controls the current, voltage, temperature and state of charge (battery level).
- The DC-DC voltage converter lowers the voltage supplied to the battery so that it can be utilized in other parts of the EV.
- The low-voltage DC supplies ancillary loads in the EV, like radio, heat and other accessories.
- The motor controller controls the energy going to the motor for the torque and speed it needs to deliver.
- The electric motor uses the energy to move the wheels. When the EV is breaking, the electric motor generates AC, which is then converted and supplied back to the battery.

Charging process of electric vehicles

The EV can be charged in different ways. It can be charged at a commercial charging station or at home. As much as 80% of all charging happen at home, 15% at semi-public charging stations (e.g. at work) and 5% at commercial charging stations [17]. Only residential (at home) charging is considered for this thesis. The voltage level supplied by the IT or TN grid partially determines the power with which the EV charges [39]. More power for charging means the energy is transferred faster, resulting in a faster charging. The charging would then also draw a higher instantaneous demand from the grid. Table 2.3 shows some of the different charging powers. Level 1 charging is charging from straight from the socket, and Level 2 is charging from an at-home charging station. Level 3 charging is charging at a commercial charging station, and would not be possible for residential charging. The EV can be charged with both AC and DC currents. As briefly mentioned, when parts of the grid is upgraded to $400V$, the charging powers in Table 2.3 will increase. This results in a faster charging, but also higher instantaneous demand from the grid.

Table 2.3: Table of charging levels for an EV in Norway inspired by [6]. Level 1 is charging from the socket, Level 2 is charging from an at-home charging station and Level 3 is charging at a commercial charging station.

Level	**AC**	**DC**
Level 1	$2.3kW(10A, 230V)$ $2.76kW(12A, 230V)$ $3.68kW(16A, 230V)$	up to $36kW(80A, 200-450V)$
Level 2	$3.98kW(10A, 230V)$ $6.37kW(16A, 230V)$ $12.74kW(32A, 230V)$ $31.86kW(80A, 230V)$	up to $90kW(200A, 200-450V)$
Level 3	$< 31.86kW$	up to $240kW(400A, 200-600V)$

The charging power is also related to the type of cable and connector. In Figure 2.8 are the five types of charging plugs displayed, two for AC charging and three for DC charging. For AC charging, the two charging plugs are called Type 1 and Type 2. For DC charging the plugs are CHAdeMO, CCS and the Tesla Supercharger. Type 1 and 2 are the plugs used for residential charging and can deliver a maximum of $7.4kW$ and $22kW$ respectively [59].

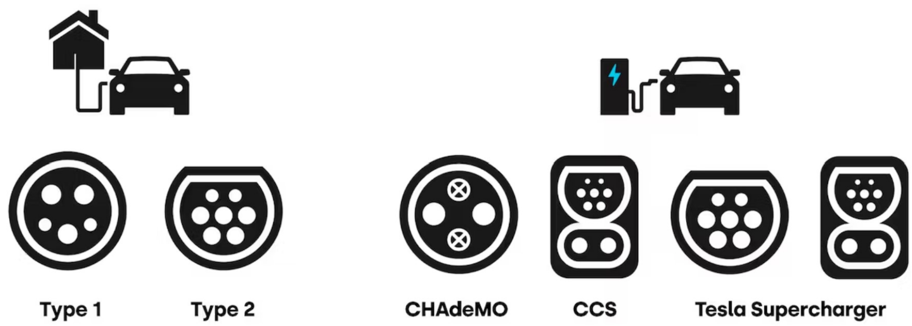

Figure 2.8: Overview of the different types of charge plugs. Reprinted with permission from [60].

The CHAdeMO, CCS and Tesla Supercharger can deliver up to $100kW$, $350kW$ and $250kW$ respectively [59, 61]. Residential charging, regardless of being Type 1 or 2, is included in the data used for this thesis.

Smart charging

There are two possible ways of exploiting flexibility from a charging EV. First, the owner can manually connect and disconnect the EV from the charging, consequently providing flexibility. However, the more user-friendly solution is by using a smart EVSE. For the rest of this thesis the term smart charger is used for the smart EVSE. The minimum requirement for a charger to be considered smart is that it has to be able to turn on and off the charging, commonly called scheduling. Some smart chargers can also modulate the charging current. In this case, the charger can decide what current is supplied to the EV. Consequently, this also determines the power the EV draws from the grid [17, 62]. Scheduling and modulation can be used to minimize the cost of charging. For a scheduling strategy, the charging can be set to start when the electricity price falls below a certain price threshold and stop when the price increase beyond another threshold. Scheduling based on price is what Tibber offers to their customers. A modulating charging strategy can adjust the current, and consequently the power, of the charging down and up. The difference between the charging powers and the duration of the modulation is what determines the volume of the flexibility [17]. Modulation of charging has a faster response time compared to the scheduling due to delays related to turning on and off the charging completely [63].

Residential EV as a source of flexibility

The flexibility of an EV comes from controlling the charge. Charging an EV at home draws powers between $2.3kW$ to $22kW$ depending on the car, the charging plug, and the grid connection [64]. Scheduling and modulation of the charging are two smart charging strategies that can be used for exploiting flexibility from EVs. For most people, the strategy of charging is irrelevant as long as the battery is fully charged when needed. This means that flexibility is available as long as the car is connected, and the connection time is longer than what is needed to reach the desired battery level.

The coincidence factor (CF) is the probability of simultaneous charging [31], and quantifies the percentage of the EV fleet that is connected for charging. This is of importance for the grid operators when they predict demand. At the same time, the CF indicates the times that EVs are connected to the grid. If flexibility is obtained by restricting the charging power of EVs the CF indicates how many EVs could potentially be available for this purpose. This flexibility could then be offered into the flexibility market. The FFR, the first reserve to be activated, could be suitable because the EV can respond fast and is more likely to be available for a shorter period of time.

To further examine EV as a source of flexibility, some of its characteristics needs to be understood. Figure 2.9 shows the efficiency of the EVs related to different temperatures. During periods of low temperatures the EV consumes more energy due to heating for the driver and the battery. Consequently, low temperatures makes the EV's battery to discharge more rapidly. Due to Norway's cold climate, this would lead to an increased need for charging in the winter. Subsequently, this means that the grid might face even higher loads, but the potential of flexibility of EVs could increase.

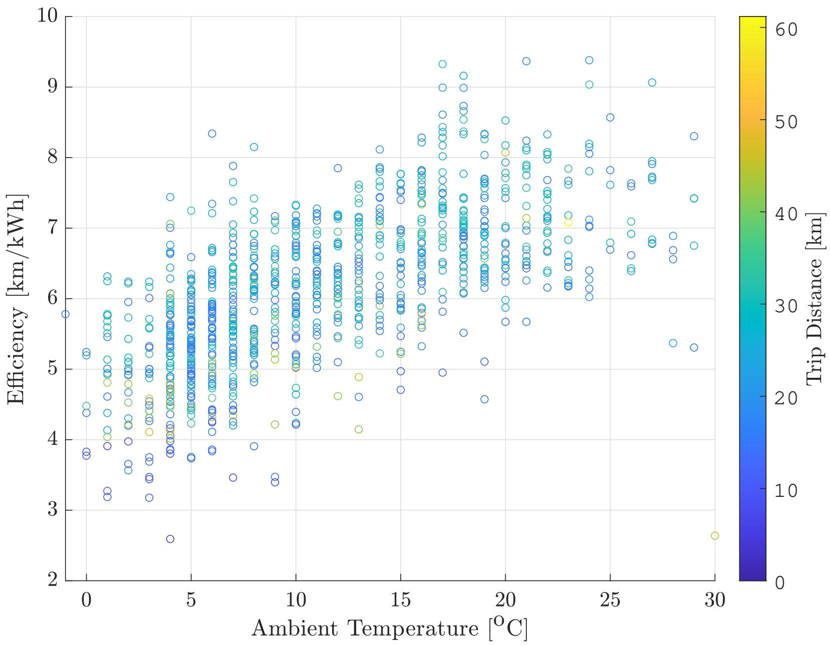

Figure 2.9: Correlation of EV battery efficiency and temperature [20].

Another way of exploiting flexibility from EVs is through bi-directional charging called vehicle-to-grid (V2G). With V2G EVs connected to the grid can act as storage (batteries). When the grid faces a deficit of power the EV can operate as a power source. On the other hand, in times of power surplus, the EV can operate as a power consumer. This concept is outside the scope of this thesis, but will likely play a role in using EVs as an advantage to the grid in the future [65].

2.2.3 Residential electric heating

Different from many other countries electric heating is common in Norwegian households, both for water and space [66, 15]. The most common source of space heating is the electric panel heater [10], often supported by underfloor cables, heat pumps and wood stoves [15]. In bigger cities district or shared heating systems for both space and water also occur [15].

A list of electrical heating sources regularly seen in Norwegian households is provided, see Table 2.4.

Table 2.4: List of the most common electrical heating sources with their consumption in $[kW]$ [67, 68, 69, 70].

Source	Power
Panel Heater	$0.5 - 1.5kW$
Underfloor cable	$60 - 80W/m^2$
Heat-pump	$1 - 5kW$
Water boiler	$1.5 - 2kW$

For households, especially apartment blocks, in bigger cities, district and shared heating systems are rather common [15]. The most usual solution for apartments is to have both district space heating and shared water heating. These systems can have either an on-site electric boiler or furnace that is used to heat the water and space in the apartments. Another possibility is the connection to an off-site source of heat [71]. This could for example be heat from burning of waste or biomass. The common factor for these systems is that the customer does not have a demand for space and water heating, or one of them on their own electricity meter. Their measured electricity demand is from cooking, light and other appliances. Comparing consumption profiles of households with and without electric heating as a part of their consumption could potentially indicate what time of the day the heating is in use. Comparing the size of consumption could also show how much electricity is actually used for heating purposes.

Heating as a source of flexibility

The thermal inertia of air and especially water makes it possible to exploit heating as a source of flexibility [10, 72]. When turning off or down the source of heat the temperature would still remain close to the initial temperature for some time, due to its thermal capacity. This would be the window of flexibility.

Due to Norway's climate, heating is a big part of the residential consumption [10]. Naturally consumption is higher during colder periods meaning the consumption and temperature is negatively correlated. As demonstrated by Sidqi et al., space heating is negatively correlated with temperature while water heating consumption is more even throughout the year. Although the outside temperature is low the consumption for water heating does not change much. This would mean that flexibility from water heating would stay pretty constant over the seasons while flexibility for space heating varies more with season [21, 49]. The potential for flexibility related to electric water heater would change more over the course of a day, related to when the household consumer hot water.

Turning off electric heating could raise an issue called the rebound effects. A study with direct load control of electric water heaters in Norway shows that disconnecting the load can contribute to reduce consumption peaks, but may create a new peak when turned back on [26, 21]. According to Sidqi et al. the rebound effect increases when the off-time increases [21]. If the electric heating is turned on again gradually or at a time with generally low consumption, this rebound effect might not cause a significant problem. The rebound effect still needs to be considered when exploiting flexibility from electrical heating.

Many Norwegian households have more than one source of heating, often referred to as a "multi-energy" system. Especially interesting is the combination of electric and non-electric heating. For the coldest days, electric heating can be supplemented or substituted with non-electric alternatives, like wood stoves [8]. This would free up consumption and avoid the highest peaks, and thus providing flexibility to the grid.

2.2.4 Flexibility potential

Independent of source, the flexibility of a household can be exploited both explicitly and implicitly. Explicit flexibility is a change in consumption that consumers actively offer to the balancing market, often through an aggregator [10]. The role of an aggregator is explained in the next paragraph. Implicit flexibility is the consumers reaction to the electricity price. High prices could motivate a consumer to cut or move consumption, consequently exploiting their flexibility [73].

An aggregator is a third-party operator that aggregates the flexibility of a number of households with the goal of offering flexibility to the balancing market [74]. The aggregator can acquire flexibility by activating and deactivating consumption remotely, following constraints set by the user. Tibber is an electricity company in Norway that offers smart control of different loads like EVs and hot water boilers. Tibber can move the charging of an EV or move the consumption of heating to hours with low electricity prices and can therefore operate as an aggregator [75]. With Tibber, the customer can potentially lower their electricity bill at the same time as more flexibility can be used in the balancing market. Customers of Tibber also have the option to alternate between letting Tibber control their loads or not.

