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Utilization of the Flexibility Potential of Electric Vehicles

- an Alternative to Distribution Grid Reinforcements.

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Problem Description

The Norwegian distribution grid is facing great challenges with the expected increase of power intensive appliances, such as electric vehicles. The aim of this thesis is to propose how distribution system operators (DSOs) can use different control methods to avoid congestion in the distribution grid in the short run, and to postpone investments in the grid in the long run.

More specifically, a framework for indirect control of EV charging will be given. Here, the DSO can use a forecast of the expected congestion in the distribution grid to provide the EV users with dynamic price signals in order to avoid damaging peak loads. Furthermore, there will be given a proposal of how the EV charging can be controlled directly, in compliance with user preferences. Lastly it will be discussed how indirect and direct control methods can be used in combination.

Preface

This thesis concludes our Master's degree in Managerial Economics and Operations Research under the department of Industrial Economics and Techonolgy Management at the Norwegian University of Science and Technology. The thesis was written during spring 2015. The main topic of the study was proposed by our supervisors Asgeir Tomasgaard and Stig Ø. Ottesen, but the final topic question was formulated by the authors.

We are very interested in future energy solutions which can contribute to a more sustainable world. We hope that this thesis can contribute to the positive trend of the increasing number of electric vehicles, and a greener transport sector.

We would like to thank our main supervisor, Asgeir Tomasgaard, for interesting and enlightening discussions, and for guiding us in the right direction. We would also like to thank Stig Ø. Ottesen for his practical approach to, and knowledge of, the subject. Lastly, we would like to thank Steffen M. W. Breivik for helping us with the graphical design of the thesis, and Eirik S. Grytli for his insight in the power system.

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Abstract

Today, the transport sector accounts for a large share of global emissions. Electric vehicles have many environmental advantages compared to conventional petrol vehicles. Hence, if electric vehicles can replace petrol vehicles, the transportation sector's total emissions can be significantly reduced. In Norway, due to policy incentives, it is expected that the number of electric vehicles will increase considerably in the near future. Despite the great advantages of electric vehicles, large penetration of EVs poses many challenges for the electricity grid. When several EVs within the same distribution grid charge simultaneously, this may cause overloading of network components. The traditional way of solving capacity problems is to reinforce the grid to handle the highest peak load during a year. However, this is not optimal seen from a socio-economic perspective, as the grid will be underutilized during a large part of the day and the year. With the grid of the future, smart grid, and Advanced Metering Infrastructure (AMI), alternatives to the traditional methods of handling grid congestion can emerge. With smart grid, real-time information concerning electricity consumption and grid conditions will be available, enabling the electricity consumer to supply, and the distribution system operators to utilize, demand response. Demand response is flexibility of electricity consumption on the demand side. The EV is an electric load which is well suited for demand response, as the use is decoupled from the electricity consumption. As long as the EV is ready for use when the owner needs it, most EV owners will be indifferent regarding how and when the EV was charged.

It can be avoided that the distribution grid becomes a limiting factor for the electrification of the transport sector by utilizing the potential of smart grid. The purpose of this thesis is to provide the distribution system operators (DSOs) with guidance on how to prepare for the increasing penetration of EVs. The aim is to find good alternatives to grid reinforcements based on demand response, which can be adopted by a grid operator or a third party.

Principles and considerations regarding optimal design of grid tariffs suited for the new consumption pattern, were presented and discussed. The main categories of proposed grid tariffs were evaluated based on different criteria important to reveal the flexibility potential of consumers and ensuring socio-economic utilization of the grid. Two different price models for EV charging were developed, which were a composition of some of the already proposed price models. As price signals do

not *guarantee* the desired response from EV users, a direct control model for EV charging was also developed. The model could be used in combination with price signals to reduce the risk of congestion in the grid. Predictability of charging costs and complying to user preferences, was emphasized when creating the model. The model maximized the total charging power for all EVs within a substation, while operating within the limitation of the grid and fulfilling the EV users preferences regarding desired battery level at the time of disconnection. In order to reveal the potential of the model, the model was tested on a fictitious network with fictitious EV users.

By comparing the properties of the different already proposed price models, a trade off was found between predictability for the EV user (how simple it was to plan load-shifting) and how accurately the tariff reflected the actual grid condition (if a congestion fee was charged only when there was congestion). A price model which tried to minimize this trade off was created: a real-time purpose based tariff with fixed price lists. The aim of the model was to ensure predictability for the EV users regarding prices, while still having the ability to utilize real-time information regarding grid condition. This was achieved by giving different price lists to different EV users, depending on when they connected to the charging point. As this could be a demanding model to operate, and as it also could be perceived as unfair for the EV users, another model was also created: a progressive purpose based day-ahead tariff. This model priced the charging power which exceeded what is referred to as normal charging, by a higher price per kWh, and the aim of the model was to find the prices for normal and fast charging, as these should vary with changing grid conditions. The results from the testing of the direct control model showed that by utilizing direct control of EV charging, the distribution grid could tolerate a high penetration of EVs, which would have been very problematic if the charging was uncontrolled or controlled indirectly through price signals.

This paper demonstrates that with a high penetration of EVs there is a need for controlled charging to avoid large investments in increased grid capacity. Price signals can be used to control the charging of EVs indirectly, but also to ensure that an adequate amount of flexibility is offered when the charging is controlled directly. To ensure the success of demand response, the consumers must be taught to respond to price signals. Hence, the existence of educational signals is critical. Further, characteristics of the consumers and how they respond to prices must be recognized. Control models which are developed without understanding the consumers will never be a real alternative to grid reinforcements.

Sammendrag

Transportsektoren bidrar i dag til en stor andel av de totale globale klimautslippene. Elbiler har mange miljømessige fordeler sammenlignet med konvensjonelle bensinbiler. Dersom elbiler erstatter bensinbiler kan transportsektorens totale klimautslipp bli vesentlig redusert. I Norge er det forventet at antallet elbiler vil øke betraktelig de neste årene blant annet grunnet politiske insentiver. Til tross for de mange positive fordelene med elbiler så kan et stort antall elbiler føre til store utfordringer for elektrisitetsnettet. Når flere elbiler i samme geografiske område lader samtidig, kan dette føre til overbelastning av nettverkskomponenter i distribusjonsnettet. Den tradisjonelle måten å løse slike kapasitetsproblemer er å forsterke nettet slik at det kan tåle den høyeste effekttoppen i løpet av et år. Dette er ikke optimalt sett fra et samfunnsøkonomisk perspektiv, ettersom nettet vil være underutnyttet store deler av dagen, og av året. Med fremtidens elektrisitetsnett, smart grid, og med Avanserte Måle- og Styringssystemer (AMS), kan det oppstå alternativer til den tradisjonelle måten å håndtere flaskehalser på. Med smart grid blir sanntidsinformasjon om elektrisitetsforbruk og tilstander i nettet tilgjengelig. Dette legger til rette for at elektrisitetskonsumentene kan tilby forbrukerfleksibilitet, mens nettselskapene kan utnytte denne fleksibiliteten. Elbilen er en typisk last som er godt egnet som kilde til forbrukerfleksibilitet, da bruken av elbilen ikke skjer samtidig som den trenger elektrisitet fra nettet. Så lenge elbilen er klar til bruk når elbileieren trenger den, er det rimelig å anta at elbileieren er likegyldig til når og hvordan bilen har blitt ladet.

Ved å utnytte potensialet til smart grid kan det unngås at distribusjonsnettet blir en begrensende faktor for elektrifiseringen av transportsektoren. Hensikten med denne oppgaven er å hjelpe nettselskapene med å forberede seg på den store forventede økningen av elbiler. Målet er å finne gode alternativer til nettforsterkninger basert på forbrukerfleksibilitet, som kan brukes av nettselskapene eller en tredjepart.

I denne studien ble det presentert og diskutert viktige prinsipper og hensyn som må tas når det gjelder utforming av optimale nettariffer tilpasset det nye forbruksmønsteret. Hovedkategoriene av nettariffer som allerede har blitt foreslått, ble evaluert basert på ulike kriterier som er relevante for å frigi fleksibilitetspotensialet til konsumentene, og samtidig sikre samfunnsøkonomisk utnyttelse av nettet. To ulike prismodeller for elbillading ble foreslått. Disse var en sammenslåing av noen av de allerede foreslåtte prismodellene. Ettersom prissignaler ikke *garanterer*

at ønsket forbrukerfleksibilitet blir tilbudt, så ble en direkte styringsmodell for elbillading også utviklet. Modellen skulle kunne brukes i kombinasjon med prissignaler for å redusere risikoen for flaskehalser i nettet. Forutsigbarhet når det gjelder ladekostnader og det å tilfredsstille elbileierens brukepreferanser, ble vektlagt da modellen ble laget. Modellen maksimerte den totale ladeeffekten for alle elbilene innenfor en nettstasjon, samtidig som kapasiteten i nettet ikke ble overgått. Samtidig ble elbileiernes brukepreferanser tilfredsstilt hva gjelder ønsket batterinivå når bilen skulle frakobles. For å undersøke modellens potensiale, ble modellen testet på et fiktivt nettverk med fiktive elbileiere.

Ved å sammenligne egenskapene til de ulike foreslåtte prismodellene, ble det observert en trade off mellom forutsigbarhet for elbileieren (hvor enkelt det var å planlegge lastflytting), og hvor nøyaktig tariffen reflekterer den faktiske tilstanden i nettet (om en flaskehalsavgift kun ble innkrevet når det faktisk var en flaskehals i nettet). En prismodell som prøver å minimere denne trade off'en ble laget: en sanntids formålsbasert tariff med fikserte prislister. Målet med denne prismodellen var å sikre forutsigbarhet for elbileierne når det gjelder priser, samtidig som det kunne utnyttes sanntidsinformasjon om tilstanden i nettet. Dette ble oppnådd gjennom å gi ulike prislister til ulike elbileiere, avhengig av når de kobler til ladepunktet. Ettersom dette kunne være en krevende modell å drifte, og ettersom det kunne oppleves som urettferdig for elbileierne å få ulike priser, ble det også utviklet en progressiv formålsbasert dagen-før tariff. Denne modellen priset ladeeffekt som overgikk det som kalles normallading, med en høyere pris per kWh, og formålet med modellen var å finne priser for normal- og hurtiglading ettersom disse skulle variere med tilstanden i nettet. Resultatene fra testene av den direkte styringsmodellen viste at ved å utnytte direkte kontroll så kunne distribusjonsnettet tåle en stor økning i antall elbiler, som kunne ha vært problematisk dersom elbilladingen var ukontrollert, eller kontrollert indirekte gjennom prissignaler.

Denne oppgaven demonstrerer at dersom store investeringer i nettforsterkninger skal unngås når det blir en stor økning i antall elbiler, så er det et behov for å styre elbilladingen. Prissignaler kan brukes til å indirekte kontrollere ladingen av elbiler, men det kan også brukes til å sikre at en tilstrekkelig mengde fleksibilitet blir tilbudt når ladingen styres direkte. For å sikre at utnyttelse av forbrukerfleksibilitet blir en suksess, må konsumentene blir lært hvordan de skal respondere på prissignaler. Altså er det viktig at det eksisterer informasjonssignaler. Videre må man gjøre seg kjent med karakteristikkene av konsumentene, og hvordan de reagerer på prissignaler. Kontrollmetoder som er utviklet uten å forstå konsumentene vil aldri bli et reelt alternativ til nettforsterkninger.

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Abbreviations

AMI: Advanced Metering Infrastructure

BSOC: Battery State of Charge

DSO: Distribution System Operator

DG: Distributed Generation

DCO: Direct Control Operator

EV: Electric Vehicle

NVE: Norwegian Water Resources and Energy Directorate

RES: Renewable Energy Systems

TSO: Transmission System Operator

CHAPTER 1

Introduction

Today, the transport sector accounts for 13 % of global emissions (United States Environmental Protection Agency, 2013). In Norway the contribution is as much as 32 %, and has increased by 10 % the last ten years (Miljostatus.no, 2014). Electric vehicles (EVs) are vehicles which can be charged by renewable energy, while gasoline cars are dependent on fossil fuels. By replacing gasoline cars with EVs, global emissions can be reduced, and the air quality in cities can be improved when the amount of exhaust from cars diminishes. Over the last decade there has been a dramatic increase in the number of EVs in industrialized countries. In Norway, the number of registered EVs has increased by a multiple of 21 from January 2009 to April 2015 (Grønn bil, 2015). Although the increment of EVs is very positive from an emission perspective, the increase can cause great challenges on the power system, especially on the distribution grid. One of the effects on the distribution grid is overloading of network components, which can occur when many EVs are charged simultaneously. Assuming that the number of EVs continue to grow, and no management of the charging of EVs is performed, the grid companies must invest a great amount of money in grid reinforcements to make the grid able to withstand the peak-loads. The peak loads occur only a brief part of the day, and during the rest of the day the grid has excess capacity. Investing heavily in the grid to withstand the peak loads is therefore not optimal from a socio-economic point of view.

Smart grid is a new generation power grid which can facilitate demand response, which is flexibility offered to the DSO, or another party, by the electricity consumers. Smart grid uses information- and communication technology to provide real-time information about the consumption of energy in the grid. It can also provide consumers with information about electricity prices, and make it possible for consumers to act as producers when they have excess energy. This new type of electrical grid is a key factor concerning the success of the integration of EVs. When real-time information about the status in the grid is available, peak loads causing overload of grid components can be avoided. This can be accomplished by utilizing flexibility on the consumption side. This phenomena is referred to as *demand response*. The EV can be considered a flexible load. Usually, the charging of an EV is not urgent, and it is irrelevant when the EV is charged as long as the battery has the desired energy level when the owner needs to use the EV.

Much research has been done within this field. Some researches have proposed indirect control methods of EV charging, which mainly consist of sending price signals the EV/EV user can respond to. Others propose directly controlled charging methods where a third party directly controls the EV charging, and charges several EVs while operating within the grid limitations. Use of optimization is valuable for both indirect and direct control of EV charging. For indirect control methods, optimization can be used to find the optimal prices for instance for EV charging, which improves the socio-economic utilization of the grid, while not exceeding any grid limitations. In direct control methods, optimization can be used to find the optimal charging power for each EV, given the grid conditions, and the EV user's preferences.

The main goal of this thesis is to assist the grid companies in Norway to prepare for the increasing penetration of EVs, by utilizing that EVs are loads suited for demand response programs. This is done by proposing indirect control methods of EV charging, mainly by sending price signals to the EV, as well as a direct control method which emphasizes predictability for the EV user. Lastly, a proposal of how indirect and direct control methods can work in combination is given, as a combination of these methods possibly can ensure an even better utilization of the grid, than each of the control methods can in isolation.

This thesis is divided into four parts. In the first part, relevant background information is given. The second part discusses how EV charging can be controlled indirectly through price signals, and two price models are suggested. The third part proposes a directly controlled charging model, and results from a case study is presented. The last part discusses how indirect control and direct control can be used in combination.

Part I

Background Information

CHAPTER 2

From Traditional Grid to Smart Grid

In a time with an increasing focus on how to mitigate climate change, the buzzword *smart grid* has come up as a way in which the electricity networks can facilitate low-carbon generation technologies and improve demand side efficiency. In this chapter the evolution from the traditional grid to smart grid is presented, along with the possibilities arising with a smarter grid. As this thesis is a continuation of previous work done by the authors, this chapter includes some background information that was also given in Ager-Hanssen and Myhre (2014).

2.1 The Evolution of the Grid

In this section, an introduction to the traditional grid will be given, as well as a presentation of the possibilities emerging with the steady evolution towards a smarter grid.

2.1.1 Characteristics of today's electricity grid in Norway

Today's existing grid was built 80-120 years ago, and it is based mainly on large central power station providing electricity to end customers (The Norwegian Smartgrid Centre, 2014). As reported in European Technology Platform SmartGrids (2006), the traditional grid design that we see today is a result of:

- The economies of scale that comes with large centralized generation.
- The geographical location of generation resources, such as coalfields and hydro resources.

The large power stations are connected to a high-voltage transmission grid, and further the power is supplied to end-users through medium and low voltage grids.

As shown in figure 2.1, power flow is mainly one-directional, and consumer participation is very limited. According to Regjeringen.no (2012) an intelligent grid is a term used to describe how electrical infrastructure can be designed, developed and operated in order to achieve a more efficient power system in the future. Additionally, intelligent grids utilize information technology (IT), and accommodate the use of market-based solutions. In Norway, the central- and regional grid is already intelligent, because Statnett, the Transmission System Operator (TSO), already make use of these technologies. In contrast, the Distribution System Operators (DSOs) have very limited information about the state of the distribution grid (Claude R. Olsen, 2013).