In 2021 Statnett conducted a pilot for two aggregators (including Tibber) to offer explicit household flexibility in NO1 [49]. The minimum bid size was reduced to $1MW$ for the pilot period and the minimum bid duration was $1h$. Aggregators managed to deliver the full size of their bid several times. In total $12MW$ was offered to the market and $7.95MW$ was delivered. Despite some bids not being delivered the pilot showed that it is possible to exploit aggregated household flexibility in the mFRR [49]. To be able to fully utilize household flexibility in the balancing market, prediction of the size of the bids need to be reliable. Without a reliable delivery of the whole bid size, the partial activation could cause new issues for the grid operators. This may limit the system operator's desire to activate these bids.

As mentioned, flexibility can also be exploited implicitly. Statnett is currently running a project called iFleks where the implicit flexibility from customers is studied [73]. In this project consumers response to price signals is investigated to see if and how households change their consumption. The goal is to be able to predict how flexible the household consumption will be depending on price. This prediction is important for Statnett's evaluation of grid reinforcements and design [73]. Another way of exploiting household flexibility implicitly is with smart-home technology. Smart solutions, like FutureHome, provide systems of smart control over loads in the household. Underfloor heating, water boilers and more can be connected to the system, and user settings can help manage the loads as the customer prefer [76].

Chapter 3

Method

3.1 Data

The household consumption data used in the thesis originate from two separate sources. From the first source, Tibber, the data was used to look at the charging of EVs, both for smart and normal charging. The second data set belongs to the iFleks project and was used for exploring electric heating. Both data sets were provided by Statnett.

3.1.1 Tibber data

The data set from Tibber includes 1140 households owning an EV from Tesla. The data runs from November 2020 to March 2021. The households are clients of Tibber with smart chargers Tibber can control remotely. In addition to hourly household consumption in $[kWh]$ the data set consistently includes the household's price zone, city, heat source, residence size $[m^2]$, number of residents, annual consumption, and signal if the smart charger is active. The price zones in which the 1140 households are located are presented in Table 3.1.

Table 3.1: Table of the geographic distribution of the 1140 households in the Tibber data set.

Price zone	Number of households	Share of total number of households$[\%]$
NO1	690	60.5
NO2	88	7.7
NO3	186	16.3
NO4	98	8.6
NO5	78	6.8

Examples of the values for each feature are included in Table 3.2. The features City, Type, and Built year was not used for any computations. The spot price within the Tibber data set was erroneous and was not used for the analysis. Only 216 households have hourly data from the EV charger in kWh. Even fewer had data for power (measured in the car) in kW. These values of power was measured at a random second within each hour. By that reason, this feature was only used when exploring the data. The smart charging status indicates whether Tibber can control the charging or not. This feature is either "Active" or "Not active". The smart charging status is measured hourly and can be turned off and on by the customer. The data set does not include information about the size of the EV battery or the maximum possible charging power. The latter can be derived from the official production values from Tesla (the majority are 16 A three-phase).

Table 3.2: Table of features from the Tibber data set with examples.

Feature	Example
id	ID_111
City	Bodø
Price zone	NO4
Spot price	191.12
Type	active energy
Timestamp(UTC)	2021-03-31 19:00
Consumption[kWh]	1.726
Annual consumption	22395
Built year	1998
Heating source	Air2air Heatpump
Persons	4
Size	155
Energy (from charger)	$5kWh$
Power (from car)	$7kW$
Smart charging status	Active

3.1.2 iFleks data

The data set originating from the iFleks project consists of hourly consumer data in kWh from 2043 households. The geographic distribution of customers is presented in Table 3.3.

Table 3.3: Table of the geographic distribution of the 2043 households in the iFleks data set.

Price zone	Number of households	Share of total[%]
NO1	1010	49.4
NO2	86	4.2
NO3	166	8.1
NO4	595	29.1
NO5	186	9.1

The iFleks data set includes temperatures and spot prices for every hour. All the features are displayed in Table 3.4. The data runs from December 2020 to March 2021. The price signal and experiment price have not been used in the analysis. For that reason, examples for those features are not included. The different temperatures in the list are the current temperature, and average for the last 24, 48 and 72 hours in that order. The "temperature24" is the one that has been used when working with this data set. This data set provided correct spot prices, which were used for the analysis. Supplementing the data are answers from a survey issued to the participants. The survey consists of a large number of questions where information about charging of EVs and sources for space and water heating have been used in this thesis.

Table 3.4: Table of features from the iFleks data set with examples.

Feature	Example
id	-
Date	2020-12-01
Hour	1
Consumption[kWh]	0.48
Price Signal	ID_999
Experiment price	-
Temperature	4.2
Temperature24	6.4
Temperature48	6.3
Temperature72	5.7
Spot price [NOK/kWh]	0.13891

3.1.3 Spot price and temperature

Hourly electricity prices and temperatures were retrieved and used with the Tibber data set. This data was gathered from Nordpool [77] and the Norwegian Climate Center [78] respectively. The spot prices were given for all the Norwegian price zones. When finding the temperature, the "Air Temperature" was the parameter chosen for the period from November 2020 to March 2021. The temperatures were measured at the weather station in Blinderen in Oslo, named SN18700. Due to the fact that most of the households are located in the NO1 price zone, the temperature was only gathered from this single location.

3.2 Method

The data processing and analysis were performed with Python version 3.8.8. The Pyhton code for the method can be found in Git [79]. First, the method for the Tibber data set is presented with two diagrams. Following is the method for the iFleks data presented with one diagram. It should be noted that the order of the steps in the diagrams is not the same as the order in which the results were made.

The process behind the results from the Tibber data is represented in Figure 3.1 and Figure 3.2. Starting with Figure 3.1, in the first step (1.) the customers in the Tibber data set have been grouped in two different ways.

From the first box to the left (1.1) in Figure 3.1 the households were separated into groups by filtering each hour according to the status of the smart charging. Using this approach, the same customer can appear in both groups in different hours. These two groups were used in three different ways; see paths (A, B, and C) in box 1.1. First, in path A) the two groups were plotted against each other. Secondly, the groups were separated into each of the price zones. Zone NO1, which includes the Oslo area, was selected because it is the zone with the most customers. Still in path B), the average consumption of customers with smart charging in NO1 was then plotted against the spot price in that zone. Lastly, in path C) the data was found to have three separate hours where none of the households had smart charging activated. For those hours, the means of the previous hour and the following hour were used to compute an average that was then inserted into the data set. These three hours represent less than 0.1% of the total number of hours in the period. In the next step in path C), the mean profiles for the consumer groups were plotted. Lastly, a t-test was performed to compare the means of the groups.

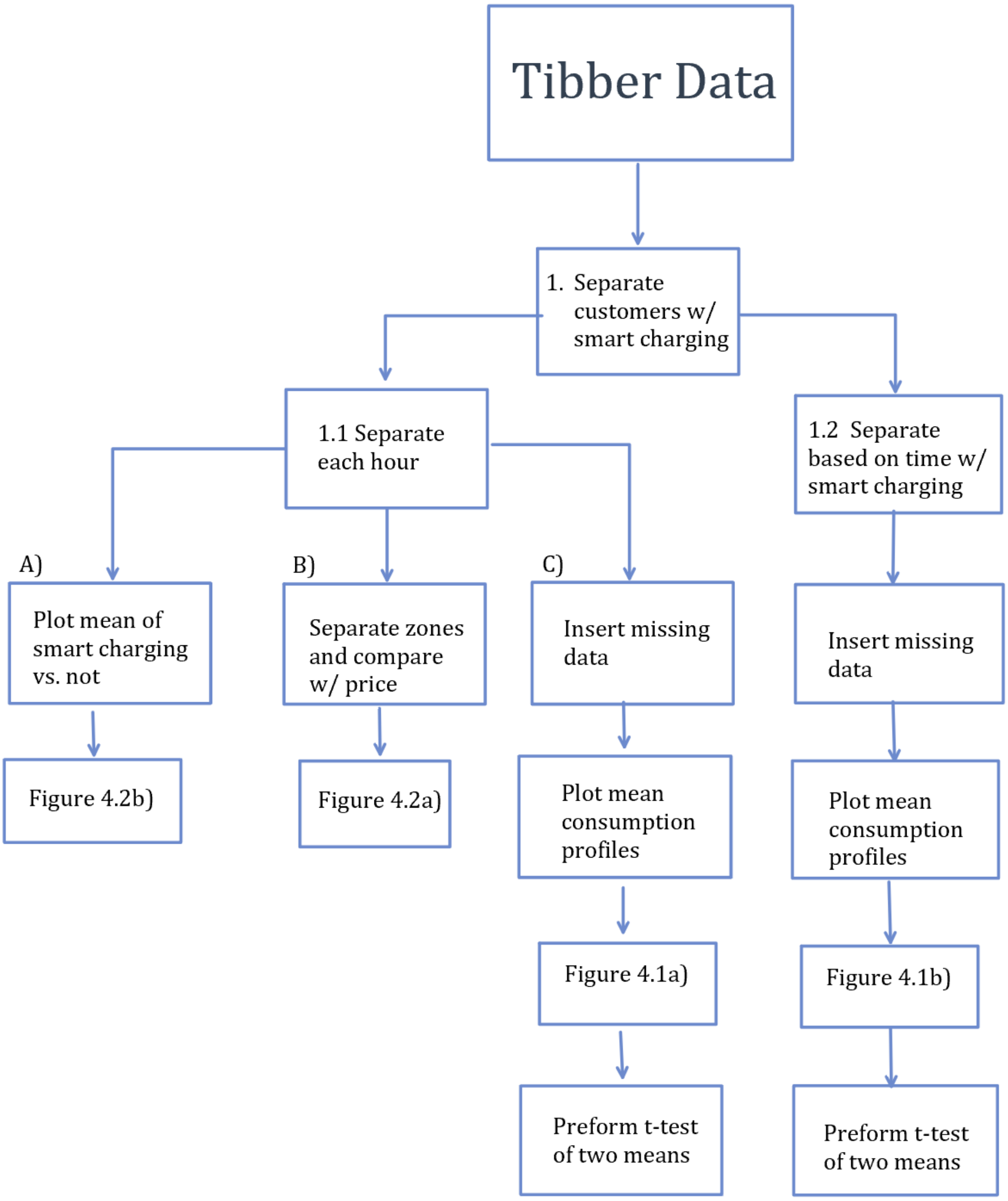

Figure 3.1: A visual representation of the process behind the results from the Tibber data set.

Going back up to box 1. and to the left path (1.2), the customers were separated with another method. This time the separation of the customers was done based on how much of the total period they had smart charging activated. For this method as well, the same three hours without any smart charging customers were inserted in the same way as in path C). The results were plotted, and a t-test was performed.

For the second part of the method behind the Tibber results, the groups of customers with and without smart charging from step 1.1 have been used.
Moving over to Figure 3.2 the charging behavior was explored. In the first step, box 2., the measurements from the EV charger were separated and further investigated. Starting with the left path (2.1) the hourly readings were used to calculate how many hours each charging session lasted and how much energy the charging accumulated. Only sessions with a duration of more than one hour were counted. Charging sessions lasting one or less than one hour were not included because this is likely charging the customer needs to have enough battery for something specific. In that case, the charging would not be flexible or relevant to include.

With the charging data from box 2., the CF was calculated for every hour of the whole period (2.2). This was done three times, one for smart charging, one for normal charging and lastly for both types. The calculation of the CF was done by summing up the number of cars with charging values over $1kWh$ for every hour and then dividing those numbers by the total number of EVs. This number was 166 for smart charging, 180 for normal charging and 216 for both. These numbers show again that the household can alternate between having smart charging and not. Consequently, customers appear in the smart charging group and the normal charging group making the sum of those higher than the total number, 216. This method will be discussed in more detail at end of the next chapter. In path A) the hourly CF was further used to make boxplots of the values for each hour of a day and over a week. Next up, in path B) the hourly CF was plotted with hourly temperatures and the spot price. As a reminder, the temperature and spot price used were gathered only from the NO1 zone because the majority of households are within this zone. Lastly for the Tibber data set the CF was correlated with the temperature as presented in path C).