Traditionally, the only interaction a typical household consumer has with the DSO, is four times a year when she must read her electricity meter, and report the current status to the DSO. Consequently, in today's grid, consumer participation is very limited.

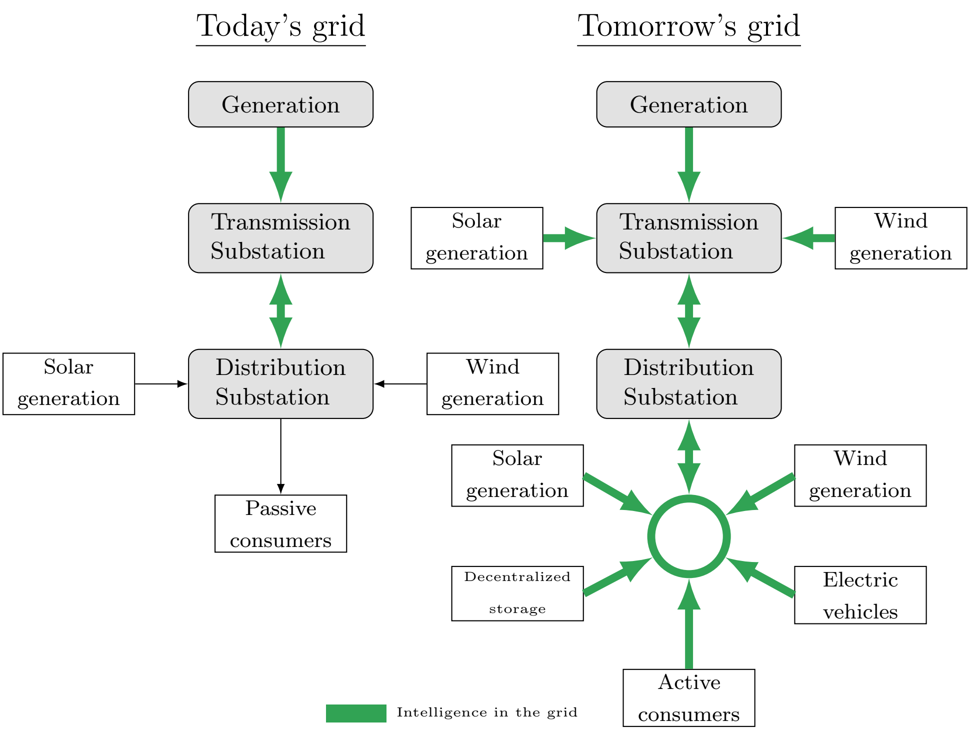

Figure 2.1: Illustration of today's and tomorrow's grid, adapted from Eurelectric (2011).

2.1.2 Drivers for change

Although the current grid functions sufficiently, future challenges and opportunities demand a change. The grid of the future must ensure secure and sustainable supply of electricity, taking advantage of new technologies, and at the same time complying with new policy imperatives (European Technology Platform SmartGrids, 2006).

By 2020, the European Union has set the following goals (Eurelectric, 2011):

- Reduce CO_2 emissions by 20% compared to 1990 level.
- Achieve a 20% share of renewable energy sources (RES) in overall energy consumption.
- Be 20% more energy efficient compared to 2008 level.

These goals have a big influence on the electricity industry. An increase in use of RES also means that the grid must accommodate more distributed generation (DG), such as wind and solar generation, in contrast to the centralized generation today. Simultaneously, to meet the goal of lower CO_2 emissions, an electrification of the transport sector is needed. The target set by the Norwegian Parliament is that by 2020, the emissions from new passenger vehicles should not exceed an average of 85 g CO2/km (Energi og Miljøkomiteen, 2012). To achieve this average, it is expected that 200.000 of all passenger vehicles in 2020 must be EVs (Grønn Bil, 2009), as it is not expected that the increasing energy efficiency of conventional fossil fueled cars will be sufficient (Transportøkonomisk Institutt, 2014).

2.1.3 Characteristics of tomorrow's grid

Smart grid is the collective term for a new generation power grid, and according to Eurelectric (2011) it is *"an electricity network that can intelligently integrate the behaviour and actions of all its users to ensure a sustainable, economic and secure electricity supply"*. Compared to today's grid, smart grid will bring intelligence to parts of the grid that today has limited access to information. One of the key enablers for smart grid is the introduction of Advanced Metering Infrastructur (AMI), often referred to as Smart Meters. In Norway, the DSOs are responsible for the installation of AMI at all end-customers by 2019 (NVE, 2014a). The AMI will have two-way communication between the meter and the DSO, and can give customers current information about their own consumption, and instant electricity- and grid prices. As illustrated in figure 2.1, the DSOs will experience a big change, as AMI and smart grid will enable them to monitor the power consumption and electricity flow within their grid. With access to consumption data, the DSO can adjust to changing grid conditions by controlling distributed generation and connected demand, or automatically reconfigure the network (Eurelectric, 2011). Utilizing flexibility on the consumption side to adapt demand to current grid conditions, is referred to as *demand response*, and will be discussed more thoroughly in section 2.4. In addition to maintaining system security, smart grid also create new opportunities for existing customers and service providers. Some of the most beneficial aspects of smart grid are discussed by Eurelectric (2011), and summarized below:

- Facilitate the integration of more renewable energy generation.
- Give the customers new incentives to take on a more active role as electricity consumers.

- Reduce power outages and related costs.
- Reduce the need for grid reinforcements by using the existing grid more efficiently.
- Enable an extensive penetration of electric vehicles with flexible recharging.

2.2 Overview of Actors in Smart Grid

The Nordic electricity market consists of a variety of actors, each with different needs and responsibilities. With the introduction of smart grid, new actors may enter, and existing actors may have their roles changed. The most important existing and potentially new actors are discussed in Wu (2013). These are summarized in figure 2.2, and discussed briefly below.

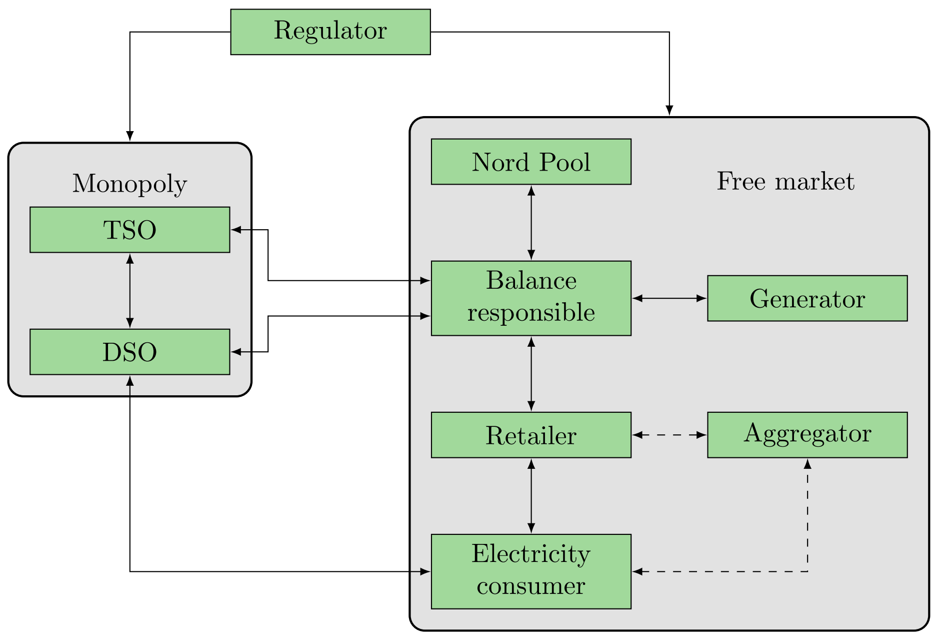

Figure 2.2: Existing and potential new actors in smart grid.

Regulator

The regulator is responsible for promoting efficient energy markets and cost-effective energy systems. In Norway, the regulator is the Norwegian Water Resources and Energy Directorate (NVE), and they exert monopoly control of the TSO and the DSO, as well as ensuring a well-functioning energy market, and protecting electricity consumers' interests through regulation, supervision and monitoring (NVE, 2013).

TSO

The TSO is the system operator, which is responsible for the overall security of supply. By balancing the power system and developing market rules, the TSO aims to ensure a well functioning electricity market. In Norway, the TSO is Statnett, and it is regulated by NVE.

DSO

Grid companies operating the distribution system are regulated monopolies, and must be independent both legally and management wise from other companies, such as retailers and generators. The DSO is through the delivery of electricity, responsible for the security of supply to customers.

Generator

The generator produce electricity, and bid in the expected power production for every hour of the upcoming day to Nord Pool. The generator is also responsible for balancing, and act as a production balance responsible, and thus balances actual production with planned production.

Retailer

The retailer is the link between the power market and the consumer, and communicates consumer demand to the power market. The retailer purchase the electricity and resells it to the consumers. In the Nordic countries the electricity can be bought from Nord Pool, or directly from local generators. Like the generator, the retailer also has balancing responsibility, and act as a load balancing responsible, meaning that they make a plan for the consumption the following day. In the case of deviations from the plan, imbalance costs must be paid to the TSO.

Nord Pool

The responsibility of Nord Pool is to manage the Nordic power exchange. This includes among others the trade in the day-ahead market (Elspot) and the intraday market (Elbas). Data on electricity consumption is forwarded from the DSO to the TSO and the balance responsible.

Aggregator

The possible new actor, often called an aggregator, is seen as a facilitator for efficient demand response. According to He et al. (2013), aggregators are *"entities that facilitate the demand response transaction between consumers, who provide flexibility, and demand response procurers, who use flexibility to optimise their businesses, through contracts"*. In the EV case, an aggregator can be a retailer or an independent actor, managing the charging of EVs in order to extract the flexibility potential.

Electricity consumer, EV user

The electricity consumer has traditionally been a passive consumer of energy, and the EV has been considered as a regular electrical appliance. However, while the electricity consumption for regular electrical appliances (TV, stove, lighting) coincides with use, the charging of EVs (and thus the electricity consumption) is decoupled from the use (the driving). This flexibility may contribute to change the role of the consumer; from a passive consumer of electricity, to also a provider of flexibility.

2.3 The Norwegian Electricity Grid

The Norwegian electricity grid includes three different levels (Regjeringen.no, 2008), as illustrated in figure 2.3:

1. The central grid.
2. The regional grids.
3. The distribution grids.

The first level, the central grid, can be considered the grid's highways. The central grid connects producers and consumers of energy from different parts of the country. Transmission lines to other countries are also included in the central grid, which makes it possible to export and import energy. The regional grids mainly connect the central grid to the distribution grids, but it also feeds customers directly from production. The distribution grids are the local power grids, which ensures that power is distributed to end users (e.g. households, businesses and industry). Large power production plants must be connected either to the central or the regional grids, while smaller production units can be connected to regional or distribution grids (Regjeringen.no, 2008).

2.3.1 How the distribution grids are dimensioned

The distribution grids carry voltages from 22 kV down to 230 V. Households and commercial buildings are supplied by 230V or 400V (Regjeringen.no, 2008). The grid consists of electrical transformers in substations, which transform voltage from high to low. Additionally, it consist of transmission lines transporting the electricity. The topology of the distribution grid can vary geographically, depending on the geology of the land. In larger cities, the distribution grid is more comprehensive than in more desert areas, considering that it covers more households and services. The electricity consumers are bound by the local DSO in their respective area.

The distribution grid is dimensioned to handle the one day of the year with the highest peak load. Thus, during other days of the year, and the other hours of

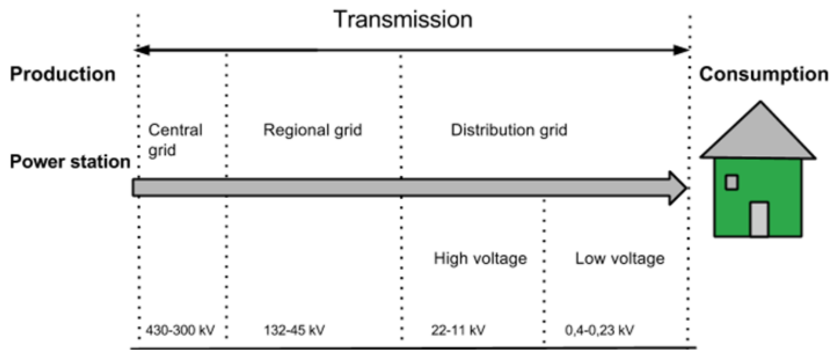

Figure 2.3: Illustration of the Norwegian electricity grid, inspired by NVE (2013).

the day, there is excess capacity in the grid. Since average cost per kWh transported decreases when the utilization increases (Regjeringen.no, 2008), this way of dimensioning the grid is not socio-economically efficient.

2.3.2 The regulation of the DSOs

To ensure a cost effctive energy system, DSOs in Norway and the rest of the Nordic countries are natural monopolies, as it is inefficient to have several parallel transmission lines in an area. In Norway, the DSOs are regulated by NVE. For each DSO a yearly income cap is determined by NVE. The income for the DSOs are mainly derived from transmission tariffs, and this income can not exceed the income cap (Regjeringen.no, 2008).

A regulated monopolist who has its costs covered, have no incentive to operate and develop its grid efficiently, which can lead to a situation where customers pay more than needed for using the grid. Consequently, it is not appropriate to base the income cap for each DSO on the individual costs. Therefore, when NVE calculate the income caps, they do not only consider historical costs for each DSO, but also a cost norm. The norm is calculated by a comparative analysis of the resource use of each DSO to the tasks they perform. When the income cap is stipulated, the cost norm is weighted by 60 percent, and the individual costs of the DSO is weighted by 40 percent. This regulation model have been used since 2007 (NVE, 2014b).

In order to provide quality in the grid, and to give incentives for the DSOs to build and operate the grid in a reliable way, NVE introduced the KILE scheme in 2001 (NVE, 2013). The KILE-element represents customers costs whenever there is disruption in the grid, and the scheme provides that the disruption costs of the customers are a part of the business evaluation of the DSOs. The disruption costs for customers depend on the time length of disruption, as well as the time of disruption. Historical KILE will be included in the cost base for the income cap, while the realised KILE for a DSO in a given year will be deducted in the income cap for this year (NVE, 2013). As a result, the DSO's income is reduced by disruptions.

2.3.3 Future challenges

The distribution grids in Norway, as well as in other countries, are facing great challenges in the near future. With an increasing focus on a low-carbon economy, renewable energy sources are required. The intermittency of these energy sources require more regulating services, which make them expensive to use (Ahn et al., 2011). When conventional fossil fueled cars are replaced by electric vehicles (EVs) the power demand from the electricity grid increases. More and more energy efficient appliances, such as induction ovens and heat pumps, are developed, but although these are energy efficient, they often require higher power (Statnett, 2014). Figure 2.4 shows the development of maximum power in the central grid, and the total electricity consumption in Norway, from 1980 to 2014. It can be seen that the maximum power and the electricity consumption have increased by 60 and 50 percent respectively, and that it is expected that the increase of maximum power is higher than the increase of electricity consumption in the following years[1]. If EVs are charged, and other high power appliances are being used simultaneously, the already existing peak load can increase significantly.

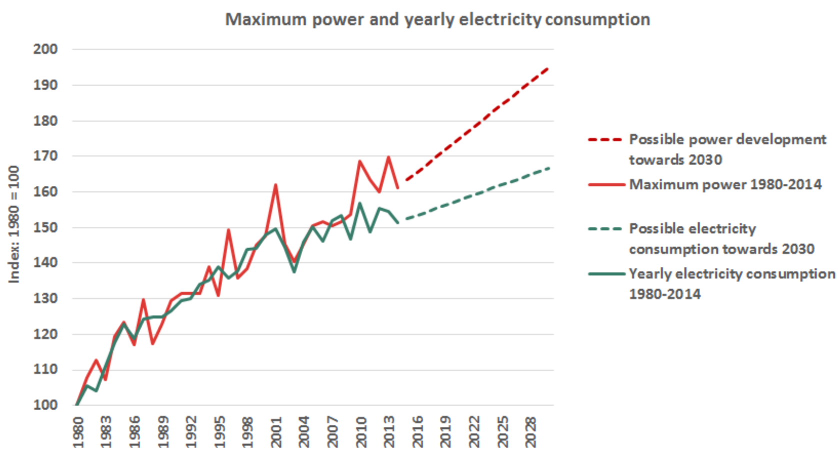

Figure 2.4: Illustration of the development of maximum power in the central grid, and total electricity consumption in Norway from 1980 to 2014, and the possible future development of these (NVE, 2015).

Every component in the electricity grid has power limitations which the power

[1]NVE does not create public extrapolations of power and electricity consumption. However, they have opinions of how they believe the development will be.

consumption cannot exceed without causing voltage problems, and at worst power outages (Controlled Power Company, 2014). Power outages are very expensive for the society (Sintef, 2014), hence it is in the society's interest that it is avoided. Power outages caused by peak loads can be avoided by reinforcing the grid, but this is very expensive, and as mentioned not socio-economic efficient. Another way of handling peak-loads and possible grid violations, is to utilize demand response. This is a method which is already used by DSOs today, but only on customers with a very high power consumption, mainly industrial customers (NVE, 2009), (Troms Kraft, 2012). It is possible for smaller electricity consumers to provide demand response as well, and this is the main focus in this thesis.

2.4 Demand Response

Utilizing flexibility on the demand side in order to reduce peak loads, is often called *demand response*. In the distribution grid, demand response aims to level out the load curve in order to avoid that the power consumption exceeds the grid capacity. By avoiding this, the need for investing in increased grid capacity, for instance buying a new transformer, is reduced. The flattening of load curves does not necessarily mean that less energy is consumed, but the maximum power output is reduced. In some periods, less energy is consumed, and in other periods more energy is consumed, resulting in a more stable energy consumption. When the peak load of a day is reduced, but the total energy is constant, it can be said that load has been *shifted*. Load shifting is beneficial from a socio-economic perspective when there is expectation of congestion in the grid, as the grid is utilized more efficiently. Electricity consumers moving load is often referred to as consumers offering *flexibility*. The terms demand response and flexibility will be used interchangeably in this thesis.

Demand response is categorized in several different ways by different authors. Albadi and El-Saadany (2007) divides demand response programs into two main categories:

- Incentive-based programs
- Price-based programs

In incentive-based programs, the customers receive payments or a discount rate in order to participate in the program, or they are rewarded (for instance by a payment) for their performance which depends on how much their loads are reduced during critical periods. In the price-based program, the prices vary throughout the day, and the objective of the program is to reduce demand in critical periods of the day by increasing the prices in these periods.

Kostková et al. (2013) and Heussen et al. (2012) have another way of categorizing demand response. They categorize it into the two programs:

- Direct demand response.

- Indirect demand response.

In direct demand response, some of the customers' appliances are controlled by a third party, for example a retailer, or by the DSO, while in indirect demand response the customer has the possibility to participate in the load reduction, and their actions are based on different signals sent to them. This can for instance be a price signal. Through the rest of this thesis the latter categorization will be used for different types of demand response, but the terms *indirect control* and *direct control* will be used instead.

2.4.1 Indirect control

With indirect control, the DSO, or a third party, sends some signal to a customer, and relies on the customers ability to respond to this signal (Ygge and Akkermans, 1997). The signal can be a price signal or another signal, for instance an information signal or an educational signal. Thus, it follows that in indirect control, the customer can decide whether to react to the load reduction signal or not. Kostková et al. (2013) divide indirect control into three categories: pricing programs, rebates and subsidies, and educational programs.

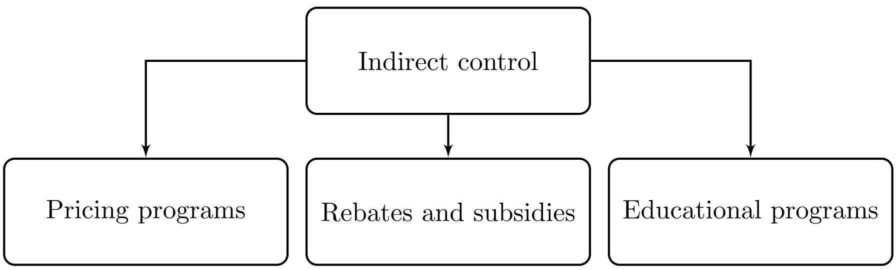

Figure 2.5: Different categories of indirect control.

The *pricing programs* include what is normally known as tariff programs. There are several types of pricing programs. One possibility is that the customer receives a price discount if he reduces his loads during critical periods. Another type is where the electricity customer has a contract with the DSO, and is informed in advance which prices that apply for different times of the day. The DSO cannot interrupt the loads of the customer, and the customer does not get a penalty when his load is not reduced. In *the program of rebates and subsidies*, customers receive price rebates or subsidies when they reduce peak demand or purchase appliances that are energy efficient. Note that although energy efficient appliances consume less energy, the required power is often high, and may contribute to higher peak loads. Hence, energy efficient *and* less power intense appliance should be rewarded. In the last program, *the educational program*, the customers are educated in order to increase their awareness of electricity efficiency.

2.4.2 Direct control

According to Ygge and Akkermans (1997) direct control is when a third party, or the DSO, remotely turns on/off or reduce/increase specific end user loads when needed. A contract usually specifies which appliances can be controlled, and under what terms (Kostková et al., 2013). Direct control of loads requires installation of additional equipment at the consumer side, in order for the third-party or the DSO to send a signal to control the demand.

In the USA, direct control has been used to remotely control the on/off cycle of air conditioners (Wu, 2013). This is known as cycling, meaning air conditioner are only permitted a certain on/off cycle, for example 50 % on. The payment to the end-user and the fraction of on-periods are adjusted to balance the need for reduction and the end-users willingness to participate. Although cycling in the US is used mainly to deal with large-area power balancing, the same concept could be used to manage congestion in the distribution grid. This would require a geographically located signal, signalling the state of the grid (Wu, 2013).

2.4.3 Different types of loads suited for demand response

He et al. (2013) emphasize that from different consumer loads, one can expect different degrees of flexibility, and divide the consumer load mix into four different load types. This is illustrated in figure 2.6. The first load type is *storable loads*, and for these loads the power consumption is decoupled from the use, as the energy is stored, for instance in a battery. These loads are very suited for demand response. The EV is a storable load. The next type of load is *shiftable loads*, which is a non-storable load. For these loads the power consumption can be shifted without affecting the use of the service. Examples of shiftable loads are dish washers. These loads are also suited for demand response, but less suited than the storable loads, as the power consumption is not decoupled from the use. *Curtailable loads* is the third load type, and it is a non-shiftable load. For these loads the power consumption can not be moved without affecting the end-user. An example of this load type is the TV. These types of loads are less suited for demand response. The fourth load type, the *base load*, is a non-curtailable load, for which the end-use service requires power instantly, and can not be shifted or interrupted. An examples is lights in the house. These types of loads are not suited for demand response.

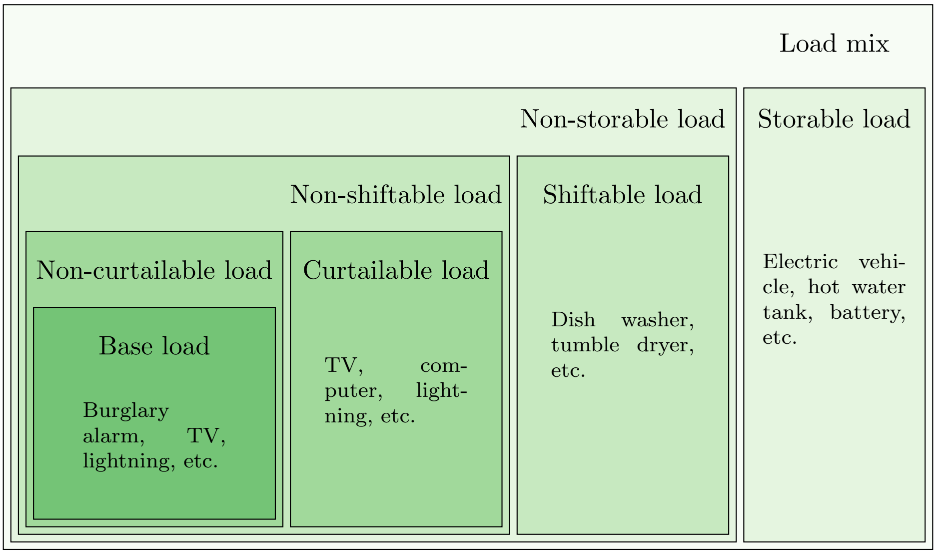

Figure 2.6: Illustration of the load mix, adapted from He et al. (2013).

2.4.4 Actors relevant for demand response

Many researchers focus on the potential of generating profit by utilizing demand response to offer flexibility in power markets. In this thesis, the focus is on how demand response can be utilized in order to prevent congestion in the distribution grid. The most important actors for this approach are the regulator, the DSOs, the aggregators and the electricity consumers (EV users). The regulator is important because they regulate the operation of the distribution grid. The DSO is essential because it operates the distribution grid where the congestion can occur. The aggregator is a new actor, considered because it is not certain that the DSO in the future will, nor can, operate demand response programs. Lastly, the the electricity consumers (EV users) are considered because they are the entities which can offer flexibility.

2.5 Electric Vehicles in Smart Grid

In Norway, the number of registered EVs has increased by a multiple of approximately 21 from January 2009 to April 2015 (Grønn bil, 2015). From an emissions perspective, the increment of EVs is very positive, however, this increase can cause great challenges on the power system, especially on the distribution grid. When EVs within the same geographical area are charged simultaneously (for instance when people arrive home from work), this power consumption comes in addition to an already existing peak-load, possibly overloading network components. To emphasize the high charging power of EVs, it can be mentioned that the average power consumption in a Norwegian household through a day during winter is 2,72 kW (Sintef, 2014). A normal charging power for EVs is $\sim$ 4 kW.

Assuming the number of EVs continue to grow, and no management of the charging is performed, the DSOs must invest heavily in reinforcement of the grid to make it able to withstand the peak-loads. A benefit with the EV is that it is a *storable* load, which is well suited for demand response. The reason for this is that the EV is not in use during large parts of the day, and most EV users are indifferent to when the charging of the EV is carried out as long as the EV is ready when they need it. Another benefit of EVs is that it is well suited in combination with renewable energy sources. EVs can be charged by renewable energy, while gasoline cars are dependent on fossil fuels. By replacing gasoline cars by EVs, global emissions can be reduced and the air quality in cities can be improved when the amount of exhaust from cars diminishes. It is expected that EVs in the future can function as a back-up energy source when the penetration of renewable energy sources and the amount of distributed generation increases. Renewable energy sources are usually not as stable as conventional energy sources. The energy produced by wind turbines naturally depends on the wind conditions, and the energy from photovoltaics depends of the amount of clouds, time of the year etc. If a house is served by local production of energy, for instance by a wind turbine, the battery of the EV can function as an energy reserve when there is not enough wind to produce sufficient amount of energy. This technology is called *vehicle-to-grid* (V2G).

The EVs can thus be seen as a grid problem *and* a solution. Although the EVs demand a high power, it is a very flexible load, and can potentially be shifted to times with free grid capacity and excess renewable energy production.

There exists many types of EVs. The main categories are (Masoum et al., 2010):

- Hybrid electric vehicles (HEV) - These vehicles combine two propulsion sources: petroleum based and electric motors. HEVs are generally not grid rechargeable. The battery is charged by the petroleum based motor.
- Plug-in electric vehicles (PEV) - This is all EV types which can be grid connected in any form. In this category one can find plug-in hybrid electric vehicles (PHEV) and battery electric vehicles (BEV). Both types of vehicles can be charged from electrical outlets in households.

In this thesis, the main focus is on EVs which can be connected to the grid, PEVs. However, these will be referred to as EVs.

Today, the charging of most EVs is executed in the following way:

1. The EV is connected to the grid when the owner wants the EV to be charged.
2. The EV is charged by a constant charging power which is the maximum power output from the charging point.

3. The EV stops charging when it is fully charged, or when the EV owner disconnects the EV.

This type of EV charging will in this thesis be referred to as *uncontrolled* or *dumb* charging. Another possible type of charging is called *smart charging*, which in this thesis will be referred to as *controlled charging*. There are several different definitions of controlled charging. Bollen (2011) states that controlled charging is methods to reduce the contribution of EVs to the peak load in the grid, while Richardson (2013) defines it as charging of EVs when it is most beneficial, which could be when the electricity price is at its lowest, demand is lowest, when there is excess capacity, or based on some other metric. The authors of this thesis have chosen to use the latter definition.

Controlled charging of EVs will be divided into two main categories, similar to demand response:

- Indirect controlled charging.
- Direct controlled charging.

Indirect controlled charging is when the decision of when and how much to charge the EV is decentralized. However, the decision depends on signals sent to the EV/EV user, for instance price signals. The signals can for instance be sent from the DSO with an objective of achieving a certain goal. *Direct controlled charging* is when a third party directly takes decisions of when and how much different EVs should be charged by. The third party could for instance be the DSO with an objective of preventing congestion in the grid.

2.6 Grid Investments or Utilizing the EV's flexibility?

Utilizing flexibility as an alternative to grid reinforcements is not exclusively preferable. It is only preferable if the socio-economic cost of utilizing flexibility is less than the socio-economic cost of reinforcing the grid. The amount of overload during for instance a year, will be critical when the cost of flexibility services is compared to the investment costs of grid reinforcement. It is during these hours the consumers are exposed to an extra cost either due to the need of increased prices in order to reduce demand, or as the demand must be directly controlled in these hours, and hence the utility of the consumer is reduced. This is illustrated in figure 2.7. The critical amount of overload (in kWh) will vary for the different components in the grid.

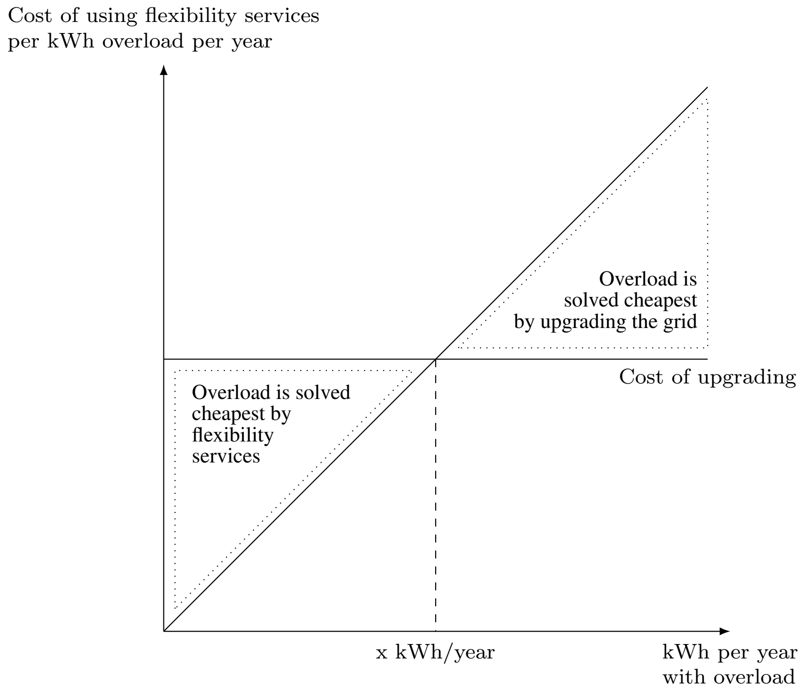

Figure 2.7: Economic motivation for the DSO to use flexibility services, adapted from (Nordentoft, 2013).

When it comes to utilization of price signals, Pindyck and Rubenfield (2013) says that when there is no capacity limitations, a regulated monopolist should set the price p of a good where the demand curve intersect the marginal cost curve, in order to ensure maximum welfare. This is where the sum of consumer surplus (CS) and producer surplus (PS) is maximized. This is illustrated in figure 2.8

If the price is set different from p^*, a dead weight loss (DWL) occurs. This is illustrated in figure 2.9, where p^2 is set higher than p^*. Dead weight losses is socio-economic losses which should be minimized as much as possible. When there is capacity limitations in the grid, and price signals must be used in order to adapt the demand to the capacity, a dead weight loss occurs as the price is not set equal to short run marginal cost. In a simplistic world, one could say that as long as the socio-economic cost associated with the dead weight losses of using price signals is less than the marginal cost of reinforcing the grid, price signals should be used in order to ensure that capacity is not exceeded. However, the real world is more complex, and several aspects must be taken into consideration when deciding whether or not to introduce price signals. This will be discussed further in chapter 3.