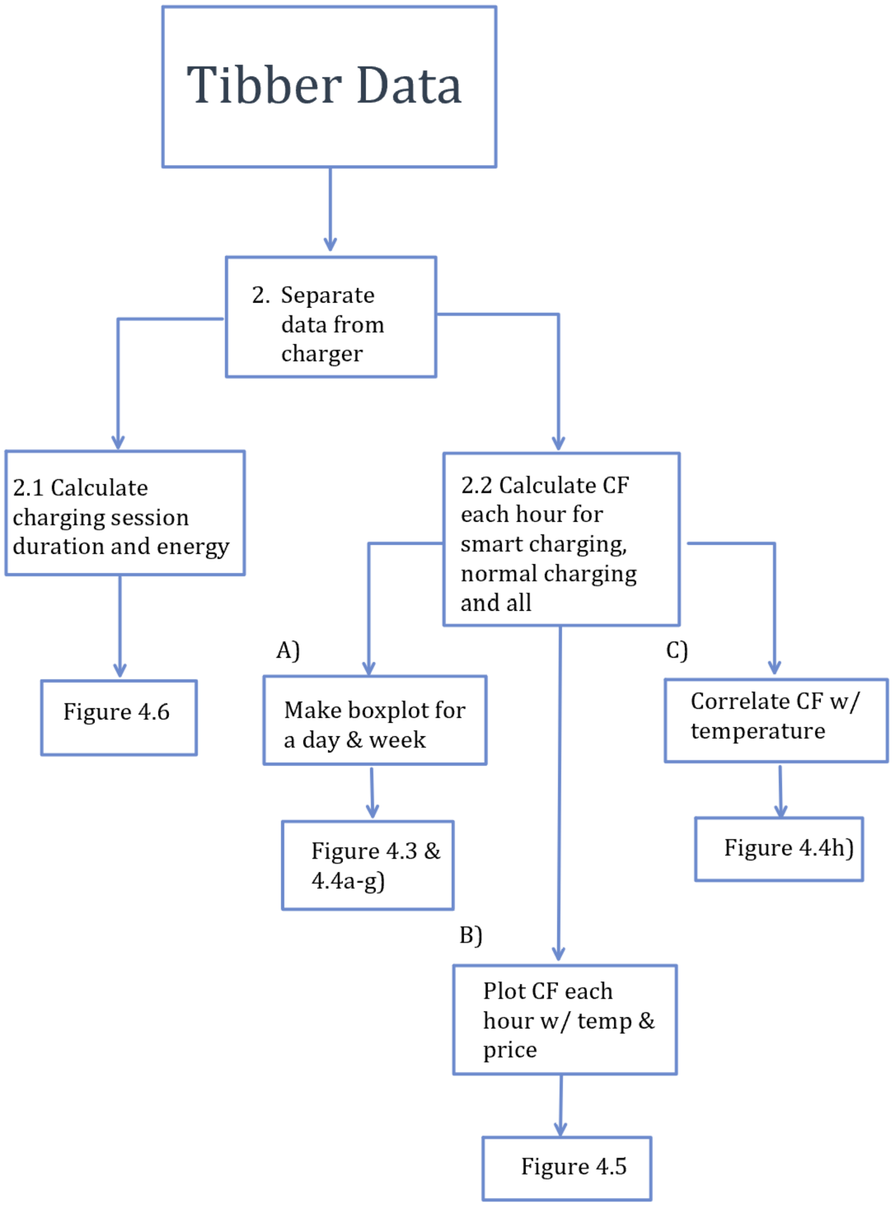

Figure 3.2: A visual representation of the process behind the results from the Tibber data set.

As for the Tibber data, a diagram for the method used at the iFleks data is presented in Figure 3.3. First, in box one, the customers who participated in the most recent part of the iFleks project were selected. This was done because of the quality of the data and a recommendation by Statnett. Firstly, at the left path (1.1) the average temperature and consumption for each hour was correlated and plotted.

Secondly, in 1.2, the iFleks customers were divided into groups based on their heating sources The four groups were "District space heating", "Electric space heating", "Shared water heating" and "Water boiler". The data used to divide the groups was from the survey. The number of customers in each group is presented in Table 3.5. Following path A) the average consumption over 24 hours was calculated for all groups. For comparing the means of the groups a statistical t-test was performed.

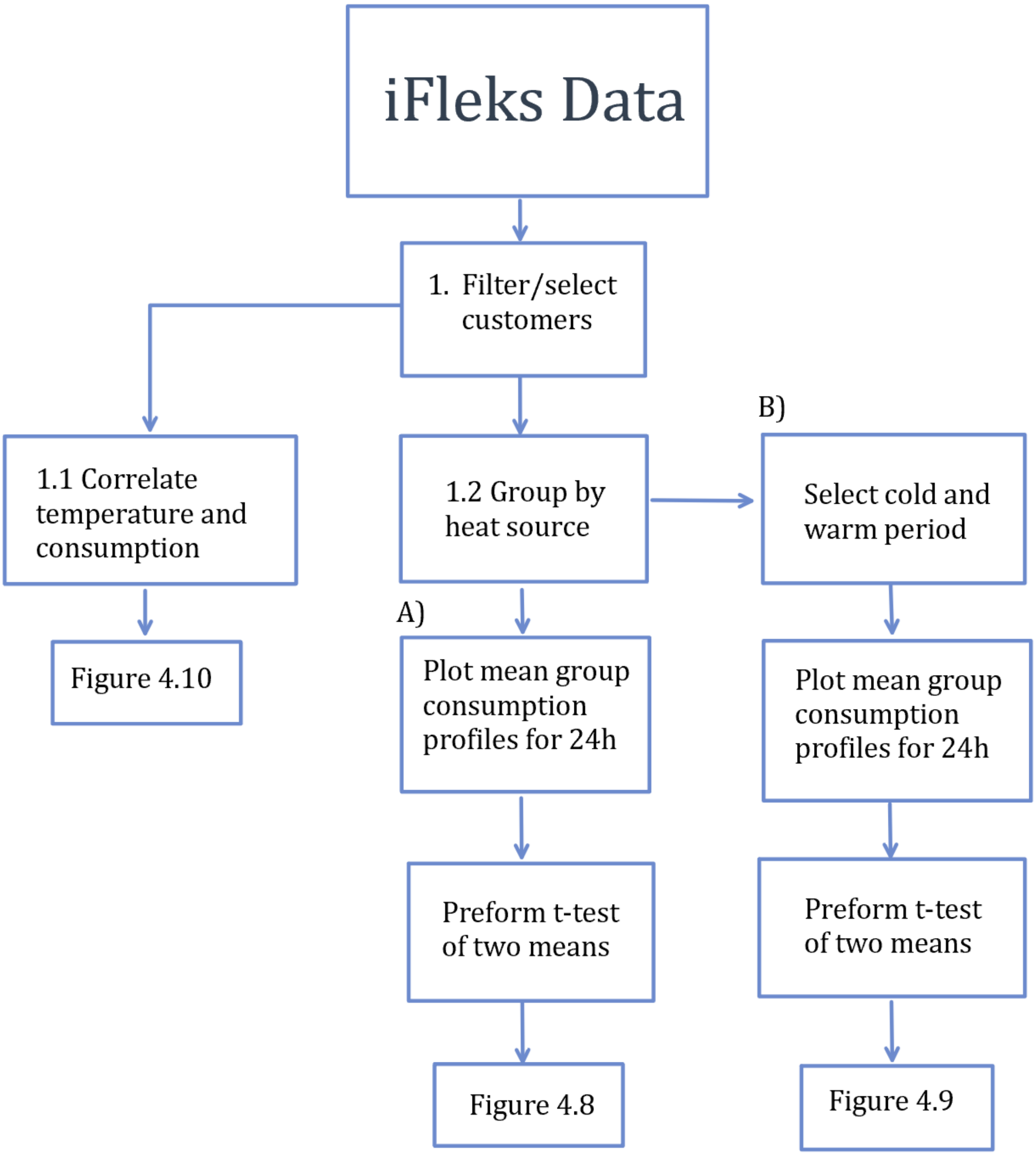

Figure 3.3: A visual representation of the process behind the results from the iFleks data set.

For the last path, B), the variation in temperature was explored by calculating the mean profiles of each group for a chosen cold and warm period. The cold and warm periods chosen lasted from "2021-01-23 00:00:00" to "2021-02-20 23:00:00" and "2020-12-02 01:00:00" to "2021-12-28 23:00:00" respectively. For the two different periods, the groups' average consumption over 24 hours was plotted and compared with a t-test.

Table 3.5: Table of number of customers in each group of heat source.

Group	Number of households
Electric heaters	2740
District heating	523
Electric water boiler	2790
Shared water heater	802

3.2.1 Statistics

For the statistical hypothesis testing the scipy.stats.ttest_ind have been used. The unpaired t-tests compare the mean consumption of two independent groups of customers. A t-test tests the null hypothesis which states that the groups have identical means. If the result of the test, the p-value, is under 0.05 the null hypothesis is discarded. A for-loop has been used to do the test for all the hours. The resulting p-values have been visualized in a data frame coloring the hours discarding the null hypothesis green, see the Appendix. A similar approach has been used by Gunkel et al. to compare the means of consumer groups with an unpaired students t-test [29].

The plots of the average consumption of a consumer group include the 95% confidence interval of the group average. There is a 95% chance that the average of the total population lies within this interval. When looking at the correlation between two variables the Pearson correlation coefficient has been calculated with "pearsonr" from scipy.stats. The "pearsonr" gives a coefficient between -1 and +1 indicating the correlation. A value of 0 means there is no correlation while a positive and negative 1 implies a perfect positive and negative correlation respectively.

3.2.2 Plots

For plotting, the libraries matplotlib.pyplot, seaborn and plotly.express have been used. The seaborn.lineplot has been used to plot the mean of the groups with the 95% confidence interval of the mean. From seaborn the scatterplot has been used to show correlation between two variables. The Plotly.express.lineplot has been used to plot consumption for all hours with a feature allowing zooming into specific time periods. The histogram and boxplots were made with matplotlib.pyplot.hist and matplotlib.pyplot.boxplot respectively.

Chapter 4

Results and discussion

In the following chapter, both the results will be presented and the discussions will take place. The discussion follows consecutively after each result. The results will be presented in the order of the research questions, starting with the EV and then the electric heating. This chapter ends with a general discussion of the results and method.

4.1 Flexibility from electric vehicles

Section 4.1 covers the results from the Tibber data set. The first subsection looks at the daily behavior of the consumption and the coincidence factor (CF). In subsection 4.1.2 the results focus on weekly variations of CF. Lastly, the final subsection looks at the relations between CF and temperatures and price.

4.1.1 Daily variations

The flexibility available from an EV varies throughout the day depending on the behavior of the owner. Most people leave the house in the morning and return from work around 16.00. This leaves hours with the possibility of charging their EV from 16.00 to 07.00. For many people, the car is also used in the afternoon postponing the charging session to later in the evening.

Figure 4.1 compares the daily average consumption profile of the groups with smart and normal charging. For Figure 4.1a) the hourly values are simply separated into active or not active. This means that one household can appear in one group for one period and in the other for another period. This is due to the users' ability to turn on and off their smart chargers. In Figure 4.1b) the households are categorized into groups depending on how much of the total period they have smart charging activated.

For example, the group "$20-40\%$" is the average consumption of households that are active between 20 and 40% of the time. In subplot b) only the groups with customers that have smart charging 0-2%, 20-40%, and 80-100% of the time have been included. This is because the remaining groups with smart charging 2-20%, 40-60%, and 60-80% made the plot hard to read and did not give any additional information.