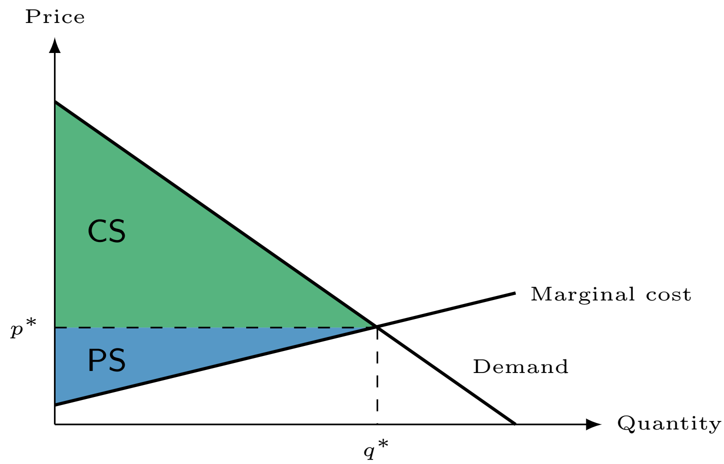

Figure 2.8: Socio-economic optimal tariff for a regulated monopolist, adapted from ECON Analyse (2006).

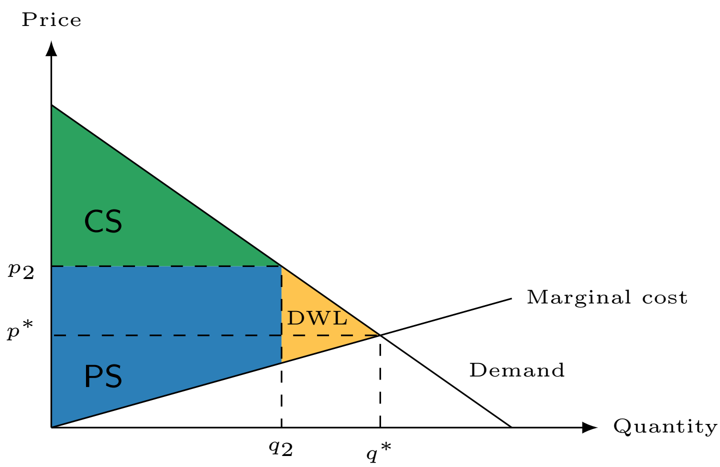

Figure 2.9: Illustration of how a dead weight loss occurs when the price it set higher than marginal cost, adapted from ECON Analyse (2006).

Part II

Indirect Control

As explained in section 2.4.1, indirect control is mainly divided into pricing programs, educational programs, and rebates and subsidies programs. In this part, the focus is on pricing programs, mainly price signals, and the motivation is to find good price models which ensure a better utilization of the grid, and which reduce the probability of congestion. As pricing of electricity does not necessarily reflect the grid conditions, these prices can not be used to inform the consumers of the grid condition. Additionally, as the electricity prices in Norway are relatively constant during a day, small variations in the electricity price will most likely not trigger demand response. Hence, when the goal is to avoid congestion in the distribution grid, price signals must be sent from the DSO, or a third party with information regarding grid conditions. This part consist of two chapters. The first chapter, chapter 3, discusses important principles and considerations when finding optimal price models for demand response. The second chapter, chapter 4, proposes two different price models suited for control of EV charging, in combination with two numerical examples and a discussion of the models.

CHAPTER 3

Indirect Control: Pricing and Tariffs

In order to find a good price model suited for demand response, general principles of finding optimal prices needs to be discussed, as well as the considerations which need to be taken into account when price signals are sent to consumers. Although the focus in this thesis is not on educational signals to consumers, the importance of these types of signals should not be underestimated. Price signals have no value if consumers do not respond to them, and as Norwegian consumers have not been used to adapt their electricity consumption in response to prices, the consumers must be informed and educated to know how to react. This chapter starts with a discussion of the purpose of grid tariffs, and what they should reflect, followed by a motivation for why new grid tariffs are needed. Then the principle of socio-economic optimal prices and consumer behavior is discussed. Lastly, possible future price models suited for demand response are assessed in terms of various criteria the authors find important when pricing to release the flexibility potential.

3.1 The Purpose of Grid Tariffs

A grid tariff is the price paid to get electricity transported to the house (NVE, 2015a). Grid tariffs should reflect the DSO's cost of building, owning and operating the grid. As the grid is a natural monopoly, the DSOs must be regulated in order to protect the customers from unreasonably high tariffs. As mentioned in chapter 2, NVE regulates the DSOs in Norway. NVE controls that the revenue the DSO receives from its customers does not exceed the revenue cap; the maximum amount of income the DSO can acquire from its customers.

According to NVE (2015) the grid tariffs has the purpose of solving two specific tasks:

1. Firstly the tariffs should give price signals which reflects the actual condition of the grid, in order to affect the consumption properly. In the short run, the user of the grid should face a price which equals the marginal cost the user inflicts on the grid. When there is no capacity limitations in the grid, the

only real cost the user inflicts to the grid is the marginal cost of loss. When there is a capacity limitation, the marginal cost will exist of an additional component reflecting the marginal willingness to pay for the limited capacity.

2. Secondly, when the right price signals for optimal use is given by the price signal in 1., the remaining costs of building and operating the grid, known as *residual costs*, must be distributed among the users of the grid. While the purpose of price signals is to affect the consumers to ensure optimal use of the grid, the optimal cover of costs-theory says that the part of the tariff covering residual costs should affect the consumption as *little* as possible, in order to avoid high pricing which gives underutilization of the grid.

3.2 The Grid Tariffs in Norway Today

Based on the revenue cap set by the NVE, the DSO establishes grid tariffs in its concession area. The DSO is obliged to offer non-discriminatory objective tariffs and conditions, but the tariff can be differentiated between the DSO's customers if it is based on relevant grid conditions (Olje- og energidepartementet, 2015). An example of a relevant grid condition is the annual energy consumption, which can form the basis for customer groups such as industry and household customers.

The components of the grid tariff can be separated into two groups; use dependent and other tariff components (NVE, 2015), summarized in table 3.1. The use dependent components are the energy component and the capacity component, and should as a general rule reflect the costs that a consumer's electricity consumption inflicts on the grid. The other tariff components are the fixed component and the power component, and as a general rule, these should reflect grid costs not covered by the use dependent components. In addition to these components in the grid tariff, the DSO can charge a construction contribution to cover construction costs of new network subscriptions, or by amplification of the network to existing customers (NVE, 2015).

NVE (2015) and NVE (2015b) identify the following requirements for the different components:

- Energy component

  The energy component of the grid tariff should cover costs related to power losses in the grid. When the consumption approaches the capacity limit, the losses become substantial, and in principle the energy term shall reflect the marginal losses in the transmission system, caused by the costumer's consumption. Today, for each customer group, the loss rate (and thus the energy component), is often based on an average of the marginal losses in the relevant area, not each costumer's contribution to the power loss. For domestic costumers, NVE allows the energy component to be set higher than the cost for marginal loss, in order to cover a share of the DSO's fixed network costs.

Tariff group	**Purpose**	**Tariff component**	**Regulatory design requirements**
Use dependent	Give the customer a price signal	Energy component (øre/kWh)	Greater or equal to the cost of marginal losses
		Capacity component (øre/kWh or kr/kW)	Should create a balance between transmission requirements and network capacity
Other tariff components	Ensure cost recovery and a reasonable allocation of costs	Fixed component	Greater than customer specific costs
		Power component	Should be based on the customers power output in defined periods

Table 3.1: Overview of the transmission tariffs in the distribution grid, adapted from NVE (2015).

- Capacity component

  To create a balance between transmission requirements and grid capacity, today's regulations allow for a capacity component, which can be used when the demand for transmission exceeds the capacity. The capacity component should apply at times where there is capacity scarcity, and can be in the form of a higher energy component (øre/kWh) or as a power term (kr/kW). Today however, NVE (2015) does not know of any DSOs which use this component to affect demand to alleviate capacity problems of short duration.

- Fixed component

  The fixed component of the grid tariff shall at least cover customer-specific costs, and is often differentiated for different customer groups. The determination of the fixed component can be based on the size of the customer's main fuse and/or pattern of use. Often do for instance cabins have a higher fixed component than regular households, as a lower annual energy consumption leads to less coverage of fixed costs through the energy component.

- Power component

  While the grid tariff of households and smaller business customers mainly consists of an energy and a fixed component, business and industry customers with an annual electricity consumption exceeding 100.000 kWh (NVE, 2015) usually has a power component as well. There are different ways of determining this component, but most commonly, it is the maximal power consumption in a month, or an average of several measurements over the same period that forms the basis for the power component settlement.

3.3 Motivation For New Grid Tariffs

With a change in both how electricity is produced and consumed, a need to rethink the traditional grid tariffs arise. On the production side, an increasing share of distributed generation and renewable energy sources impose challenges on the existing distribution grid, and for the DSO. The intermittency of renewable energy sources, combined with distributed generation, lead to new flow patterns. The DSOs must expect a role shift, from a passive grid provider, to an active intermediary between consumers and the energy system (Ipakchi and Albuyeh, 2009).
On the consumption side, some of the most important changes include:

- New power intensive appliances - With an increase of high power appliances like induction stoves, instantaneous water heaters and EVs, the maximum load increases. An induction stove can demand up to 11kW compared to a conventional stove demanding 7 kW. EV charging is a new type of demand, as it does not replace other electric appliances, but rather adds to the existing electricity loads.

- New building regulations - The current building regulations in Norway, TEK 10, require new buildings to be more energy efficient, and thus have a lower annual electricity consumption (Direktoratet for Byggkvalitet, 2015).

These new appliances combined with more energy efficient buildings, lead to changing patterns in electricity usage. As an illustrative example, one can compare a household from 1970, having a regular stove, a hot water tank and a gasoline car, with a house from 2015 with an induction stove, an instantaneous water heater, and a Tesla in the garage. The energy consumption in the 2015-house is nearly half of the 1970-house, and consequently the total transmission costs are less than half, as illustrated in figure 3.1. However, although the 2015 house has a lower annual electricity demand, it will produce higher peaks throughout the day. This is illustrated in figure 3.2, where both households have a base load consisting of energy mainly for heating. In the morning, someone is taking a shower, creating a spike in both cases, but higher in the 2015 house. After returning home from work, the Tesla is plugged in (in the 2015 house), and dinner is prepared on the stove. Then, after soccer-practice, the shower is again turned on, and the Tesla is charged.
With this example in mind, it can be discussed how the grid tariffs today fulfill the tasks mentioned in section 3.1:

1. Today's tariffs for households do not fulfill the first task of giving each customer information about how its consumption affects the grid. As the energy component is flat, the consumer has no incentive to shift consumption to times when it is more beneficial for the grid, neither does the consumer have any information about the grid conditions. Consequently, in the 2015 house, the EV will be charged simultaneously with cooking on the induction stove, creating a high peak.

Figure 3.1: Illustration of the difference in energy consumption and the cost of transmission for a house from 1970 and a house from 2015. The transmission cost is based on tariffs from Hafslund Nett.

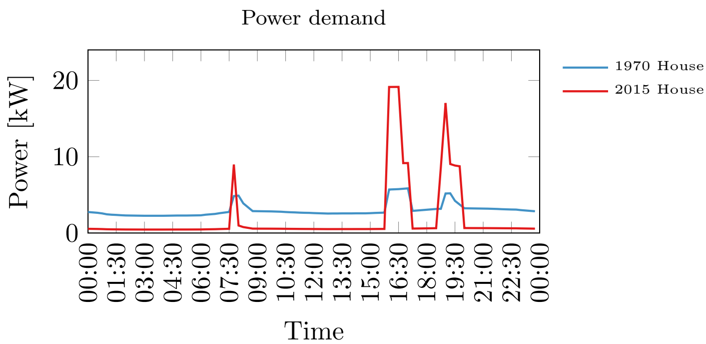

Figure 3.2: Illustration of the power demand in a house from 1970 and one from 2015.

2. As today's energy component also covers a large share of the DSO's fixed costs (for customers without a power component), the burden of the tariffs is not fairly distributed. Since the grid must be dimensioned to accommodate the peak load, it is often the simultaneous use of high powered appliances that is responsible for the need to reinforce the grid. From a grid point of view, low, but stable demand, is not harmful. In the example with the 1970 and the 2015 house, the 1970 house is cross-subsidising the 2015 house. It is the demand pattern of the 2015 house that puts the most stress on the grid through high power peaks, but because of the higher but more stable demand of the 1970 house, it ends up paying a larger share of the DSO's fixed costs related to grid investments.

With a shift in consumption pattern towards more power intensive appliances, the need for new tariffs is apparent. Important criteria and considerations when designing new tariffs will be discussed in the following sections.

3.4 Socio-Economic Optimal Prices

In this section, criteria for optimal pricing will be discussed. Optimal prices will be divided into short run optimal prices, and long run optimal prices.

3.4.1 Short run optimal prices

In this subsection it will be discussed which criteria that form the basis of socio-economic optimal prices for transmission of electricity in the short run, given that the grid is a natural monopoly. As mentioned in section 2.6, a regulated monopolist should set the price p of a good where the demand curve intersects the marginal cost curve as illustrated in figure 3.3, in order to ensure maximum economic surplus. This is where the sum of consumer surplus (CS) and producer surplus (PS) is greatest. This means that whenever grid capacity exceeds demand, the DSO should set the price equal to marginal cost in order to ensure maximum utilization of the grid. Marginal cost for a DSO is mainly costs related to power loss in the grid, which increases when the power output (kWh/h) increases (NVE, 2015).

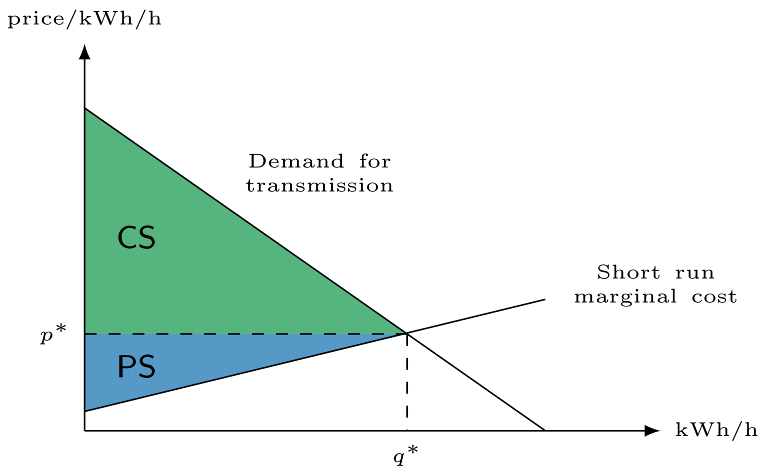

Figure 3.3: Socio-economic optimal tariff for a regulated DSO, adapted from ECON Analyse (2006).

When the demand for transmission of electricity exceeds the capacity, it is optimal to introduce a capacity fee in order to ration the capacity (ECON Analyse, 2006). This capacity fee will function as a variable component which is zero whenever there is sufficient capacity. Figure 3.4 illustrates the optimal price p^* when there is a capacity limitation, C^*. As shown in the figure, the price p^* can be divided into a capacity component, p^{cap}, and a component reflecting the marginal cost, p^{mc}. It is the component p^{cap} which ensures that the demand for transmission equals the available capacity. As the price is not set equal to p^{mc}, a dead weight loss occur. However, *given* the available capacity, the capacity component ensures maximization of welfare (ECON Analyse, 2006). As mentioned in section 2.6, in a simplistic world, one could say that as long as the socio-economic cost associated with the dead weight losses of using price signals is less than the marginal cost of reinforcing the grid, price signals, instead of grid reinforcements, should be used in order to ensure that capacity is not exceeded. However, as the real world is more complex, other aspects must also be taken into consideration, for instance the cost of the deterioration of the service provided to the consumers when price signals are used. Even though the demand can be shifted instead of reduced when price signals are used, an energy consumer will have to consume the energy in other time periods than what is most convenient for her, which reduces the consumer's utility value. Although it can be difficult to decide the real economic value of this reduced utility, it should always be taken into consideration. Additionally, reinforcements of the grid is associated with less risk of disruption of transmission of energy. Hence, the value of this should be taken into account, as disruptions is a cost for the society due to KILE.

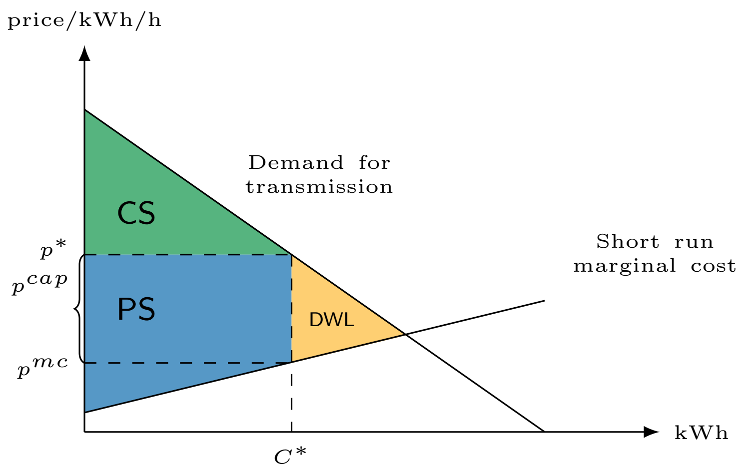

Figure 3.4: Socio-economic optimal tariff for a regulated DSO with capacity limitation, adapted from ECON Analyse (2006).

3.4.2 Long run optimal prices

In addition to the short run marginal costs, the DSOs also have long run costs, including the fixed costs, which needs to be covered. Maintenance of the grid is for instance a fixed cost for the DSO. As mentioned in section 3.1, the costs which are not covered by the component which prices marginal losses, is referred to as *residual costs*. Figure 3.5 illustrates that setting the price equal to marginal cost will not cover the DSO's long run cost, and a loss equal to the area D will occur. The loss, D, occurs as the cost is $p^{AC} \cdot q^*$, while the revenue is only $p^* \cdot q^*$. However, if the price was set to p^{AC}, the demand would be lowered and be less than what is optimal from a socio-economic point of view, as a dead weight loss occurs. This would again result in a socio-economic loss. Hence, as long as the sum of producer surplus and consumer surplus is greater than the deficit, D, the price should be set to p^* in order to ensure maximum utilization of the grid. Pricing p^* will then still be optimal from a welfare perspective (THEMA, 2013b).

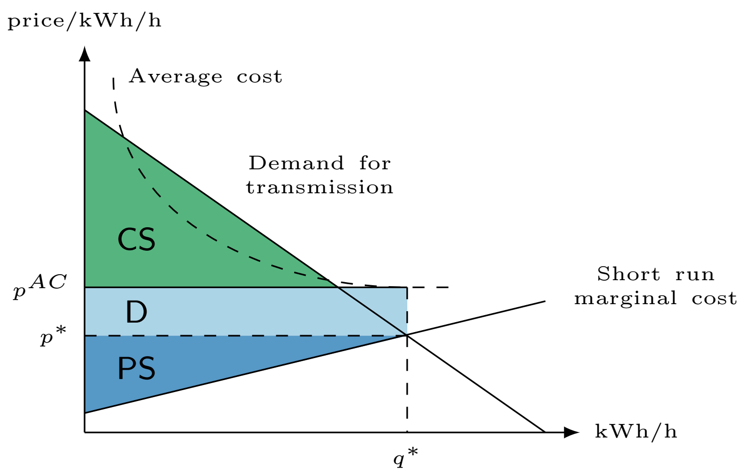

Figure 3.5: Pricing marginal cost versus long run average cost, adapted from ECON Analyse (2006).

But in order to price transmission of electricity by the price p^*, the residual costs must be covered in other ways. In order to cover long run investment costs, a natural solution would be to introduce a tariff equal to the marginal cost of expanding the transmission capacity. However, as reinforcing the grid is associated with economics of scale, it is beneficial to reinforce the grid by more than the marginal demand for transmission capacity (NVE, 2015). Hence, introducing a tariff which reflects the marginal cost of increasing capacity will not cover average cost of increasing capacity. Moreover, if all of the residual costs should be covered by price signals, the price signal would be too strong compared to the underlying marginal costs. Hence, these price signals would result in a socio-economic loss (THEMA, 2013b).

An often preferred method for a monopolist to cover residual costs is for the monopolist to charge a *two-part tariff*. A two-part tariff uses marginal charges to cover the marginal costs, and fixed charges to cover residual costs (Begg et al., 2008). How to cover the residual costs of the DSO is beyond the scope of this thesis, as the focus is on how to price transmission of electricity in order to avoid congestion.

3.5 Consumer Behaviour

When prices are used with the aim of affecting demand, it is very important to consider consumer behavior. Price elasticities and diversity of demand are ways of describing consumer behavior, and will be discussed in this section.

3.5.1 Price elasticity

In order to find optimal prices, it is important to know how the demand of consumers depends on prices. **Elasticity** measures the sensitivity of a variable to another variable. The elasticity tells us the percentage change of a variable due to the one percent increase of another variable (Pindyck and Rubenfield, 2013). The **price-elasticity** of demand describes the percentage change in demand, Q, of a good, due to the corresponding percentage change in the price, P, of the good (Begg et al., 2008), and it is expressed by the following equation:

$$E_p = \frac{\%\Delta Q}{\%\Delta P} \tag{3.1}$$

The demand of a good can for instance depend on the price of the good and/or the price of other goods. If the price of a good varies in different time periods, the demand of the good in the current time period can depend on the price of the good in this time period, and the price of the good in other time periods. Electricity is typically a commodity with a price variation for different hours throughout the day, hence in this thesis, it will be discussed how consumers adjust their demand depending on the price of the product in the same period as the good is to be consumed, and also how the demand depends on the price of the product in other time periods.

Self-elasticity

The self-elasticity-matrix describes how the demand of a good depends on the price of the good in the same period as the good is to be consumed (Venkatesan et al., 2012), and it can be expressed by equation 3.2.

$$E_t = \frac{\%\Delta Q_t}{\%\Delta P_t} \tag{3.2}$$

The self-elasticity matrix, E_t, consists of the elasticity coefficients, ϵ_t. One can imagine how the demand of electricity depend on the price of electricity in the same time period. If the price is very high, some of the electricity consumers would probably reduce their consumption of electricity or move the consumption to another time period.

Cross-time-elasticity

One can also imagine how the demand of electricity depends on the price of electricity in other time periods. Imagine someone who is considering to charge their EV after work. Although it is most convenient to plug in the EV right after work (and thus start charging right ahead), if the price of electricity two hours ahead and further on is expected to be very low, the person might wait to plug in the EV until the prices are low. The change in demand at time t due to a change in price at time t' is referred to as cross-time-elasticity (Venkatesan et al., 2012), and it is expressed in equation 3.3.

$$E_{t,t'} = \frac{\%\Delta Q_t}{\%\Delta P_{t'}} \tag{3.3}$$

The cross-time-elasticity matrix, $E_{t,t'}$, consists of the elasticity coefficients, $\epsilon_{t,t'}$ which expresses how sensitive the demand in time period t is to price changes in time period t'.

In theory, a cross-time-elasticity matrix is *loss less*, meaning that quantity is only moved not reduced or increased, if it satisfies equation 3.4 (Kirschen et al., 2000).

$$\sum_{t' \in T} \epsilon_{t,t'} = 0, \qquad t \in T. \tag{3.4}$$

The expression for the new quantity given cross- and self elasticities

The new quantity in a time period due to a change in price in the current time period and other time periods, can be expressed by the following equation (Aalami et al., 2010):

$$Q_t = Q_t^0 + \sum_{t' \in T} \epsilon_{t,t'}^h \frac{Q_t^0}{P_{t'}^0} (P_{t'} - P_{t'}^0). \tag{3.5}$$

Equation 3.5 is based on a linearisation of the mathematical expression for a new quantity caused by a new price given in equation 3.6.

$$Q_t = Q_t^0 + \frac{\partial Q_t}{\partial P_t} \Delta P_t. \tag{3.6}$$

Expression 3.6 is difficult, if not impossible, to quantify. Hence the curve is often linearized (Kirschen et al., 2000). After the linearization the expression becomes:

$$Q_t = Q_t^0 + \frac{\Delta Q_t}{\Delta P_t} \Delta P_t, \tag{3.7}$$

which again is used to derive the expression in equation 3.5. Due to the linearization of expression 3.6, whenever the original quantity, Q_t^0, is zero, regardless of how great the price difference, $P_{t'} - P_{t'}^0$, is, the new quantity, Q_t, will never be different from zero. This can be a problem in some situations, as will be seen in chapter 4.

3.5.2 Diversity of demand

The consumers' demand for electricity is partly random in nature, and due to this the maximum demand of a number of households is much lower than the sum of the individual maximum demands (Dickert and Schegner, 2010). Dissimilarities in needs and use strengthen the diversity of demand, while the more similar the end users are, the diversity decreases. With more flexible appliances, it is expected that electricity demand will become price sensitive. Indirect control through prices can then lower the randomness in electricity consumption, and result in something known as *the avalanche effect*. Avalanche effects are sudden increases in demand, in response to a price signal, induced by optimal behavior of automated devices (García-Villalobos et al., 2014). An avalanche effect can also be seen without automated devices, for instance consumers with a time-of-use tariff might plug in flexible devices in response to a shift from a high to a low price period, resulting in a demand peak. If this signal is valid for several automated devices in the same area, the result may be a peak potentially harmful to the grid. When designing indirect price models, good forecasts and knowledge of consumer behaviour is crucial to avoid harmful avalanche effects.

3.6 Price Models Suited for Demand Response

In the recent years, a large number of possible future price models for transmission of electricity which is better suited for the new consumption patterns presented in section 3.3, have been proposed by various institutions. Some of these price models will be presented in this section. The success of every price model depends on the integration of AMI, and a user friendly representation of price information. The power problem can be solved by adapting the energy component of the grid tariff, the power component, or a combination of these two. The purpose is to figure out how the capacity component discussed in section 3.4.1 should be designed. The general difference of pricing energy versus power, is that energy pricing is about finding the price per amount energy consumed (kWh), while power pricing normally is the pricing of the maximum power in a given period (for instance within a month, a week, or an hour).

How a consumer's typical load curve affects the consumer's cost, depends on which tariff it is exposed to. This is illustrated in figure 3.6. For the energy tariff, two consumers' load curves are illustrated. Although the consumer illustrated in yellow has a high peak load, potentially harmful for the grid, the price this consumer pay is equal to the consumer in green with the flat load curve, because their energy consumption is equal. Also for the power tariff, two consumers' load curves are illustrated. The consumer illustrated in pink has a very high energy consumption compared to the consumer in blue. However as they both pay for the maximum power output, they both end up paying the same.

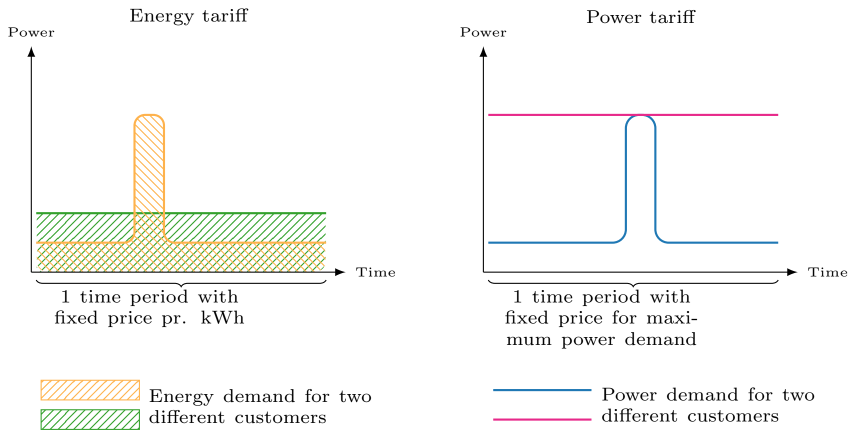

Figure 3.6: Illustration of the difference between energy and power tariffs.

Before discussing the different price models, two terms should be explained: static and dynamic pricing. According to Faruqui and Palmer (2011) *dynamic pricing* is *the charging of different electricity rates at different times of the day and year to reflect the time-varying cost of supplying electricity.* These authors focus on dynamic pricing used to balance electricity consumption and production, but dynamic pricing of transmission can also be used to prevent overload of grid components which can occur when the power demand is too high. As opposed to dynamic prices, *static pricing* is when the same rate is charged regardless of the time of the day, the week or the month.

3.6.1 The energy component

THEMA (2013a) describes three main variants of pricing models based on the energy component. All of these should give incentives for the electricity consumer to move load when there is (or is expected) a high load in the grid and hence high marginal costs. The models are:

1. Time-of-use energy tariff (TOU energy tariff)
2. Critical peak pricing (CPP)
3. Real-time pricing (RTP)

The models have different degrees of dynamics. The TOU energy tariff is the least dynamic price model, and the RTP the most dynamic price model. Higher time resolution is required when the degree of dynamic increases. The TOU energy tariff has fixed rates per kWh, but the rates varies between summer and winter, and/or day and night. Day and night prices are illustrated in figure 3.7. During time periods with an expectation of high cost of marginal losses, the rates are higher than in periods with an expectation of low cost of marginal losses. This gives an incentive to shift loads to periods with lower total power demand in the grid. CPP is a price model where the tariffs are especially high during hours with a high load. This is illustrated in figure 3.8. The price during critical hours are fixed, but it can be decided in advance which hours that are critical, or it can be decided for how many hours the tariff should apply, but which hours depends on the load in the grid. The price could be relatively low in off-peak hours, while relatively high in peak-hours. Hence, the consumers have an incentive to reduce or move the load from peak-hours to off-peak-hours. As the CPP-model is very similar to the TOU-model when prices and hours are fixed, throughout this thesis it is focused on the CPP-model where only price and duration is decided. In RTP-model the price varies with the actual cost of marginal loss, as illustrated in figure 3.9. This model requires a high time resolution of price information. RTP gives incentives to shift load from hours with high marginal cost, to hours of low marginal cost.

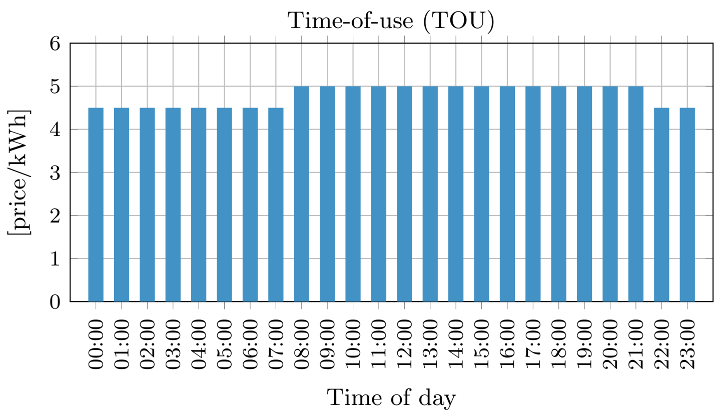

Figure 3.7: Illustration of time-of-use rates.

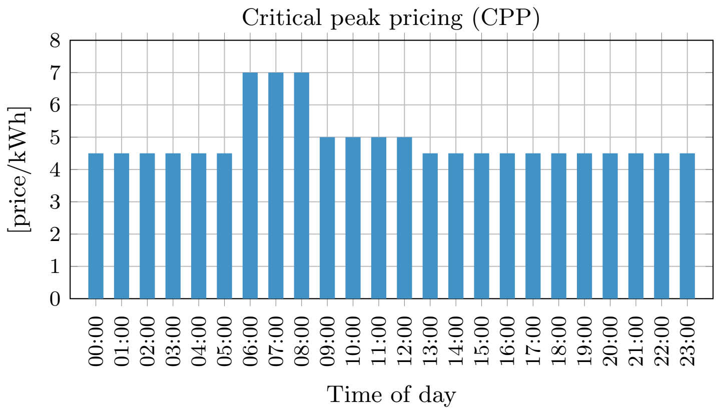

Figure 3.8: Illustration of critical peak pricing.