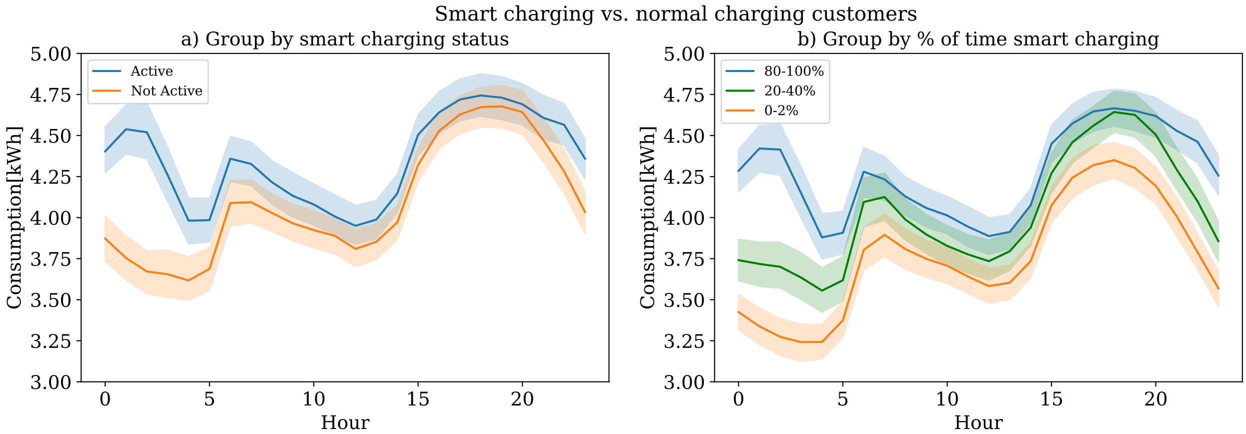

Figure 4.1: Consumption profiles comparing consumption for households with and without smart charging done with two different methods.

The two different methods of separating the customers are used to make Figure 4.1a and b). The plots show the average consumption over 24 hours including all weekdays. Independent of the method, the results show that households with smart charging activated have a third consumption peak from 00.00 to around 04.00. This has been proven with a t-test of the average consumption. The t-test yields p-values of less than 0.05 for those hours. The p-values for all the hours can be found in Figure A.1. The three groups in subplot b) has also been compared with each other with a t-test. This means that the averages of the groups are significantly different. Having smart charging from Tibber postpones the charging to later in the night. This is expected as Tibber moves the charging to hours of cheaper electricity.

In both Figure 4.1a and b), it also looks like households with smart charging have generally higher consumption. Further investigation of the groups in Figure 4.1b) shows that the households with more frequent smart charging have on average larger houses, more residents and higher annual consumption, which is presented in Table 4.1. One reason for why the bigger households with a higher consumption seem to have smart charging activated more often could be that they try to be more smart with their consumption because their electricity bill in general is larger.

When it comes to the discussion about flexibility from EVs, it is apparent that smart charging will greatly affect the time of availability of flexibility. Smart charging EVs will most of the time be available for flexibility at night between 23.00 and 05.00. This is not the time when flexibility usually is needed, as explained in the theory, but smart charging is moving the charging away from existing peaks in the afternoon. This could help prevent increasing demand peaks, and consequently prevent or postpone grid reinforcements.

Table 4.1: Mean annual consumption, residence size and number of inhabitants for groups of customers based on the percent of time they have smart charging. The size of the group is also included.

Group	Group size	Annual consumption[kWh]	Resident size [m^2]	Inhabitants
$0-2\%$	445	24698.3	162.9	3.6
$2-20\%$	87	25604.9	167.9	3.5
$20-40\%$	104	26016.8	168.6	3.5
$40-60\%$	115	27436.4	174.9	3.8
$60-80\%$	160	28543.6	177.9	3.8
$80-100\%$	229	28564.6	176.9	3.9

When further exploring the data Figure 4.2a and b) were extracted. In Figure 4.2a) the spot price and average consumption for active customers in NO1 have been normalized and plotted to see how the consumption is affected by the price. Firstly, the average consumption of the active customers shows an elevated consumption starting right after 00.00 every night. At these hours the spot price is usually low, which is also visible in the figure. This indicates an inverse relation between the consumption of active customers and spot price. During the day there are times with big variations in spot price which does not seem to affect the daily consumption considerably.

One thought that should be discussed is the effect of smart charging when the spot prices are almost the same at night and day. When the spot price is even, the customer's savings from moving the charging to the night is minimal. At the same time, many smart charging EVs might pose a problem for the grid. Consequently, a minimal saving for the customer could cause a larger issue for the grid. In these cases could offering the flexibility from the EV into the balancing market be more profitable for the customer, and at the same time benefit the grid. This could potentially increase the consumers' interest in offering their flexibility to the balancing market.

In Figure 4.2b) the average consumption of customers with smart and normal charging is presented for a selected period of time. The plot further confirms the big difference in consumption between the two groups during the night. The smart charging customers have a sharp consumption peak every night after 00.00, while normal charging customers have a consumption dip at that time. These sharp peaks are the result of smart charging. These peaks from charging are even higher than the morning and afternoon peaks. With a few EVs, the nightly peaks are not likely to affect the grid, but with a high penetration of smart charging EVs the peaks could pose a threat to the grid's capacity. Particularly in the low voltage grid, many EVs are charging in the same area can leading to an overloaded distribution station. To study the potential issues and benefits of high penetration of smart charging EVs the coincidence factor (CF) needs to be studied.

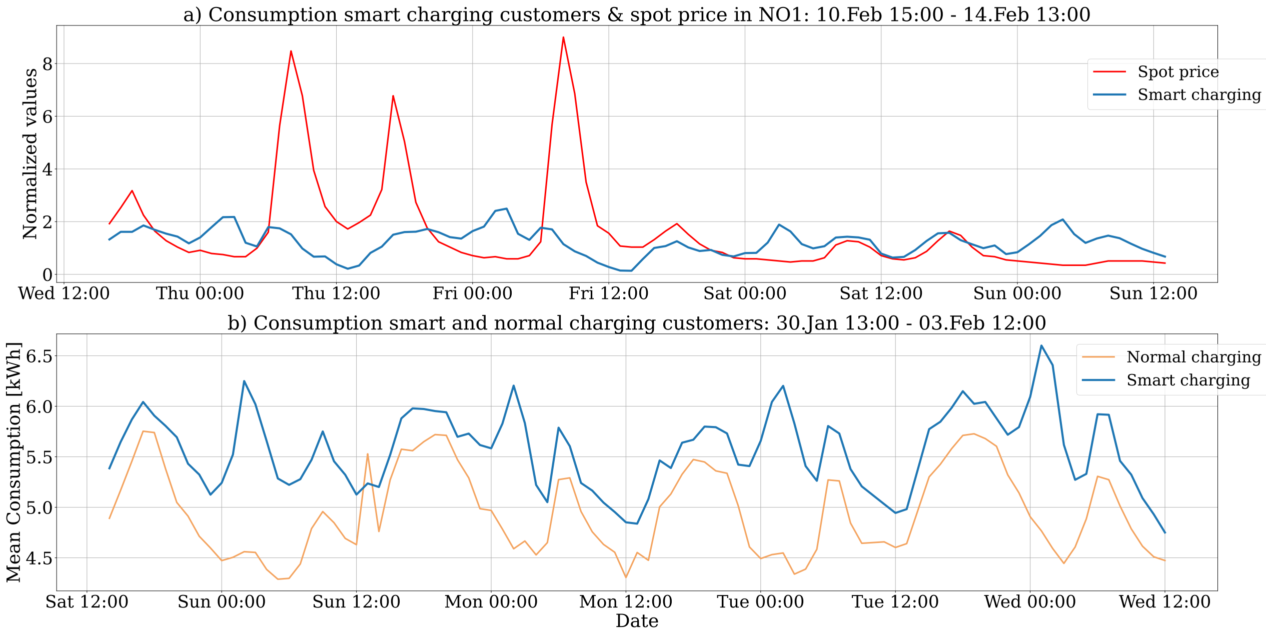

Figure 4.2: Plot a) shows prices and consumption for smart charging customers in NO1. b) shows the means of smart and normal charging customers independent of area.

The coincidence factor (CF) has been calculated for each hour in the whole period. Figure 4.3b,d and f) show boxplots of every CF calculated for each hour of a day. Subplot a,c and e) will be covered in the next subsection. The top row is plotted for CF calculated when smart charging is active, the second row originates from normal charging and the last row is from both types of charging. Starting from the top, the smart charging CF lie between $5-20\%$ during night with some values reaching over 30%. For customers with normal charging, the CFs range between $5-10\%$. Lastly the combination of both types of charging show roughly the same CFs as for smart charging. Gunkel et al.[29] have calculated a CF reaching just over 17% for EVs with normal charging. Quantification of CF for normal and prize-optimized charging in

Denmark shows results concurring with the results for normal and smart charging in this thesis. For normal charging Unterluggauer et al. found CF to lie around 5% during the peaks with outliers mainly reaching between 10-15%. For their cost-optimized charging the CF was usually between 10-15% with peaks reaching up to 30% [19]. Unterluggauer et al. have found results coinciding well with the results found in this thesis.

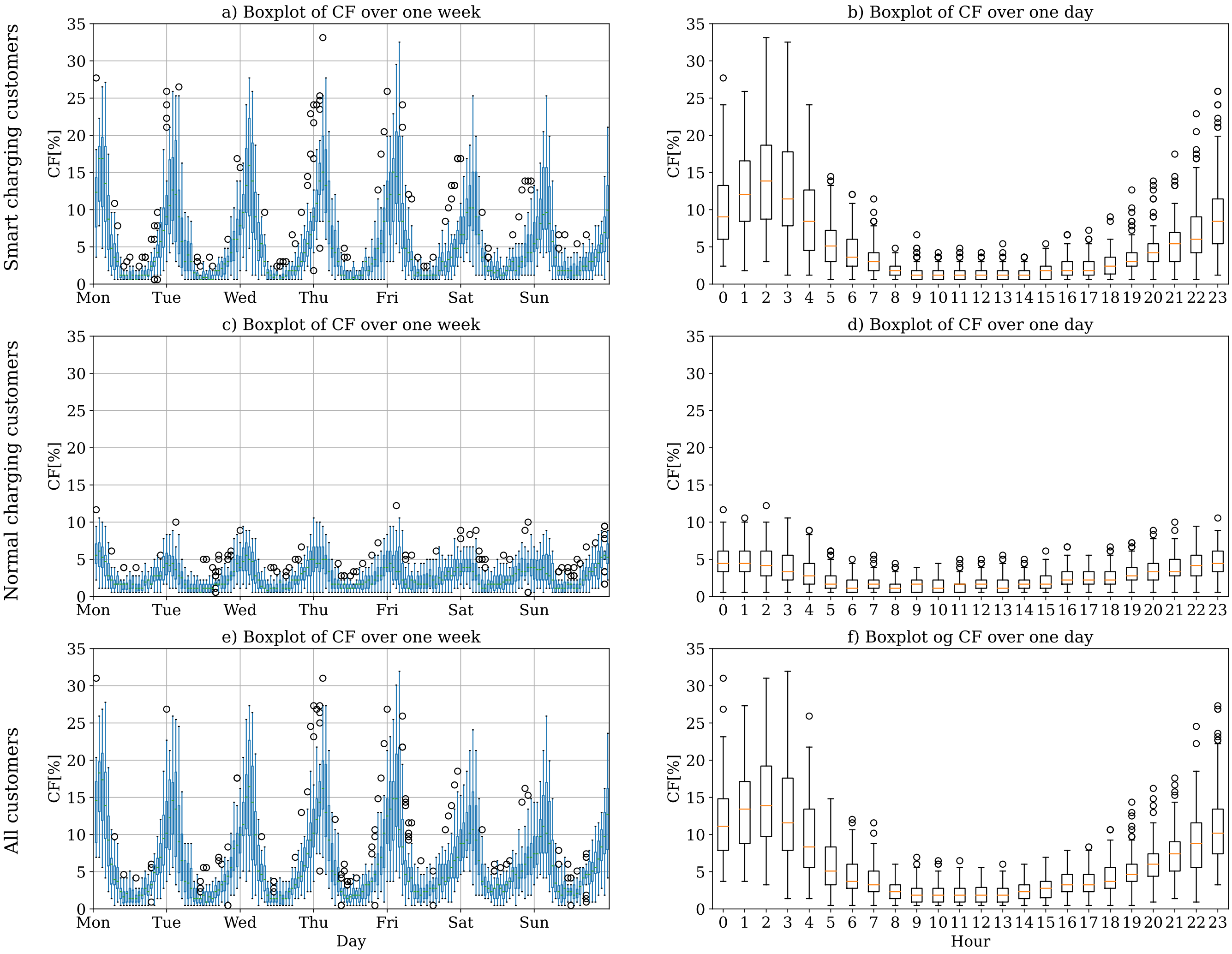

Figure 4.3: Row one shows boxplots of the CF for each hour over the course of a week. In row two the boxplots over 24 hours are plotted. The rows include smart charging, normal charging and all charging in row one, two and three respectively.