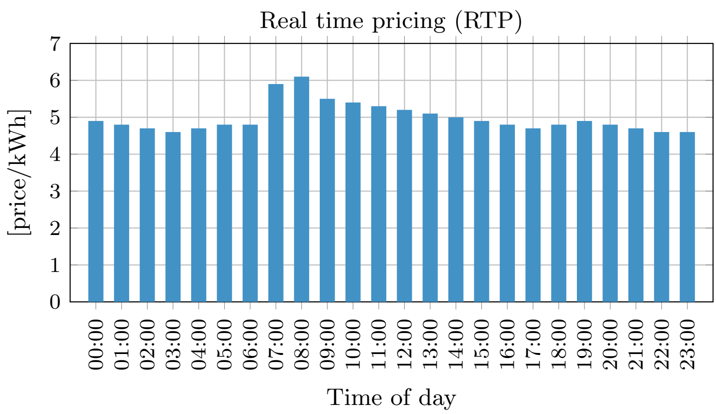

Figure 3.9: Illustration of real time pricing.

3.6.2 The power component

In order to prevent congestion in the grid, power based tariffs could also be used. KANAK (2014) divide power based tariffs into five main price models:

1. Time-of-use power tariff (TOU power tariff)
2. Dynamic tariff
3. Subscribed tariff
4. Progressive tariff
5. Purpose based tariff

TOU power tariff imply that the customer has fixed tariff levels per kW related to specified times of a day, week and/or year. With the Dynamic tariff the customer has fixed tariff levels per kW, but the timing of when the different tariff levels apply is dynamic, and the customer is notified in advance by the DSO. In this way, the DSO can link high tariffs for hours with expected capacity problems in the grid. With a Subscribed tariff the customers pay an amount per kW per year, which is the minimum power output they believe they can keep within. The customers must pay extra for every hour their power output exceeds what they have subscribed for, and this fee is relatively high. The Progressive tariff is increasing with increasing power output, and the DSO sets the tariffs. For instance up to 3 kW consumption the price can be x per kW, and for consumption over 3 kW the price can be x+y per kW for every kW exceeding 3 kW. With a Purpose based tariff the customer has two or more tariff levels which are related to what the power is used for, for instance EV charging. In order to provide something else than just a distribution effect, the tariff must be combined with a TOU power tariff or a dynamic tariff which helps making an incentive to shift the power consumption for precisely this purpose.

3.7 Discussion of Price Models Suited for the New Consumption Pattern

The price models presented in section 3.6 are price models trying to satisfy the purpose of grid tariffs presented in section 3.1, given the new consumption patterns presented in section 3.3. In this section it will be discussed how well these price models can ensure utilization of the existing grid, given the new consumption patterns.

3.7.1 Temporal and spatial resolution

Regardless of which price model being discussed, there are two important aspects that affect the accuracy of the price models; temporal and spatial resolution. *Temporal resolution* relates to the duration of a price signal. When the goal is to avoid grid congestion, the temporal resolution of the price signal is crucial. The higher the resolution, the more precisely the actual grid condition can be reflected. In a situation where a price signal is applicable for a longer time period than what is necessary, underutilization of the grid can occur. *Spatial resolution* reflects the size of the geographical area affected by a price signal. Similar to the temporal resolution, the higher the spatial resolution, the more precisely the actual condition of the grid is reflected. If the price signal is applicable for a geographical area larger than the congested area, underutilization of the grid in the non-congested areas can occur.

The importance of considering temporal resolution can be illustrated by the following example:

Consider for simplicity a group of consumers with a power demand resulting only from *flexible* loads. If congestion is expected in some critical hours as illustrated in figure 3.10, in order to avoid overloading of components, the price must be increased in the critical hours in order to reduce demand. However, if the temporal resolution is low, here meaning that the duration of the price signal is long, an undesirable effect is that the demand in the non-critical hours also is affected, resulting in a decrease in consumption. This is illustrated in figure 3.10. As discussed in section 3.1, the price signal should reflect the actual grid condition, which will not be the case for the non-critical hours.

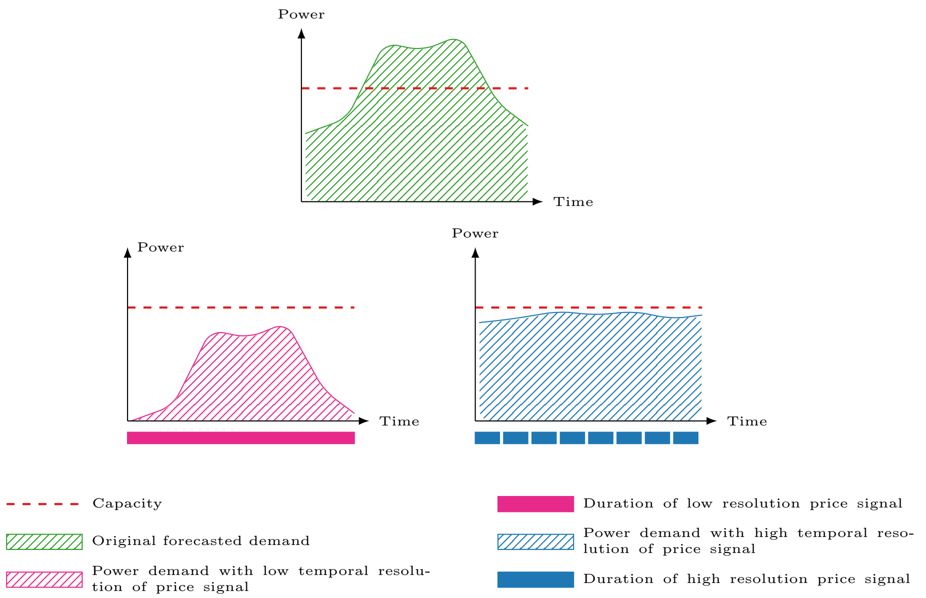

Figure 3.10: Ilustration of original forecasted demand, and the resulting demands if the price signal has low and high temporal resolution.

If the temporal resolution was higher, meaning that the duration of the price signal is shorter, the demand could be reduced in the critical hours only, by increasing the price here, and the demand could be increased in the uncritical hours by reducing the price in these hours. This would to a larger degree ensure that the demand is shifted, instead of reduced. The resulting demand is illustrated in figure 3.10. Although high temporal resolution ensures better utilization of the grid, a trade-off is that it can be difficult for the consumer to relate to constantly changing prices. Additionally, it can be demanding for the DSO to find and communicate the prices.

The importance of considering spatial resolution, can also be illustrated by an example. In figure 3.11, it can be seen that the demand does not exceed the capacity on a high level in the grid, and neither in two of the tree lower levels. However, at times, the capacity is expected to be exceeded in the third lower level component. With a low spatial resolution of the price signal, more customers than necessary are affected. With a higher resolution, only the customers in the overloaded area are affected. Even though high spatial resolution ensures more efficient utilization of the grid, different prices for different customers can be perceived as unfair. Additionally, as for high temporal resolution, it can be demanding for the DSO to find and communicate the prices.

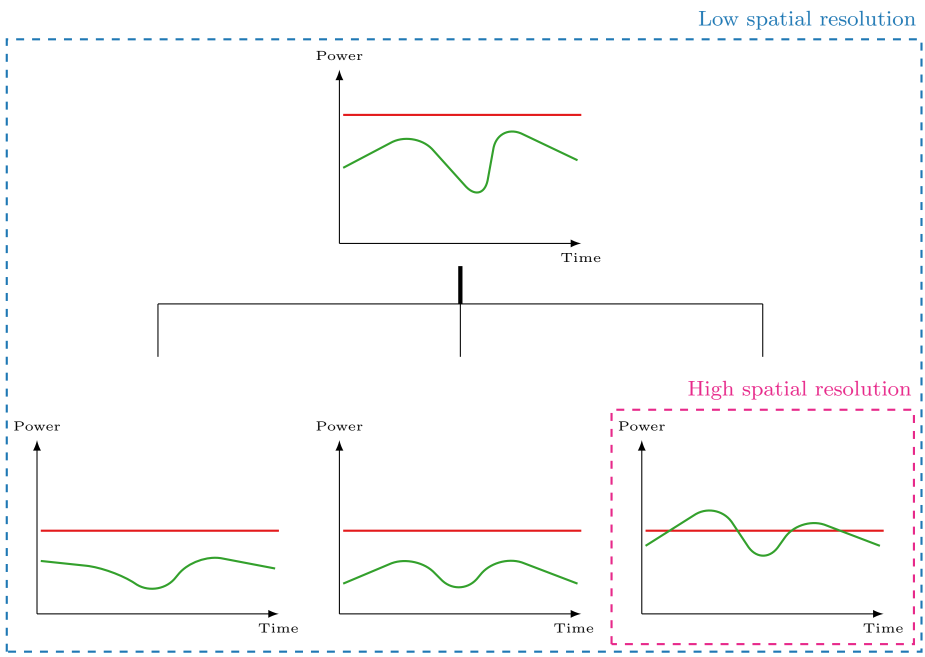

Figure 3.11: Relevance of spatial resolution in grid tariffs.

3.7.2 Criteria for evaluating the price models

How well the price models suggested in section 3.6 ensure better utilization of the existing grid, and prevents the need for grid reinforcement, is discussed based on the following five criteria:

1. How well the price model only prices congestion when there actually is congestion in the grid.
2. How well the price model distributes costs fairly among the consumers.
3. How predictable the price model is for the consumers, as predictability gives the consumer the possibility to *plan* her consumption.

4. How understandable the price model is for the consumers.

5. How administratively simple the price model is.

For all models it is assumed that the temporal and spatial resolutions are relatively high.

3.7.3 Evaluation of price models

In this section, the price models proposed in section 3.6 will be evaluated based on the criteria in the previous section. The aim is to find a price model which can ensure that demand does not exceed grid capacity, while at the same time utilizing the grid as socio-economic as possible. It should be mentioned that every price model should be combined with a fixed component covering the residual cost of the DSO. Further, the models which are pricing power, should be combined with an energy component reflecting the marginal cost of transmission.

Time-of-use energy tariff

1. As this model has the same price list every day (for instance within one season), the price signals must take into account the few days with the highest power demand. Hence, the prices will affect the consumption for the hours and days without congestion as well.

2. When the model has been implemented, the consumption of others cannot affect the price of an individual consumer. However, the need for the implementation of the model can be caused by others.

3. The price model is very predictable as the price list is equal every day. As the consumers knows the price of energy in advance, they can plan their consumption. Hence the price model contributes to load shifting, and not only load reduction.

4. The price model is understandable, as it is a nearly static model.

5. The price model is very administratively simple, as it only requires the price list to be determined once every season.

Critical peak pricing of energy

1. The model prices congestion better than TOU, as it is not determined when the critical peak price should apply. However, since the duration is fixed, it must sometimes price congestion in hours there is no congestion.

2. With this model the consumption of other consumers can be the reason that the critical peak prices apply in a time period, and even though an individual consumer has a smooth consumption, he must pay more per kWh consumed. This phenomena is called *cross-subsidization*.

3. The model is not very predictable, as the consumers do not know when the critical peak prices will apply. The predictability depends on how many hours in advance the critical peak price is notified. As the consumers do not know when, or if, it will be critical peak pricing, it contributes less to load shifting than TOU, as it is difficult to plan consumption depending on the price. However, if the consumers are notified well in advance, they can be able to plan their energy consumption and hence shift loads.

4. It can be somewhat difficult for consumers to understand when and which prices applies.

5. As it is not fixed *when* and *if* critical peak prices should apply, the DSO must forecast the consumption frequently, and hence the model can be administratively demanding.

Real-time energy pricing

1. Since the prices in this model reflects the actual grid condition, the model is accurate at pricing congestion only when there is congestion.

2. Since the price per transmitted kWh is higher during some hours of the day due to the possibility of congestion, the consumers with a flat consumption throughout the day also have to pay more for each kWh they consume in peak hours, although their consumption is not a problem, only the consumption of others. Hence, cross-subsidization occur.

3. The model is not predictable, as the prices varies dynamically. As the prices are not known in advance, it can be difficult to plan consumption, and hence it is difficult to shift loads.

4. The model is relatively difficult to understand, as the prices varies dynamically and the consumers are exposed to frequent new information.

5. The model is administratively difficult, as the prices must be decided in real time for every hour. It requires much monitoring and communication of prices.

Time-of use power tariff

1. Since this model has the same price list every day (for instance within one season), the price signals must take into account the few days with the highest power demand. Hence, the prices will affect the consumption for the days without congestion.

2. When the model has been implemented, the consumption of others cannot affect the price of an individual consumer. However, the need for the implementation of the model can be caused by others.

3. The price model is very predictable, as the price list is equal every day. Since the consumers know the price of transmission in advance, they can plan their consumption. Hence the price model contributes to load shifting, and not only load reduction.

4. The price model is understandable, as it is a nearly static model.

5. The price model is very administratively easy, as it only requires the price list to be determined once every season.

Dynamic power tariff

1. Since the price lists are fixed, but the time and duration of when the price lists applies varies, the price model reflects the actual condition of the grid better than the time-of-use power tariff, but not optimal.

2. Since the price per kW increases when there is a possibility of congestion, even the consumers with a smooth consumption have to pay more per kW, so although they do not contribute to the peak, they have to pay more. Hence, cross-subsidization occurs.

3. The model is not very predictable, as the consumers do not know when the different prices apply. Since the prices are not known in advance, it can be difficult to plan consumption, and hence it is difficult to know in advance if is profitable to shift consumption.

4. The model is relatively difficult to understand, as it requires that consumers pay attention to and react to frequently varying prices to avoid unnecessary consumption in peak price hours.

5. The model is administratively difficult, as it must be decided in real time which prices apply. Requires much monitoring and communication with customers.

Subscribed power tariff

1. As the price model considers the consumption on an individual level, not on a system level, the model does not reflect the actual condition of the grid, and can contribute to underutilization of the grid.

2. When the model has been implemented, the consumption of others cannot affect the price of an individual consumer. However, the reason for the implementation of the model can be caused by others.

3. The price model is very predictable, as one pays for a maximum power output, and the price per kW exceeding this level is known. It is easy to plan the consumption to avoid exceeding the maximum level, hence the model contributes to load shifting. The model must be combined with an energy tariff in order to avoid that consumers is encouraged to increase their power consumption in every hour to the maximum level.

4. The price model is understandable, but the consumers must be guided in deciding which subscribed level that is best suited for their demand pattern.

5. The price model is administratively easy, but it requires communication with every customer before implementing the model.

Progressive power tariff

1. Since this is a static model, a customer will be charged an extra fee if exceeding the first level, regardless of whether or not the grid the grid is congested.

2. When the model has been implemented, the consumption of others cannot affect the price of an individual consumer. However, the reason for the implementation of the model can be caused by others. Additionally, the consumers with a low power demand pay on average less per kW than the consumers with a higher power demand. This is reasonable as the consumers with a higher power demand contributes contributes more to the peak load.

3. This model is very predictable to customers as it is a static model. Due to the different levels in the progressive tariff, consumers have an incentive to shift flexible consumption to time periods where non-flexible consumption of the household is low, in order to stay within the first(and cheapest) tariff level for all time periods. Because the consumer is aware of the different levels, and the price associated with these, she can plan her electricity consumption in advance.

4. The price model is relatively easy to understand, but it requires user friendly devices which informs the customer of his current consumption compared to the level limit.

5. The price model is administratively easy to implement.

Purpose based power tariff

This model will only make sense in combination with an other tariff, and its fulfillment of the criteria depends on which other tariff it is combined with. The advantage of this tariff is that the price signal can be directed to flexible consumption, thus avoiding exposing inelastic, non-flexible consumption to price signals. However, this models is administratively demanding, as the consumer must have several meters to measure the consumption for the different purposes.

3.7.4 Summary of the price models' properties

The properties of the different price models have been summarized in figure 3.12. In the figure, the color red means that the price model perform poorly in this area, yellow means that price the model perform okay in this area, and green means that the price model perform well in this area. It can bee seen that the more dynamic a price model is, the harder it is to plan load shifting. With the most dynamic

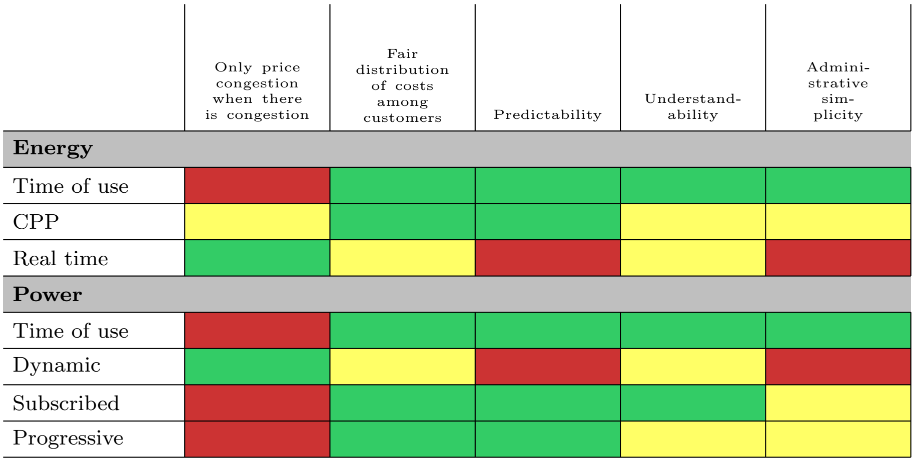

Figure 3.12: Overview of how the different price models score on the various criteria.

price model, real time pricing, one does not know the future prices, and thus it can be difficult to know if one should charge the EV now, or wait for potentially lower prices in future time periods. However, the more dynamic, the more accurately the grid condition can be reflected in the tariff. The less dynamic a price model is, the less it reflects the true condition of the grid, possibly resulting in underutilization. However, the less dynamic, the more predictable the tariff is, which makes it easier to plan shifting of flexible loads. As shown, it is generally a trade-off between predictability and representation of the true grid situation in the price models.

CHAPTER 4

Pricing of EV-charging

The aim of this chapter is to create a price model which can prevent the increasing number of EVs from becoming a major problem for the distribution grid. The focus is on domestic EV charging, as public charging stations often have upgraded grid components, and hence bottlenecks on lower levels in the distribution grid is not mainly caused by charging stations. The authors realize that the EV user responds to the total price of electricity, meaning the cost of transmission *and* the cost of electricity itself. However, as the electricity price in Norway today is rather stable during a day, it is assumed that this situation will persist, and hence, it is in this thesis assumed that the EV user only respond to changes in the transmission price. This chapter starts with a problem description, then the characteristics of the EV/EV user is discussed, followed by relevant criteria when creating a good price model for EV charging. Then related work is presented. Lastly, two price models for EV charging, aiming to avoid grid congestion, are proposed. For each price model, a brief numerical example is given.

4.1 Problem Description

The DSOs in Norway, as well as in other developed countries, will experience an increasing number of bottlenecks in the distribution grid when the number of EVs increases. Considering how fast the number of EVs is increasing, the DSOs must react quickly to ensure that the customers' power requests can be delivered, without damaging the electricity grid. Without utilizing demand response, the DSOs must dimension the distribution grid to handle the one day of the year with the highest peak load. This requires high investment costs, but during a large part of the day there is much excess capacity. When the number of EVs increases, this problem escalates, as most of the EVs charge at the same time during the day. Indirect control of EV charging by sending price signals, can contribute to reduce the need for investing in grid reinforcements. When grid congestion is expected in a time period, the prices of EV charging can be increased in this time period to ensure that flexible EV users reduces the demand during this time period, while increasing it in other time periods with a lower price.

4.2 Characteristics of the EV and the EV User

In order to propose a price model suited for EV charging, the characteristics of EV's power demand must be discussed.

1. First, unlike flexible, unstorable loads, the energy consumption related to EV charging is decoupled from the use of the EV. The EV is a 100 percent storable load, and the comfort level is not affected by load shifting. Hence, as long as the EV has the desired BSOC when the EV user needs the vehicle, it is reasonable to assume that the EV user is indifferent to *how* and *when* the EV has been charged (as long as the charging profile does not damage the battery). This makes the EV a *very* flexible load.

2. Secondly, when the EV has the desired BSOC when the owner needs the vehicle, it is reasonable to assume that the next priority of the EV owner is that the EV has been charged at the minimal possible cost.

3. Further, as the EV is a very flexible load, price signals can cause the *avalanche effect*. For instance, if the price in a period is low (to induce load shifting to this hour), one can imagine that many EV owners shift EV charging to this time of the day, and as the power consumption of EV charging is high, this can cause a new load peak.

4. Without price signals, by habit, the EV owner plugs in the EV when she gets home from work, regardless of whether she needs the EV later that day, or only the next morning.

5. The EV is normally charged by the same power for a relatively long time (often hours). The load curve for EV charging is flat compared to other power intensive appliances, for instance instantaneous water heaters which are characterized by sudden spikes for short durations.

4.3 Creating a Good Price Model for EV Charging

In this section relevant criteria for creating a good price model for EV charging, in order to avoid grid congestion, will be discussed.

4.3.1 Energy or power

As the EV is a load which normally has a flat charging curve, there is not as much need for a power tariff as for loads characterised by spikes in power consumption. The main motivation for introducing power tariffs is to avoid spikes during time periods with possible congestion, however when it comes to EV charging it is not the individual spikes that are challenging, as this is non-existent with EVs, but it is the total aggregated demand of all the EVs being chaged simultaneously. Hence, in the case of EVs, given that the temporal resolution of the price signal is high, the energy tariffs serves equally good to avoid power peaks (as illustrated in figure 3.6).

4.3.2 The target of the price signals

As mentioned in section 2.5, the EVs can be a problem for the distribution grid, but also a solution. Thus, it is desired to create a price model which utilizes the flexibility of the EVs by sending price signals the EV can respond to. However, it is not desired that other less flexible loads should be ”punished” by the price signals sent to the EV. Hence, the authors believe that a *purpose based* price model which only sends price signals to EVs, is a good solution. The remaining electricity consumption should be controlled by other price signals suited for the characteristics of this consumption. The price model for EVs could also apply to other existing, or future, flexible loads, but as a simplification, the price model in this thesis is only directed to EVs.

4.3.3 Forecasting

A prerequisite for creating a good price model for EV charging is to have a good forecast of the demand for EV charging. How to forecast demand is not the main focus of this thesis, however some aspects the authors believe is important to forecast is mentioned:

1. In a purpose based tariff directed to EVs, the base load, meaning the non-flexible consumption, as well as the demand for EV charging, in the relevant area, should be forecasted in order to know when the utilization of EVs as a flexible load is needed.

2. One should forecast how the EVs in the area are charged. Some are controlled indirectly by prices, and have either a smart algorithm minimizing charging costs, a timer, or they have no assisting devices at all (dumb charging). Some are direclty controlled, either by the DSO, or a third party. This will give more information regarding how the EVs respond to price signals.

3. How the EV users, or the EV's embedded algorithm, respond to price signals (price elasticity) should be forecasted, in order to calculate the response to a price signal.

4. Arrival times to a charging point, and the amount of energy needed when charging the EV, should be forecasted.

4.3.4 Predictability

When the goal of a price model is to ensure load *shifting* and not load *reduction*, it is beneficial that the price model is predictable, ensuring that the EV user can plan the charging depending on when the charging is cheapest. An EV user is more suited to plan the charging of the EV if she is given a price list for the hours ahead. Load shifting can be executed either by a timer, which ensures that the charging of the EV starts when the owner desires, or by an embedded algorithm minimizing charging costs. This points in the direction of a price model that gives a static price list to the EV user when she plugs in her EV. Compared to real-time varying prices, predictable prices ensures low uncertainty about the actual cost of charging, which the authors believe will increase the consumer acceptance of a new tariff.

4.3.5 Reducing avalanche effects

A synchronized response by several EVs to a price signal, may result in a new peak. Possible ways to reduce avalanche effects are:

- By issuing customer-specific TOU-plans to different consumer groups. This will make the aggregated response less synchronized than if all consumer groups have the same TOU-plan.

- To improve the forecasts. With perfect information of consumers' demand and reaction to prices, the avalanche effect could be avoided, given a high temporal and spatial resolution. Hence, improving forecasts can reduce the problem of avalanche effects.

- To introduce a progressive tariff where the price per kWh for the first kWhs consumed in one hour is less than the price per kWh for the further kWhs consumed in this hour. This can ensure that it is more economically beneficial for the EV user to charge for a longer time period with a lower charging power, than for a short time period with a high charging power.

- To use price models which do not send specific price signals to specific time periods, for instance a subscribed tariff-model. These models are not contributers to the avalanche effect as they preserve the randomness among consumers, as there is no incentives created by price signals causing the consumers to behave uniformly.

The authors propose two different price models which takes the considerations mentioned in this section into account.

4.4 Related Work

A lot of research has been done by different scientists when it comes to optimal charging of EVs *given* different prices. However, as far as the authors know, there has not been the same amount of research performed with the aim of *creating* the right pricing model for EV charging in order to avoid grid congestion. However, a few articles with the aim of finding optimal prices in order to utilize demand response, will be mentioned:

Liu and Ge (2013) present an optimization model which finds the optimal time periods during a day for time-of-use electricity tariffs (TOU), with the purpose of ensuring that the EVs are charged in a way which ensure peak-shaving and valley-filling in power systems. Using TOU *electricity* tariffs with the aim of ensuring better utilization of the grid, is best suited in countries where grid and electricity services are vertical integrated. The optimization model has the objective of minimizing the peak-to-valley ratio. Although this is an optimization model which ensures a smoother electricity consumption, as discussed in section 3.7.3, TOU is a price model which performs poorly when it comes to only pricing congestion when there actually is congestion, as the price list is the same for for instance a whole season. Additionally, the objective of minimizing the difference between peak and valley load will contribute to a reduction of demand even when there is not a need for it, which is not efficient from a socio-economic point of view. Lastly, it should be mentioned that the price model do not focus directly on EVs.

De Sa Ferreira et al. (2013) have designed an optimization model with the aim of designing good TOU electricity tariffs in order to utilize demand response to maximize total utility of the consumers, less the cost of supplying the electricity. The price elasticity of the consumers are taken into consideration. The model is based on quadratically constrained quadratic programming, and stochastic optimization techniques, as there is an uncertainty regarding the real price elasticity of the consumers. The consideration of price elasticities is relevant for the price models that the authors will propose, however the article does not focus on efficient utilization of the grid, and it does not focus directly on EVs, and the characteristics of EVs. However, how to find optimal tariffs to achieve certain goals, is relevant. Nonetheless, as mentioned, the authors do not believe that TOU-tariffs ensure efficient utilization of the grid.

O'Connell et al. (2012) has developed a day-ahead grid tariff aiming to avoid distribution grid congestion from EV charging. A step-wise structure has been proposed, where, the DSO predicts congestion for the following day, and publishes day-ahead grid tariffs. EV fleet operators (aggregators) then optimize the charging schedule for their EVs based on this tariff and predicted day-ahead electricity prices, to avoid congestion and minimize charging costs. However, the success of the concept proposed depends on how well the EVs adapt their demand in response to the day-ahead grid tariffs. If there is a mismatch between predicted congestion and the actual demand, congestion can occur. Hence, the DSO would be dependent on direct control, or other more real-time methods, to alleviate congestion.

The above mentioned work have been used to gain insight into how prices can be used to achieve certain goals, for instance alleviate grid congestion. Nonetheless, the authors have mostly used economic theory and principles of pricing, when finding a price model suited for EV charging to avoid grid congestion. Additionally, the characteristics of the EV as a load, and the EV user, has been researched.

4.5 Alternative One: Real-Time Purpose Based Tariff with Fixed Price Lists

The first alternative proposed is what the authors call a real-time tariff with fixed price lists. This model utilizes real-time information about the customers' consumption, and re-optimizes when new information is available. The model creates a price list for T hours ahead, and every time it re-optimizes, a price list for the following T time periods is posted. The purpose of this is to avoid pricing congestion when there is no congestion, and also to have the ability to correct forecast inaccuracies. If there are no inaccuracies in the forecast used to calculate the prices for the T following hours from time period t, the price list posted in time period $t+1$, will be the same price list as posted in time period t (but the price list posted in $t+1$ includes one extra time period). The authors believe the consumers value price predictability. Hence, when an EV connects to a charging point, a price list, which will remain constant, is provided to the EV. This should make it easier for the EV/EV user to plan the EV charging.

4.5.1 Model description

A price list with a rolling horizon, where the prices are fixed for the next T periods, is illustrated in figure 4.1. In this figure the new price list is valid for the next 12 time periods, and is published at the beginning of each time step. The price is the same for every households within the area considered. An EV owner connecting at time step 1 will receive the published price list P_t^1, and an EV owner connecting at time step 2 will receive the price list P_t^2. If the forecast is perfect, the price for a specific time period in different price lists should be equal. If the forecast turns out to be inaccurate, the DSO has the possibility of correcting the price signal in subsequent price lists.

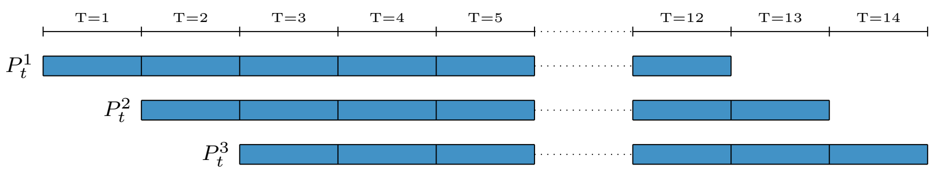

Figure 4.1: Illustration of a published price list with rolling horizon.

In this framework, for each time step, the procedure of finding the prices to be published is illustrated in figure 4.2 and explained below:

1. Information regarding which EVs are connected is sent to the forecast model, where the initial forecast is being updated with this new information.

2. In the forecast model, several operations are done:

   - For EVs which have connected in previous time steps, and have received a previous price list, the estimated demand must be locked. This demand, must be deducted from the otherwise available capacity. So, based on the locked estimated demand, the expected baseline in the households (the non-flexible consumption), and expected grid conditions, the available grid capacity for charging in the next 12 time periods, CAP_t, is sent to the price model. In the this price model, only one grid component and its respective capacity is considered, but the model can be expanded to include several grid components.
   - Based on historical data and given an initial price, P_t^0, the forecast model estimates the initial charging demand, $Q_{h,t}^0$, for each household. This is sent to the price model.
   - The relevant price elasticity matrix, $E_{h,t,t'}$, consisting of the elasticity coefficients $\epsilon_{h,t,t'}$ is sent to the price model.

3. If the sum of the estimated demand for every household found in the previous step, for some time period exceeds the grid capacity, then the model finds new prices, p_t, and new expected demand, $q_{h,t}$, which satisfies the grid conditions. p_t is published to the EV users connecting to the charging point in this time step, while both p_t and $q_{h,t}$ is sent back to the forecast model for subsequent comparison.

4. Lastly, after each time period, the actual demand, $Q_{h,t}^{actual}$, from all households is sent back to the forecast model. $Q_{h,t}^{actual}$ is compared to $q_{h,t}$ in order to improve the forecast model.

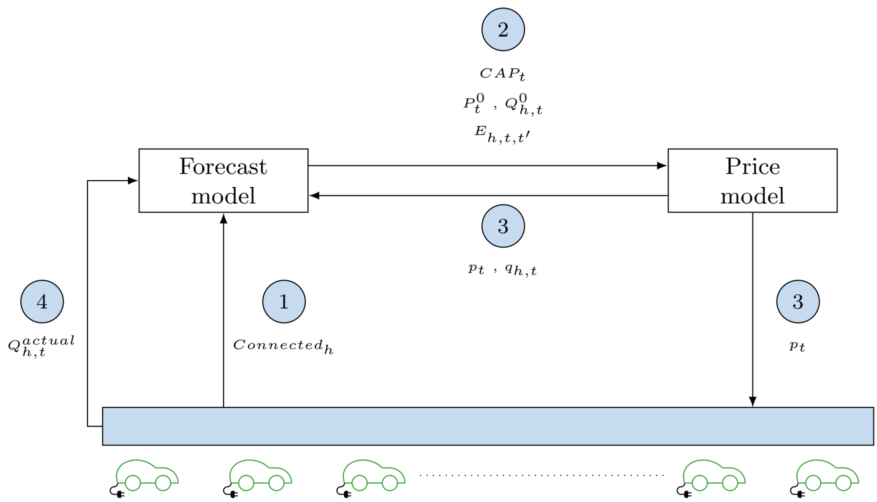

Figure 4.2: Schetmatic representation of the real-time purpose based tariff with fixed price lists.

4.5.2 Mathematical Model

The following proposed pricing model for domestic EV charging is a very simple example of how a real time price model with fixed price lists could be formulated. The following mathematical model describes how the prices for the next T time periods are found in each time step.

Definition of sets, parameters and variables

Indexes	
h	Household.
t	Time period.
Sets	
H	Set of households.
T	Set of time periods.
Parameters	
$Q^0_{h,t}$	Initial forecasted demand for household h in time period t.
CP^{max}_h	The maximum power in the charging point in household h.
P^0_t	Initial price in time period t.
P^{min}_t	The lower bound for the new price in time period t.
CAP_t	Remaining capacity of grid component in time period t.
$\epsilon_{h,t,t'}$	Elasticity coefficient of household h describing the percentage change in demand in time period t, as a result of a percentage change in price in time period t'.
D	The share of one hour that a time period constitutes.
Variables	
p_t	Price in time period t.
$q_{h,t}$	New forecasted demand for household h in time period t.