Independent of having smart charging or not the CF has a peak at night and a bigger variation of CF. As stated in the beginning of the results, evening and nightly charging is the most common due to the normal behavior of the user. For the customers without smart charging the CF is much lower and the peaks are less prominent. The combination of the results from Figure 4.1 is showing that smart charging creates a significant consumption peak during the night and Figure 4.3 is showing that up to 30% of the EV fleet might charge during the night. This can become a problem for the DSO, as stated by Bollerslev et al.[31]. Unterlagguer et al. also present modeled transformer loading for their cases of smart and normal charging. It is showing that their model of smart charging with similar CF as this case causes the load of the transformers in the case to reach over 100% at night [19].

It needs to be noted that the low CF for normal charging EVs in this thesis could be because the users can activate the smart charging when they intend to charge, resulting in fewer cars charging without smart charging, and a lower CF calculated in this case.

4.1.2 Weekly variations

Continuing to look at Figure 4.3. Subplots a, c and e) show that the CF peaks are at their highest at nights leading up to a work day, and lower on nights leading up to Saturday and Sunday. This implies that more cars charge at those nights, likely because the customers want to be certain that they have enough battery to get through their day. During weekends people might move less around and have a different driving pattern resulting in a lesser need for charging. The CF peaks during the weekend have a slight shift to the right which might be the result of getting home late and waking up late. For all plots, night to Friday show the highest CF. This could be the result of more customers wanting to go into the weekend with enough battery for social plans and errands. In general, the CF seems to be related to people's work schedules. Consequently, home-office and covid-19 restrictions would likely reduce the nightly CF peak. Bollerslev et al. also stated that range anxiety and user psychology can impact the CF, which could be part of the reason behind the observed pattern [31].

Figure 4.4a through g) show Figure 4.3e) split into each day of the week for closer inspection. With Figure 4.4e) it is easier to see that the highest peak occurs at night to Friday with CF of over 30%. At night to weekdays, the CF is around 15% with a range from around 5% to 25%. For night to weekend days, the CF is around 10% with a range from 5% to 20%. The shape of the peaks clearly distinguish the night to Saturday and Sunday from the remaining days, further confirming that user behavior related to work schedule affects the charging. Consequently, the work schedule also will affect the flexibility potential. As briefly mentioned above, home office and or events (like covid-19) changing work behavior will likely have an effect on availability of flexibility from EVs.

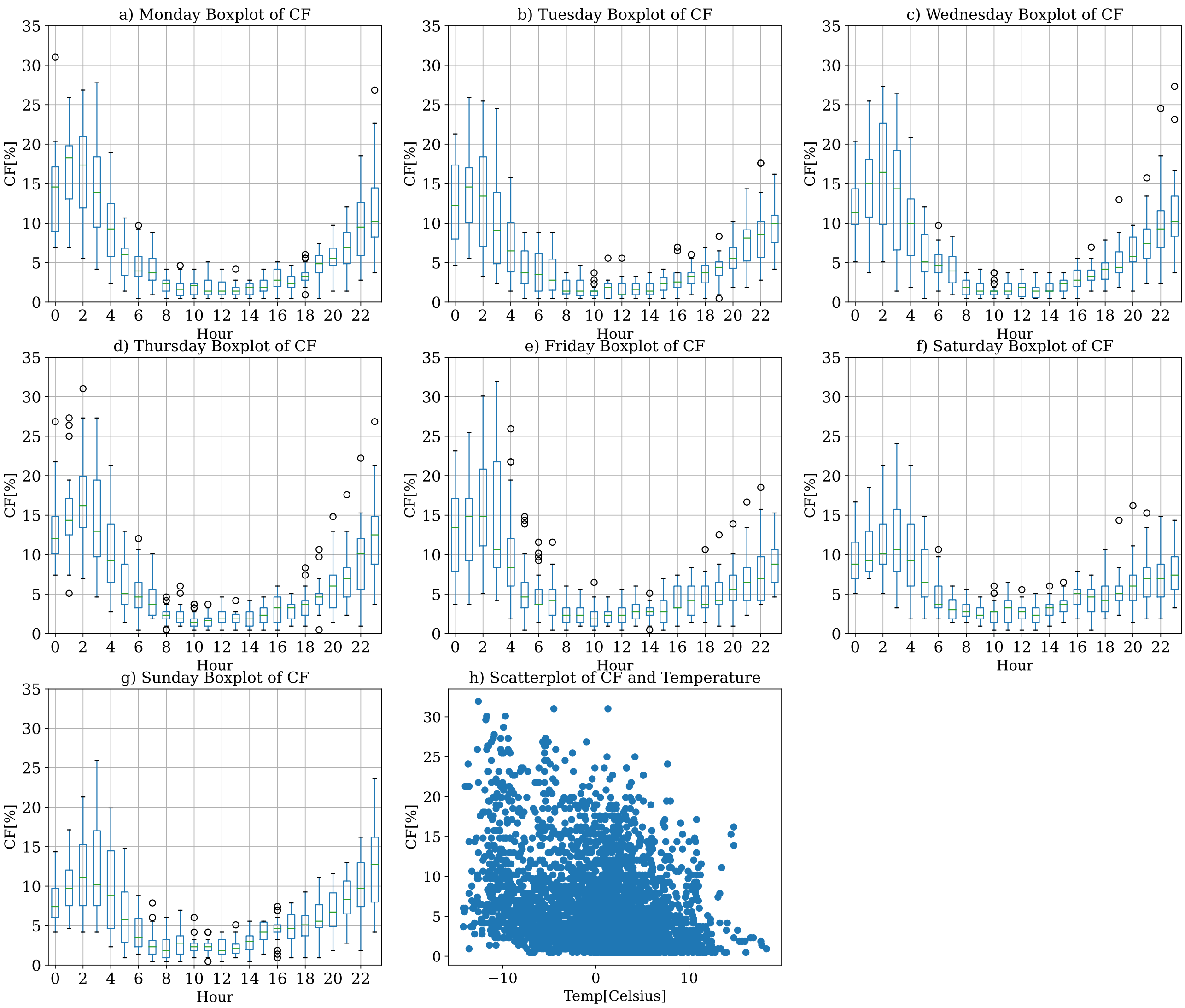

Figure 4.4: a-g) show boxplot of CF for all customers split for every day of the week. h) shows a scatterplot of CF for all customers and temperature.

Without a need for driving to work the EV would be less used, subsequently requiring less charging. In that case, the flexibility potential could decrease. At the same time, the home office would possibly open up for having more EV's connected in the daytime. This would increase the potential for flexibility during the consumption peak in the morning with for example V2G integration.

4.1.3 Seasonal Variations

Figure 4.4h) shows the correlation between CF and temperature. The "pearsonr" test gave a correlation of -0.305. A negative correlation implies that lower temperatures lead to a higher charging demand. This result is backed up by [80, 31]. This negative correlation is also visible in the plot. A higher demand for charging is also established by Andersen et al.[80]. A higher CF means that the EVs are connected to the grid more often and are available as flexibility sources. The colder months are also the periods with the highest consumption, and consequently the highest need for flexibility. In those periods the EVs would also contribute to higher demand.

The bottom plot of Figure 4.5 shows the CF and temperatures as line plots. During the two coldest periods in January and February where the orange line is low, the CF peaks increase. Even the increased temperature in the end of January is visible as a dip in the CF. This shows how the need for charging is closely related to temperature, which substantiates Figure 4.4h).

The top plot of Figure 4.5 shows the CF and the spot price in NO1. The spot price peaks increase greatly in periods, reaching $2.5NOK/kWh$. The baseline of the spot price increases during December, and even more in the beginning of January. The CF does not appear to have a strong correlation with the spot price at first glance. When looking closer at Figure 4.6 the CF peaks clearly fit the time of the lowest price, at night. This indicates an inverse correlation between CF and spot price when looking at a period of a day. Over the course of a longer period, the increase of the baseline spot price does not seem to have an impact on the CF. This is likely because the EV will need to charge at some point independent of an increased price.

The potential impacts of a high penetration of smart charging EVs in the grid is important to discuss. If the fleet of EVs in Norway reached 600000 and 50% of them start with smart charging, this adds up to 300000 EVs. As the results have shown, up to 30% of those 300000 EVs might charge at the same hour at one point. If it is assumed that the 90000 EV charge with $7kW$, this multiplied gives an instantaneous power consumption of $6.3GW$. To put this number into perspective, this is around the same maximum power demand Statnett expects from all of Oslo region in 2070 [81]. Such instantaneous power is four times more than the entire Nordic synchronous area primary reserve, which is $1.45GW$ [35].

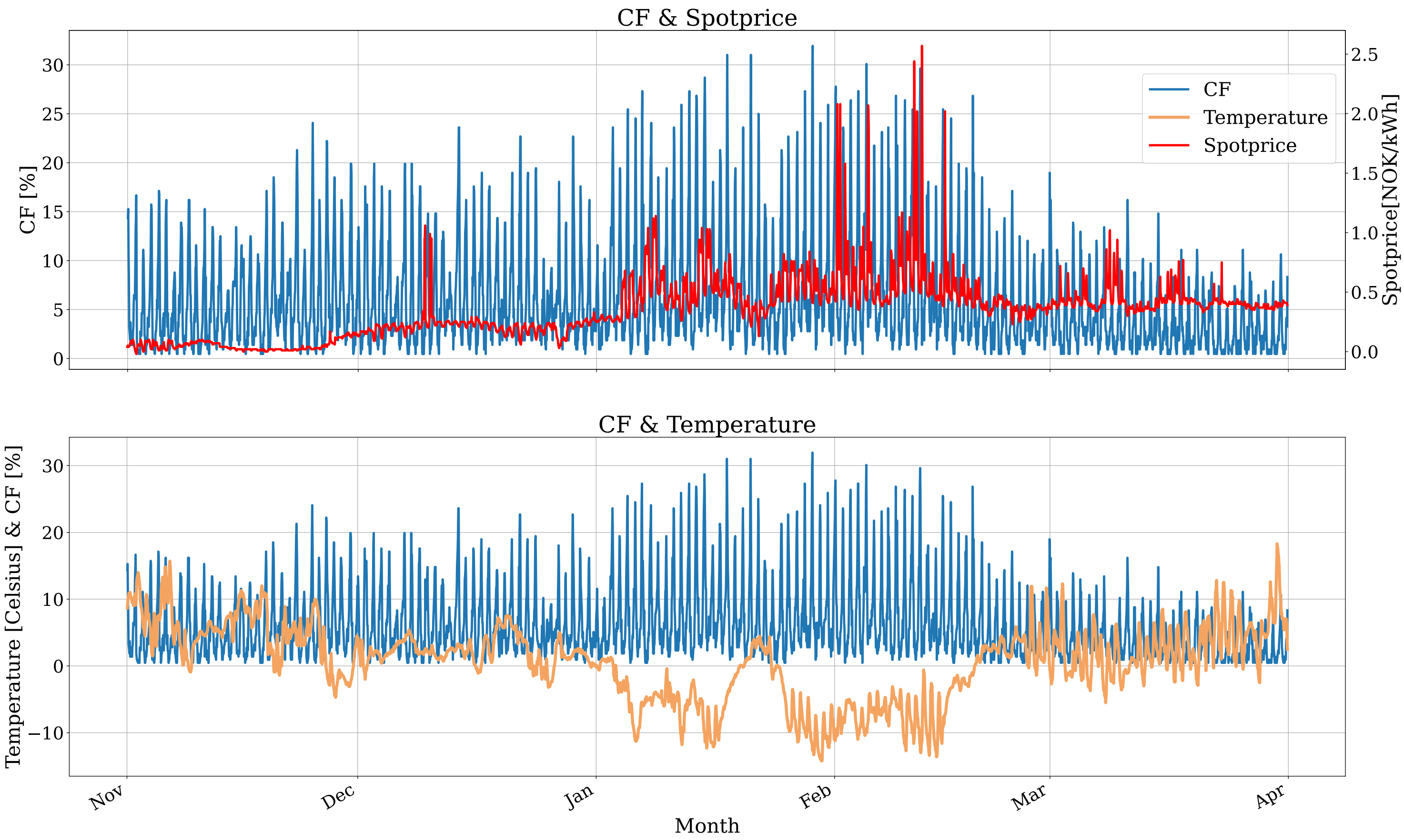

Figure 4.5: Plots of CF and spot price (top), and CF and temperature (bottom) for November through April.

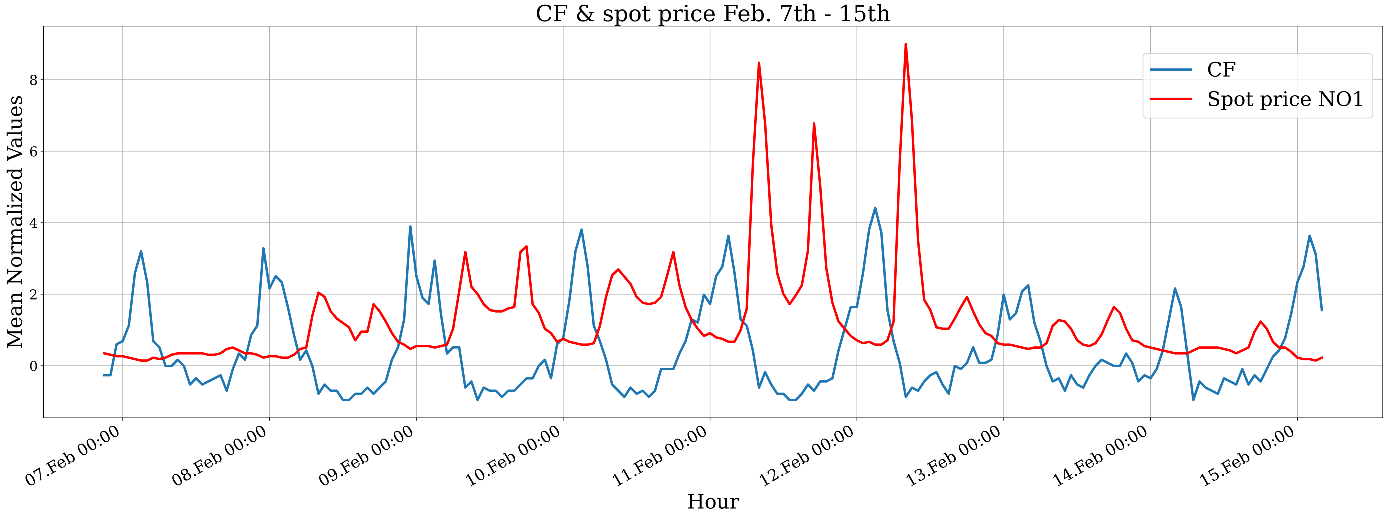

Figure 4.6: Plots of CF and spot-price from February 7th to 14th.

4.1.4 Charging sessions

The EV does not only need to be connected to the grid to be used as a flexible resource. The EV needs to be connected for a longer period of time than what is needed to reach the desired battery level. For this reason, the charging sessions in the data set have been explored.

The EV charging session data is presented in Figure 4.7. Columns one and two show the distribution of the charging session duration. Column three shows the distribution of the energy delivered in each charging session.

The distribution of charging session duration and delivered energy seems to be independent of having smart charging activated or not as all three columns show rather similar plots. The boxplots for charging session duration show a median right under 5 hours. The charging duration histograms show a large share of charging sessions with a duration under 5 hours. This could be charging for a couple of hours in the afternoon to have enough battery for chores, hobbies and other errands. For the energy delivered during one session, the median is just over $20kWh$.

Both the charging session energy and duration show several outliers. The outliers for duration could be households charging more than one EV consecutively, or EVs with a big battery charging at home on a low current over a long period. The longer the EV is connected to its charger the more time it is available as a resource for flexibility. The energy delivered on a charging session also shows outliers over

$70kWh$ reaching $100kWh$. These outliers are likely from Tesla's newer models with battery sizes up to $100kWh$ charging up from a nearly empty battery [54].

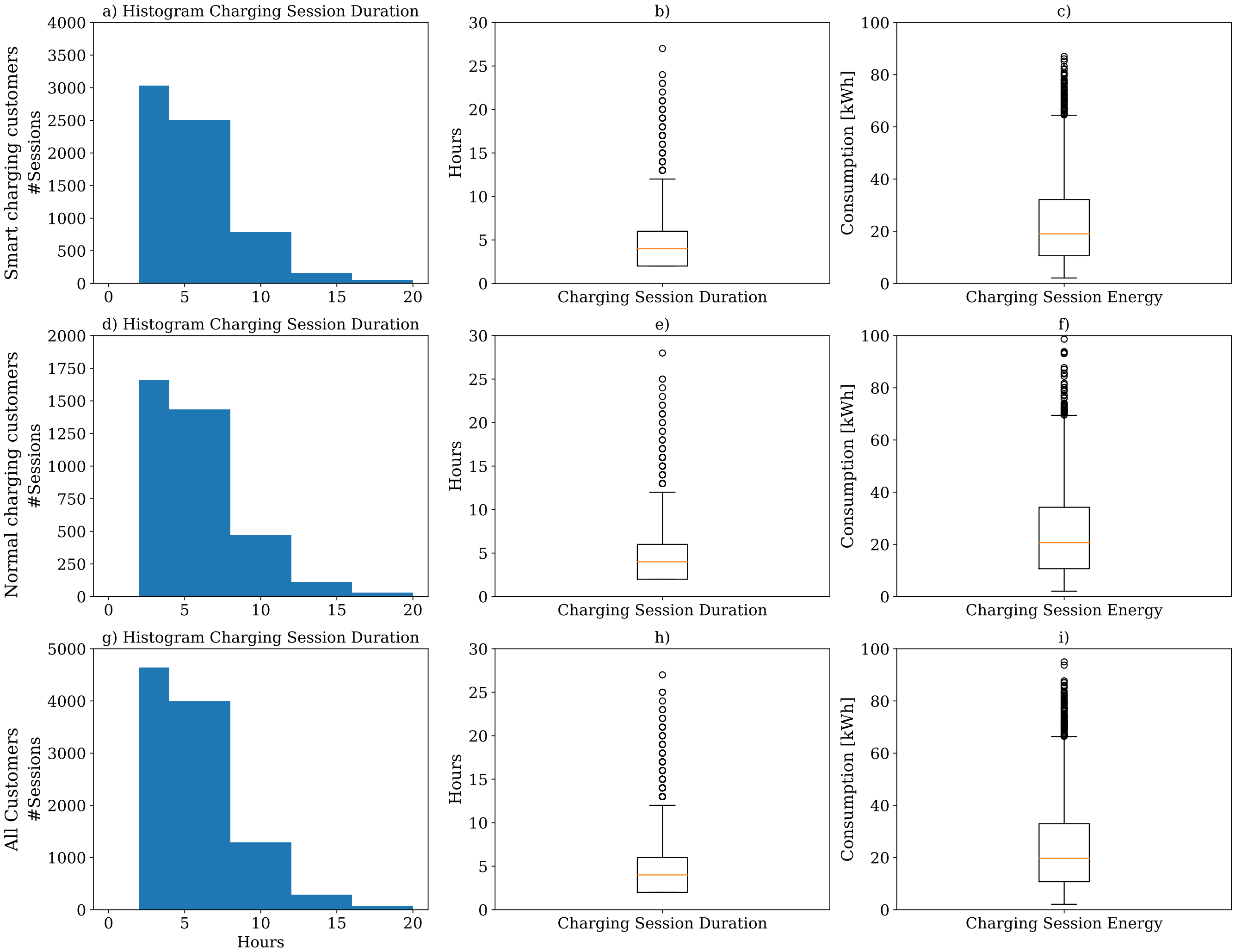

Figure 4.7: Charging Session energy and duration for smart charging customers (row one), normal charging customers (row two) and all customers (row three).

Table 4.2 shows the exact calculated mean of charging session energy and duration for the different types of charging. Independent of whether the customer has smart charging or not, the averages are right under 5 hours. This is slightly shorter than $5.6h$ which is the time usually used as a flexibility window for EVs [30]. With small variations, the mean of the energy delivered during one charging session is right over $20kWh$. From these results, the period available as a flexibility reserve would be the difference between the time the car is connected and the time it would need to charge the desired energy. The results for the EVs show that smart charging does not affect the characteristics of the charging, only the time of the charging. Adopting smart charging is therefore only likely to shift the consumption of the EV to late evening and night.

Table 4.2: Mean of charging session energy and duration.

	Duration $[h]$	Energy$[kWh]$
Active	4.67	22.69
Not Active	4.87	24.20
All Customers	4.77	23.34

If it is assumed that an EV charges with a $6.37kW$ charger, is connected for five hours, and requires $20kWh$ of energy, the flexibility can be estimated. For example, there is a possibility of charging $6.37kWx5hours = 31.85kWh$. For this case, the EV would need right under three hours to charge the desired amount $(20kWh)$, while it is connected for five. This would mean there is a window of two hours where the EV can be flexible. To calculate this specifically the power rating of the EV chargers is needed for each household.

4.2 Flexibility from electric space & water heating

This section covers the results from the iFleks data set. The first subsection provides profiles of average daily consumption for the groups with and without electric heating. The second and last subsection looks at variations with season and temperature.

4.2.1 Daily variation

One way to determine when flexibility from heating loads could be available is by determining the time of use. The consumption data does not have separate readings for the consumption used for heating purposes. By separating consumers into groups based on their heating sources, average profiles can be used to distinguish consumption. Figure 4.8 shows the mean profiles with the 95% confidence interval for the mean. In Figure 4.8a) the groups are households with electric water boilers and shared water heating. The goal was to distinguish the consumption from the electric boiler by comparing the consumption profile of households with and without electric boilers. The same strategy was used in Figure 4.8b) where the groups are households with electric space heating and households with district space heating. The average profiles follow a normal household consumption. Both graphs seem to follow the same pattern with small differences during the night and afternoon and a bigger difference in the morning.

It also needs to be noted that the households with shared water heating often also have district space heating. Similarly, households with electric water boilers often have electric space heating as well. So it is expected that the two plots follow the same trend. Regardless, a t-test for the means of the groups proves that the households with electric heating have a significantly different consumption in the morning. The p-values can be found in Figure A.2. The difference is likely due to morning showers and space heating. Consequently, the morning is the only time the difference from the electric heating consumption is visible.

Specifically for the water heating, it is a possibility of delaying the heating process into the mid-day. The hot water needed in the morning is heated during the night when the price is lower. Since the household is expected to leave for work, new hot water does not need to be reheated as soon as it is used. The water boiler can easily move its consumption to some hours later without affecting the user. At the hours in the middle of the day the spot price is also usually lower. A rebound effect could be seen in the middle of the day.

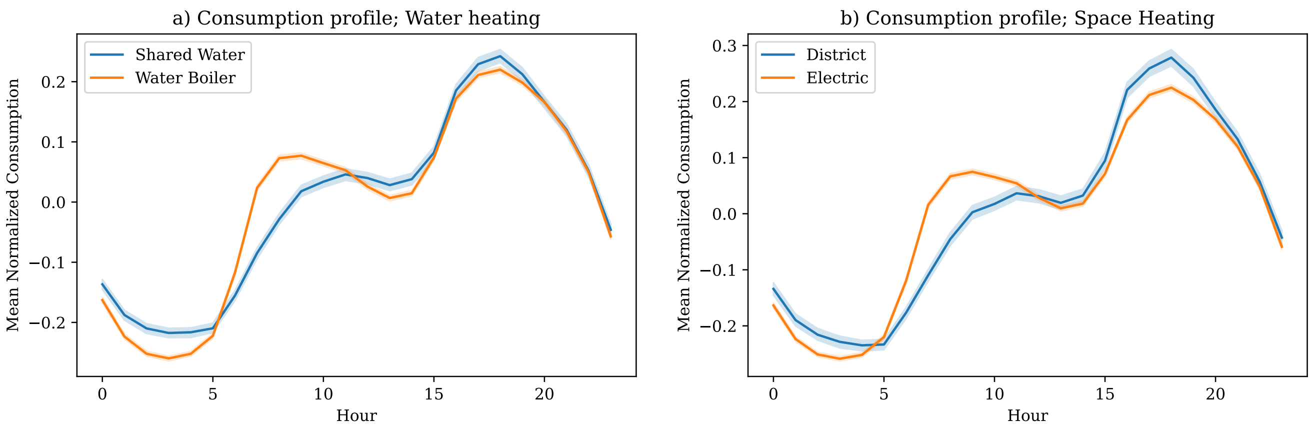

Figure 4.8: Plot of normalized mean consumption profiles for groups with different heat sources. Plot a) and b) compare households with and without electric water and space heating respectively.

As Statnett explains, the consumption from electric space heating is more consistent through a day compared to electric water heating. The electric water heater would have a high consumption after hot water is used and a lower consumption the rest of the time. The electric water heater would as a result have increased consumption in the morning and afternoon, and less on the remaining hours. Space heating, without smart control, on the other hand would have a consistent consumption throughout the day [10]. This difference is is not apparent from Figure 4.8 likely because the customers with electric water heating also have electric space heating and likewise for shared systems.

At night, the consumption in a household decrease. This is often true for both space and water heating, given that the customer turns off some of the heat sources at night. This can be done both manually or with systems like FutureHome. This reduction of consumption might counterbalance some of the potential EV nightly charging. As seen in Figure 4.2b) the consumption for the EV charging might surpass the rest of the household consumption, but turning off heating loads at night will decrease the nightly peak after introducing an EV with smart charging.

4.2.2 Seasonal variations

Norway is a country with big differences in outdoor temperature, and it is expected that consumption for heating will vary throughout the season. During the summer, the consumption from space heating is limited, meaning the load is not available as a source of flexibility. When the temperature is lower the consumption from heating increases. Figure 4.9 shows the average consumption for two different time periods. The periods have a duration of approximately a month, one with cold temperatures and one with warm. It needs to be noted that the data set only ranges from December through March, limiting the difference between the cold and warm periods.

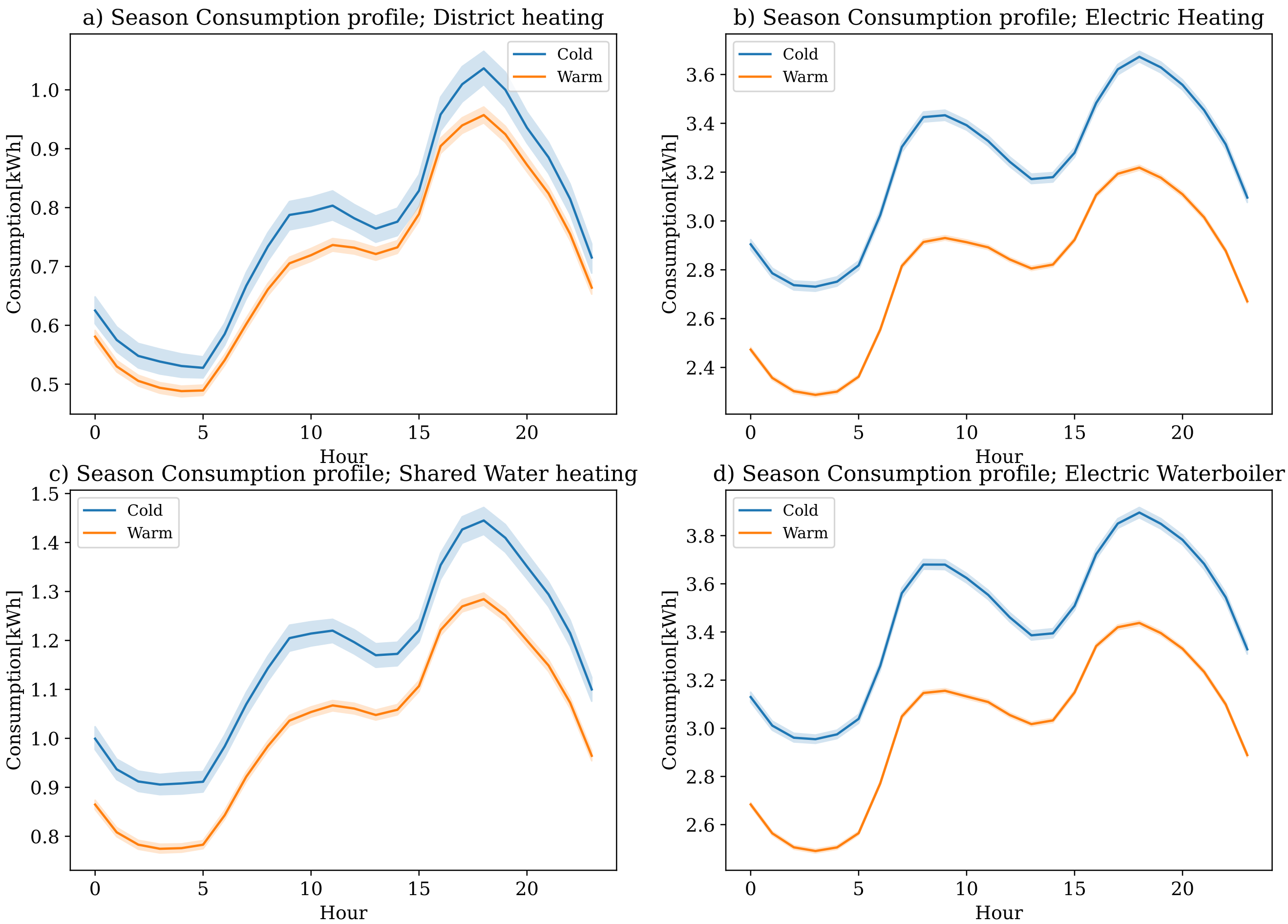

Figure 4.9: Plot of mean consumption profiles of different heat sources comparing cold and warm periods for customers with different space and water heating. Plot a,b) and c,d) cover district and electric space heating, and shared and electric water heating respectively.

Figure 4.9a) and b) show the difference in average daily consumption for the cold and warm periods for the groups of consumers with district and electric space heating respectively. Figure 4.9c) and d) show the same information for shared and electric water heating. Electric heating shows bigger differences with temperature as a direct result of having heating on their electricity meter. Customers with district heating show the least difference between the two periods because they do not have measurements of electricity for heating in their household's electricity meter. In this group it is likely that many also have shared water heating. This would mean that the slight increase in consumption during the cold period could be from lighting. In the group with shared water heating, some households might have additional electric space heating. That might be why the difference between the cold and warm period for plot c) is bigger than plot a). The consumption for water heating is not expected to change a lot with season because people likely shower regularly throughout the year as discovered by Sidqi et al. [21]. The showers might be a little longer and warmer, but consumption for hot water is still not expected to change as much as consumption for space heating.

This method of grouping consumers based on what they have listed as source of water and space heating could have been done differently. Consumers with electric space heating are likely many of the same that have electric water heaters. This would mean that Figure 4.9b and d) represent many of the same households. The plots would as a result of this not show the true difference in consumption related to the source of heating.

Yet the results still provide value in the sense that they show the difference between having electric heating and not. When households have electric heating, either boiler, panel heaters, underfloor cables or heat-pumps their consumption rises. Electric heating elevates a household's consumption greatly, as apparent when comparing the average consumption on the y-axis on Figure 4.9. This further proves that heating is the main source of consumption in a household. Gunkel et al. back this up by finding that heat-pumps are base loads and contribute more to peak consumption than an EV because they are on at most hours [29]. Households without an EV or electric space and water heating would have little to no resources to provide flexibility with. Households with electric space heating can provide flexibility in the cold months when the electric heating is in use. Households with electric water heating or an EV can provide flexibility the whole year.

Figure 4.10 substantiates the negative correlation between consumption and temperature. The pearsonr coefficient was calculated to be -0.73. In the plot the months are of different colours. The warmest months in the data sets, December and March are colored yellow and blue respectively. These two months clearly occupy the warmest temperatures in the right of the plot. At the colder temperatures January and February are colored with dark and light purple respectively.

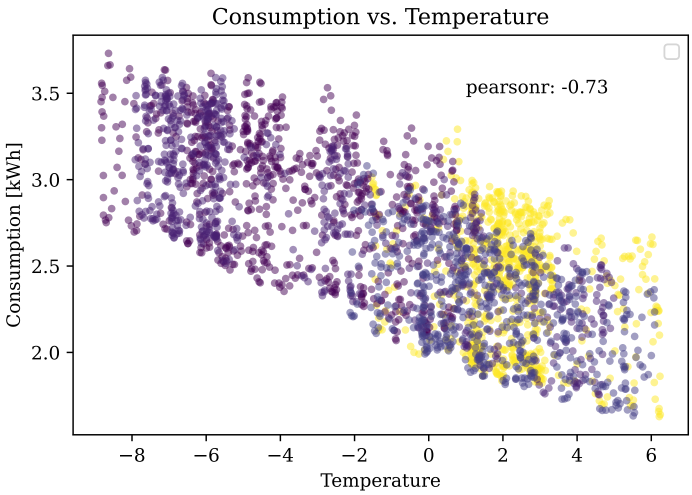

Figure 4.10: Plot of correlation between consumption and temperature with different months in different colors. Yellow-December, Blue-March, Dark Purple-January and Light Purple-February.

4.3 General discussion of results

This section will sum up the findings in this thesis with a general discussion of their impacts. The quantification of CF for smart EV charging shows that over 30% of the fleet charges at the same hours during the night. The CF varies with the hours of the day, the day of the week and temperature. The CF could help the DSO estimate the demand from EVs and consequently contribute to grid development. Additionally, the CF could be used to estimate the flexibility potential if combined with the results from the charging sessions. The difference between the time the EV is connected and the time it needs to charge the required amount is the time when the EV is flexible. This time, in combination with the CF, could be used to estimate the size of the flexibility available. Estimation of the volume of flexibility is important when it is offered into one of the reserves in the balancing markets. Flexibility from electrical space and water heating changes with the use of heating. In colder periods, more electricity is used for space heating resulting in a larger potential for flexibility. In the summer it is expected that almost no space heating is used, so there is no potential for flexibility. The use of hot water does not change so much with temperature and could be used as a flexible source throughout the whole year. Especially does a large consumption for hot water in the morning open up the possibility of moving the reheating of the water to the middle of the day.

Flexibility from electrical water heating and charging of EVs can be offered into the balancing markets depending on volume size, response time and duration.

Aggregators can combine controllable loads which together can be offered as one bid into the market. In the eFleks project, aggregators have already proven that they managed to deliver bids over $1MW$ into the mFRR. With remote control of smart chargers and water boiler the demand can be turned down or off for a period of time. The response time of this remote control is important to find the suitable reserve. Based on the response time measured in the eFleks project the response time of the aggregated loads could possibly also be quick enough for the aFRR. The aFRR and mFRR reserves have a potentially long duration. In this case the aggregator might need to rotate between different loads to meet the duration requirement without causing inconvenience to the household.

Modulation and scheduling can provide the same volume of flexibility but with different characteristics. Modulation of EV charging turns down the power of the charging. This means that the EV is still charging, but slower. For scheduling the charger is turned on and off. Consequently, modulation of one EV provides a smaller instantaneous volume than scheduling but is available for a longer time. With many EVs the type of smart charging might not be significant because the aggregator could control many loads to meet the volume and duration requirements. The response time would then be the important factor. Turning on and off charging have larger delays than modulating the charging [63]. This could mean that flexibility from modulation of charging might be offered in faster reserves like FFR and FCR.

Lastly the results for the smart charging shows that high penetration of smart charging EVs might be a concern that needs to be addressed due to the high CFs. Despite smart charging being associated with something purely good, it might cause issues in the future. To be able to fully utilize the flexibility from EVs without harming the grid, more research on smart charging is crucial.

4.4 Discussion of method

To finalize this chapter, the method will be discussed. In the method, there are particularly three points that need to be discussed. Firstly, because of the Tibber customers' ability to change their smart charging status, they are complicated to separate. In this thesis, two different methods of separating customers depending on their smart charging have been tested. Both methods show similar results in figure Figure 4.1. To be able to sort the consumption into groups with and without smart charging the method which separated based on smart charging status was chosen. Choosing this method resulted in a problem, which lead to the second point.

Secondly, the calculation of the CF was done by dividing the number of cars charging every hour by the total number of EVs. For all types of charging this number is the same over the whole period, but when calculating the CF for the smart charging and normal charging customer groups it changes. Since the customer can change from having smart charging one day, to not having it the next the number in which the number of EVs is divided by changes. In this thesis, the number of EVs using a smart charger has been divided by the total number of EVs that have had smart charging activated at one point in the period. The same goes for the calculation of the CF for normal charging. This might lead to errors in the CF. The CF should for that reason be calculated with different methods to compare the results in the future.

Lastly, the groups of customers with and without electric heating need to be discussed. Customers with electric water heating often also have electric space heating. Similarly, customers with distributed space heating often also have shared water heating. The results would be that many of the households appear in both groups. It could therefore be discussed if the groups needed to be separated based on water heating and space heating, or if it would suffice to separate into electric heating and non-electric heating. The difference between plots a) and c) in Figure 4.8 is noticeable. This is likely because of the apartments in subplot c) have shared water heating and electrical space heating. These households would consume more electricity during the winter resulting in a bigger gap between the consumption in a cold and warm periods.

4.5 Future flexibility

In this section thoughts about the availability of flexibility in the future and what trends and technology could affect the availability will be discussed. The technology of smart meters and remote control already let people monitor and control their consumption [10]. Household flexibility has yet to be fully included in the balancing markets due to its small size and limited predictability. To exploit the potential of household flexibility in the markets, aggregation and prediction of volumes need to be reliable.

4.5.1 Electric vehicles in future

As mentioned, the Norwegian fleet of EVs has grown exponentially in the past years. By 2025, Norway aims for all new personal vehicles and small vans to be emission-free [56]. The sale of EVs in Norway is already on that course, and if this growth continues there might be 200 000 newly registered EVs in 2050 alone [82]. Statnett predicted in 2018 that the demand for EVs would increase from $0.4TWh$ to $6TWh$ in 2030 [10]. It would also be expected that the potential for flexibility will increase with the demand.

The EV itself is also developing. The driving range of the new EVs continues to increase and has more than tripled from 2011 to 2020 [83]. This means that the size of the EVs battery has increased. To look at one example, the first Nissan Leaf was released with a 24 kWh battery. Just four years later Nissan released the Leaf Plus with a $60kWh$ battery [54]. Despite a bigger battery and longer range the driving habits are not likely to change. So bigger batteries would mean that the EV can charge more rarely, but would require a longer period of charging if charged at home. This could affect the potential for flexibility.

More EVs increase the need for electricity but also increase the potential for flexibility. Without smart charging the normal EV owner starts charging in the afternoon, some maybe already right after work. This consumption adds to the afternoon peak, possibly creating grid issues. To prevent charging at peak hours with high prices more and more EV owners acquire smart charging. One company that offers smart charging is Tibber. Over the course of 2021 they tripled the number of customers now adding up to over 400000 [84]. As established, Tibber moves the charging into the night. If more and more EVs start with smart charging this would change the time of availability for flexibility, and possibly increasing the potential.

In the future, charging at work might become more common. This would open up for a potential for flexibility during the day.

4.5.2 Household trends

Since 2010, the number of Norwegian people wanting to live in apartments has increased. If a family moves from a house to an apartment their average living area would likely decrease [85]. As discussed, heating is the main source of consumption in Norwegian households, and it is mainly electric [66]. So a decreasing average area of a household would also mean less volume to heat up. The amount of hot water used per resident is not expected to change depending on living in an apartment or house. A person would likely shower and use hot water similarly independent of living in an apartment or not. Less electricity consumption for heating per household is of benefit to the grid, especially during the winter when the grid is pressed to its limits. On the other hand, it reduces the resources of the household available for flexibility. In bigger cities, many apartment complexes have distributed and shared systems for heating space and water. In those cases, the consumption for heating is in a way already aggregated for a bigger number of households. Smart control of big-scale heating systems could give a bigger potential for flexibility possibly at a lower cost.

New regulations for the construction of houses and more smart houses also limit the need for electricity for heating purposes. Yet again the availability of flexibility will decrease but still benefit the grid by reducing consumption.

Despite the covid-19 restrictions ending, working from home is still favored by many people. The covid-19 regulations forced people to work from home, changing their daily consumption profile. As mentioned by Valøy, the differences between household consumption profiles on a weekday and the weekend became more diffuse [86]. Working from home would likely also affect the availability of flexibility. The consumer would then be in a position to distribute their consumption more evenly over the day. The consumption peak in the morning would decrease as Valøy discovered [86]. The need for charging EVs would also change if the consumer does not drive to and back from work. In this case, the EV might be charging at different times of the day potentially being available as a flexible load.

Chapter 5

Conclusion

Grid flexibility is important to facilitate both VRE and electrification. Consequently, the goal of this thesis was to explore residential flexibility from EVs and electrical heating. This has been done by studying both the smart and normal charging of EVs and consumption profiles for households with and without electrical heating. The results can be summarized by looking back on the research questions, in that very order.

The CFs have been calculated for smart and normal charging, but also for both types combined. The results show that the CF peaks at night independently of the type of charging. For the customers with smart charging these peaks reach over 30% at a maximum while normal charging reaches over 10%. This is because smart charging synchronize the charging to the hours of the lowest price, resulting in a high share of the EVs charging at the same time. High CF of EV charging could pose a problem when the fleet of EVs keeps increasing. Many EVs charging at the same hours can create large consumption peaks, which can potentially overload the grid. On the other hand, the CF can point to what times EVs are connected to the grid, possible being available as a flexible consumption.

The CFs have weekly patterns of increased values at night to workdays and lower values at night to weekend days. The underlying cause of this could be more driving on weekdays and the effects of range anxiety and user behavior. CF has also been proven to be negatively correlated with temperature. In practice, this means that people charge their EVs more when the temperature is lower. This is likely due to the EVs decreasing efficiency with decreasing temperatures. For the grid operators, this implies that the demand for electricity for EV charging is higher in winter times. At the same time, more EVs would be connected to their charger possibly available as a source of flexibility.

Data from EV charging sessions shows that the mean duration of a charging session is longer than the time needed to charge the mean energy delivered in a session. In practice, this would mean that the difference between those two times would be the window of time where the EV could be flexible. The mean duration of a charging session is just less than five hours while the average energy delivered is just over $20kWh$. In combination with the CF the charging session results could be used to quantify the flexibility potential.

Electric heating, both for space and water, contribute greatly to a household's consumption. In this study, the customers have been grouped by having electric space and water heating or not. The differences in their total normalized mean consumption show that electric heat sources have a significantly higher consumption during the morning proven by a t-test. This is expected to be electrical heating for both space and water and the energy used for making breakfast. Particularly could electrical water boilers be postponed to turn on in the middle of the day to decrease the consumption peak in the morning. The consumption of a Norwegian household is greatly impacted by a cold climate. Consequently, household consumption is negatively related to temperature with a pearsonr coefficient of -0.73. The seasonal variations in consumption give rise to a higher electricity demand during the winter. Consequently, the consumption also increases the availability for heating as a source of flexibility.

5.1 Further work

The main contribution of this thesis is knowledge about the charging patterns of EVs with and without smart charging. This has been done by quantification of CF and studying charging session data. Additionally, differences in consumption patterns for households with and without electric heating have been found. As established, CF is correlated with temperature, so having data for all seasons will likely prove to be important for future studies.

In addition, the data used to compute the CF originate from only 216 EVs. The data set should be extended to include more EVs with a good dispersion across Norway. Especially interesting would be to have more specific geographic data to further investigate the CF connected to the same transformer station. From there on it could be investigated what degree of CF would overload the capacity of the local grid. This information will be beneficial for the local power supplier. To get a broader research the data should include different types of EVs. As of now the Tibber data set only include Tesla EVs. These EVs have a generally large battery pack and are not representative of the total Norwegian EV fleet. To look closer at the charging session and potential for flexibility in a session, battery size and maximum possible charging power should be available for each household.

Knowledge about heat sources as a flexibility asset is hard to pinpoint without disaggregated consumption data for the heating. When the data studied is total demand, quantifying and disaggregation have proven to be difficult. The study of consumer profiles gives an indication of the size and time of use, but more precise measurements are needed to quantify the actual potential of flexibility from electric heat sources.

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Appendix A

Appendix

	Smart vs. not	2v40	2v100	40v100
0	0.000000	0.000288	0.000000	0.000000
1	0.000000	0.000023	0.000000	0.000000
2	0.000000	0.000006	0.000000	0.000000
3	0.000000	0.000024	0.000000	0.000003
4	0.000266	0.000498	0.000000	0.001131
5	0.001715	0.005631	0.000000	0.002160
6	0.009432	0.004284	0.000003	0.083991
7	0.015781	0.019059	0.000430	0.279034
8	0.035299	0.041083	0.000267	0.117294
9	0.057099	0.079331	0.000320	0.061367
10	0.072074	0.147812	0.000310	0.032157
11	0.169303	0.103101	0.000267	0.049599
12	0.090871	0.060310	0.000148	0.066069
13	0.102188	0.017654	0.000086	0.149335
14	0.031326	0.012662	0.000018	0.096427
15	0.032394	0.022619	0.000009	0.038408
16	0.199729	0.014459	0.000134	0.193238
17	0.305046	0.006852	0.000136	0.324914
18	0.427789	0.000975	0.000185	0.796640
19	0.562243	0.000408	0.000059	0.783567
20	0.613946	0.000694	0.000002	0.218081
21	0.157864	0.001538	0.000000	0.009940
22	0.004205	0.000464	0.000000	0.000117
23	0.000925	0.000813	0.000000	0.000010

Figure A.1: Table over p-values from t-tests. The columns show p-values from t-test comparing the average consumption of two groups. To the left, the t-test tested the average consumption for hours with smart charging with hours with normal charging. The three last columns starting from the left tested the average consumption for groups of customers that had smart charging for 0-2%, 20-40% and 80-100% of the time.

	Water: Shared vs electric		Space: District vs. electric
0	0.000000	0	0.000002
1	0.000000	1	0.000000
2	0.000000	2	0.000000
3	0.000000	3	0.000000
4	0.000000	4	0.002426
5	0.008148	5	0.018021
6	0.000000	6	0.000000
7	0.000000	7	0.000000
8	0.000000	8	0.000000
9	0.000000	9	0.000000
10	0.000000	10	0.000000
11	0.202570	11	0.006909
12	0.007540	12	0.689198
13	0.000053	13	0.130880
14	0.000012	14	0.026439
15	0.144138	15	0.000601
16	0.021138	16	0.000000
17	0.002918	17	0.000000
18	0.000226	18	0.000000
19	0.019538	19	0.000000
20	0.996571	20	0.016259
21	0.693184	21	0.059493
22	0.725247	22	0.201912
23	0.042722	23	0.012360

Figure A.2: Table over p-values from t-tests. The columns show p-values from t-test comparing the average consumption of two groups. The left column compares the average consumption of households with shared water heating with households with shared water heating. The right column compares households with district space heating with households with electric space heating.

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