Standard objective function

The standard objective function is formulated as

$$minimize \sum_{h \in H} \Big| \sum_{t \in T} \left(Q^0_{h,t} - q_{h,t}\right) \Big|. \tag{4.1}$$

The objective of the model is to minimize the absolute difference of the the sum of the original demand, $Q^0_{h,t}$, for every household h and the sum of the new forecasted demand, $q_{h,t}$, for every household h. The authors believe the objective function will contribute to *shifting* demand instead of only *reducing* demand, as it is beneficial for the value of the objective function to keep the sum of the consumed demand over all time period for a household as close to the original demand as possible.

Constraints

Constraint 4.2 restricts the total demand in a time period t to be less than the capacity in the same time period.

$$\sum_{h \in H} q_{h,t} \leq CAP_t, \qquad t \in T. \tag{4.2}$$

Constraint 4.3 restricts the new price to be greater than the minimum price:

$$p_t \geq P_t^{min}, \qquad t \in T. \tag{4.3}$$

The energy consumed by an EV in a household, h, in a time period, t, must be less than the maximum power in the charging point in the household times the share of an hour a time period constitutes.

$$q_{h,t} \leq CP_h^{max} \cdot D, \qquad h \in H, t \in T. \tag{4.4}$$

The equality 4.5 expresses the percentage change in demand due to a percentage change in price in the current time period and every other time period. The self and cross time elasticities is used to express the change in demand.

$$q_{h,t} - Q_{h,t}^0 = \sum_{t' \in T} \frac{Q_{h,t}^0}{P_{t'}^0} \epsilon_{h,t,t'} (p_{t'} - P_{t'}^0), \qquad h \in H, t \in T. \tag{4.5}$$

Discussion of price model

The objective of the model is to minimize the absolute difference of the the sum of the original demand, $Q_{h,t}^0$, and the new forecasted demand $q_{h,t}$, in order to ensure that it is better to *shift* demand instead of only *reducing* demand. However, whenever it is not possible to only shift demand, the model tries to find a solution with as little reduction/increase as possible. In order to *guarantee* that the model do not reduce or increase demand, a restriction ensuring this could be added. Nonetheless, when the authors run the model including this restriction, it was very difficult to find feasible solutions. Using a *loss less* elasticity matrix, $E_{h,t,t'}$, contributes to load shifting instead of reduction.

There exist other objective functions which could have been more suited to find the optimal prices. A suggestion could be an objective function which minimizes the probability of the grid component getting overloaded. However, this type of objective function is suited for a stochastic model, as it is demanding to find the right associated possibilities. Another possibility is to minimize the total cost the EV users pay for the charging, in order to ensure that the users do not have a high economic disadvantage when the tariffs are introduced. A disadvantage is that the model then will have a non-linear objective function, which is difficult to implement in a linear solver.

The model is *deterministic*, meaning that it is assumed that how the EV/EV users respond to price signals is known. Absolute certainty regarding price elasticities is a big assumption, and if the EVs/EV users respond to price signals in a different way than expected, this can have adverse consequences for the grid. A stochastic model which handles uncertainty of the elasticities, could possibly give better results. However, as the model re-optimizes when receiving new information, a deterministic model can give relatively good results, and additionally a deterministic model is easier to solve.

As discussed in section 3.5.1 an implication of having equality 4.5 in a price model with the aim of shifting load from time periods with high demand, to time periods with less demand, is that whenever the initial demand, $Q^0_{h,t}$, for a household, h, in a time period, t, is 0, no matter how large the price change is in this and other time periods, the new estimated demand, $q_{h,t}$, will never be different from 0. In many situations it can be unreasonable to assume that no matter how much the price of a good decreases, a consumer would not buy it only because its initial demand was zero for a given price. A solution to this problem could be to say that whenever the initial forecasted demand is zero, the price sensitivity is not as it would have been by inserting $Q^0_{h,t} = 0$ in equation 4.5, but the same as for an other value for $Q^0_{h,t}$. It is natural that it requires a relatively high price reduction in a time period in order to shift load to this time period, but it is in many situations unreasonable to assume that even though the price was set to zero, the demand would never increase from zero.

Sending the same price signal to every consumer in an area (low spatial resolution) causes several challenges. Restriction 4.4 is problematic if one of the consumers has an initial expected demand equal to CP^{max}_h, while the others have a low demand. Then it is not possible to reduce the prices in this time period in order to increase the demand of the consumers with low demand, as this would cause the demand for the consumer with demand equal to CP^{max}_h to exceed CP^{max}_h, which is not a feasible solution. Similar, if one consumer has an initial expected demand equal to zero, while other consumers have a high demand, then it is not possible to increase the price in order to make the other consumers reduce demand, as this would cause a negative consumption of the consumer with initial demand equal to zero. This problem could be solved by introducing restrictions saying that whenever initial forecasted demand is equal to CP^{max}_h then the demand for this household is only sensitive to price *increments*, and whenever the initial forecasted demand is zero, the demand for this household is only sensitive to price *reductions*.

It is assumed that the DSO is notified when an EV connects to a charging point. The purpose of this, is to update the forecast so that the expected demand of this EV is taken into account in the calculation of the price list the EV user is presented with. Another possibility, rather than sending information about when an EV is being connected, can be that the DSO estimates how many EVs which are connected based on the information of the total demand in an area. This estimation can be relatively precise, as the baseline normally is rather constant.

4.5.3 Numerical example of the price model

In order to illustrate how the model presented in section 4.5.2 in each time step finds the optimal prices for the T next time periods to solve a congestion problem, the model was tested on a few fictitious EV users in a fictitious network.

The input data used in the numerical example

In the numerical example, the model created a price list for the four subsequent time periods, which was regarded as hours. In the example, five households were considered and these consumers were divided into two *consumer groups*. The first consumer group was relatively inflexible, hence the value of $\epsilon_{h,t,t'}$ in the different time periods was low. An EV user of this type would for instance not have automatic control of the charging, only a timer that could postpone the initiation of the charging. The second consumer group was more flexible (it typically had an embedded algorithm in the charging point which controlled the charging) and had a larger value for $\epsilon_{h,t,t'}$. In the example, the first two households were in the first consumer group, while the last three households were in the second consumer group, as illustrated in figure 4.3. However, regardless of consumer group, every consumer was exposed to the same price.

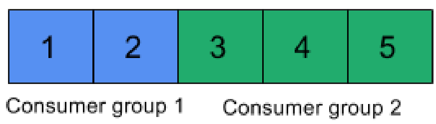

Figure 4.3: Illustration of the consumer group each household is associated with.

The initial prices, P_t^0, were here considered to be a flat tariff of 20 øre/kWh, where 10 øre was regarded as the energy component reflecting short run marginal cost, while the other 10 øre was regarded as a capacity component. Thus, in this example, the lower bound on the new price, P_t^{min} is set to 10 øre/kWh, to account for the marginal cost.

In the numerical example, only one grid component and its related grid capacity was considered, and the capacity used in the model was the capacity of the component less the base load in the network. Hence the capacity could vary every time period. The remaining capacity, CAP_t, the initial prices, P_t^0, the initial forecasted demand, $Q_{h,t}^0$ and the elasticities coefficients, $\epsilon_{h,t,t'}$, were all fictitious data created by the authors, and the data used is listed in table 4.1, 4.2, 4.3, 4.4 and 4.5. The model was implemented and run in Xpress 7.7.

	t=1	t=2	t=3	t=4
CAP_t	18	18	18	18

Table 4.1: The capacity for every time period, used in the numerical example.

	t=1	t=2	t=3	t=4
P_t^0	20	20	20	20

Table 4.2: The initial prices in øre/kWh, for every time period, used in the numerical example.

$Q_{h,t}^0$	t=1	t=2	t=3	t=4
Household 1	4	4	1	1
Household 2	4	4	1	1
Household 3	4	4	2	1
Household 4	4	4	1	1
Household 5	4	4	2	2

Table 4.3: The initial forecasted demand for the different households in the different time periods, used in the numerical example, given the prices in table 4.2.

The total initial forecasted quantity was 51 kWh. Given the initial forecasted quantity and the prices, the total cost the consumers would pay for EV charging was 10,2 NOK.

The elasticity matrices used in the numerical example is shown in table 4.4 and 4.5. The values in the different *columns* in the matrix says how much the quantity in every other time period than the time period related to that column, would be affected by a percentage price change in the time period related to the column. The values in the different *rows* says how much the quantity in the time period related to this row would change, if the price in every other time period was changed by one percent. For instance, the value marked in blue says how great the percentage change of the quantity in time period 1 would be if the price in time period 2 was changed by one percent. The value marked in red says how great the percentage change of quantity in time period 2 would be if the price in time period 1 was changed by one percent. The elements on the diagonal of the matrices, the *self-elasticities*, describes how the quantity in a time period would be sensitive to price changes in the same time period. The values of the elements on the diagonals is negative, as it is natural to assume that if the price in a time period was increased, the demand for EV charging in the same time period would decrease. The elements which are not on the diagonal, the *cross-time-elasticities*, has positive values, as it was natural to assume that whenever there would be an increase in price in other time periods, the customers would increase the demand for EV charging in the current time period (if possible) in order to consume less in the expensive time periods. As discussed, in this example consumer group 1 was less price sensitive than consumer group 2. Hence the value of the elasticity coefficients for consumer group 1, $\epsilon_{1,t,t'}$, had a lower absolute value than the elasticity coefficients for consumer group 2.

$E_{1,t,t'}$	**t=1**	**t=2**	**t=3**	**t=4**
t=1	-0,015	0,007	0,005	0,003
t=2	0,007	-0,015	0,005	0,003
t=3	0,005	0,007	-0,015	0,003
t=4	0,003	0,005	0,007	-0,015

Table 4.4: The elasticity matrix for consumer group one, used in the numerical example.

$E_{2,t,t'}$	**t=1**	**t=2**	**t=3**	**t=4**
t=1	-0,5	0,25	0,15	0,1
t=2	0,25	-0,5	0,15	0,1
t=3	0,15	0,25	-0,5	0,1
t=4	0,1	0,15	0,25	-0,5

Table 4.5: The elasticity matrix for consumer group two, used in the numerical example.

As it was desired to only shift demand instead of reduce demand, the elasticity matrices were made loss less, meaning that the horizontal sum of the elasticity coefficients was 0, as explained in section 3.5.1. Other than the fact that consumer group 1 was less flexible than consumer group 2, and that both matrices should be loss less, the values of the elasticity coefficients, $\epsilon_{h,t,t'}$, were chosen rather randomly.

Results

Table 4.6 shows the new optimal prices found by running the price model, while table 4.7 shows the new estimated quantity given these prices.

	t=1	**t=2**	**t=3**	**t=4**
p_t	29,93	25,57	28,68	10,00

Table 4.6: The new optimal prices for every time period.

The new total estimated demand was 50,2 kWh. Given the new estimated quantity and the new prices, the total cost the consumers would pay for EV charging was 12,6 NOK.

Figure 4.4 show how the new estimated quantity is feasible regarding grid capacity.

$q_{h,t}$	**t=1**	**t=2**	**t=3**	**t=4**
Household 1	3,981	4,000	0,996	1,013
Household 2	3,981	4,000	0,996	1,013
Household 3	3,346	4,000	1,754	1,450
Household 4	3,346	4,000	0,877	1,450
Household 5	3,346	2,000	1,754	2,900

Table 4.7: The new estimated quantities for every household in every time period, given the optimal prices in table 4.6.

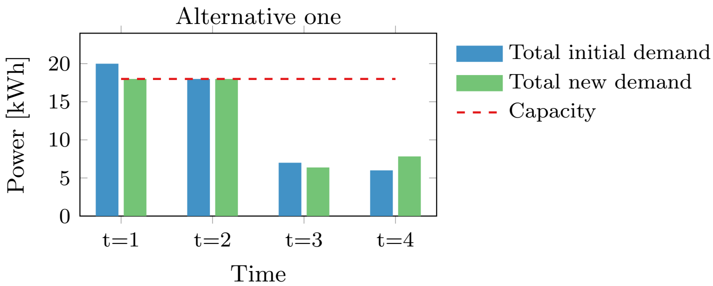

Figure 4.4: Initial and new demand for price model alternative one.

Discussion of the test results

As seen in figure 4.4, the new estimated demand was feasible regarding grid capacity. However, the total demand was reduced by 0,8 kWh instead of only being shifted. Hence, although the elasticity matrices were supposed to be loss less, the new total forecasted demand was a little less than the initial forecasted demand. The reason for this could be that the elasticity matrices were created in such a way that the quantity in the first time period only could react to price changes in consecutive time periods, while the quantity in the last time period only could react to price changes in previous time periods. The loss less-restriction on the matrix would most likely be better in a situation with an infinite number of time periods, where every time period had previous and consecutive time periods which the quantity could be price sensitive to.

The total cost of the EV charging increased from 10,2 to 12,6 NOK. In order to avoid congestion, the price must be increased in some time periods, while it can be decreased in other time periods. The total cost for the EV users will depend on how much load is being placed in different time periods. In a simplistic world, one could say that as long as the excess amount paid by the consumers for EV charging over a longer time period does not exceed the marginal cost of increasing grid capacity, the consumers will be better of by being exposed to price signals compared to the situation where the DSO reinforces the grid.

In order to avoid the problem where $Q^0_{h,t}$ is zero and thus demand is price insensitive, the authors chose initial demand to always be greater than zero. This also solved the problem of not being able to reduce demand of households which had an initial estimated demand greater than zero. The initial forecasted demand for every household was set to less than P_t^{max} in time periods where any household had an initial forecasted demand less than P_t^{max}. This was done in order to avoid a situation where the demand for the households with initial demand less than P_t^{max}, could not be increased, as the demand for the household with initial forecasted demand equal to P_t^{max}, could not be increased.

As consumer groups 1 and 2 had different elasticity matrices, it can be seen in table 4.7 that it differed how the households reacted to the prices. The households in consumer group 1 adjusted their demand relatively less to a price change, than what consumer group 2 did. For instance, in time period 1, household 1 decreased demand by 0,019 kWh (0,5%), while household 5 decreased demand by 0,654 kWh (19,5%), in response to the same price signal.

4.6 Alternative Two: Progressive Purpose Based Day-Ahead Tariff

Another price model which ensures a smoother consumption when needed, is what the authors call a progressive purpose based day-ahead tariff. When prices vary within day, and a price list is posted for instance the day ahead, one can imagine how an EV owner places all her consumption in the cheapest hours, by charging with maximum power in these hours. As a result, it can be difficult to ensure a smooth consumption with time-varying prices posted day-ahead. A progressive tariff can act as an incentive for the EV owners to charge their EV with a lower power. With a progressive energy tariff, the price per kWh per time period, will be less for consumers with a low demand (normal charging), than for consumers with a high demand (fast charging). This can prevent too many EV owners from fast charging their EV.

In addition to smooth consumption, this tariff has another benefit. It ensures a more fair distribution of costs among consumers, as only the consumers with a high power consumption need to pay more per kWh causing problems for the grid, while the consumers with a low power consumption do not have to pay more per kWh as they are not the ones contributing the most to congestion. This gives a more fair distribution of costs compared to a dynamic non-progressive tariff, where every consumer must pay more per kWh during peak hours.

4.6.1 Model description

The model is based on two different price levels. One price level for the first kWhs consumed in an hour, and one price level for the excess kWhs. The first kWhs consumed is referred to as *normal charging*, while the excess kWhs is referred to as *fast charging*. Normal charging can for instance be regarded as up to 4 kWh/h, while fast charging is the amount of charging power exceeding this limit. An excerpt of a possible price list is illustrated in figure 4.5. In this example, the price between 14:00 and 15:00 is 10 øre/kWh for normal charging, and 20 øre/kWh for fast charging. Thus if an EV is charged by 7 kW in this time period, the cost will be (4 kWh x 10 øre/kWh + 3 kWh x 20 øre/kWh) 1,00 kr. In time periods with no expected grid congestion, the price for normal and fast charging could be set equal and relatively low, while in time periods with expected capacity problems, the price for both fast and normal charging can be increased in order to induce time shifting of the EV charging.

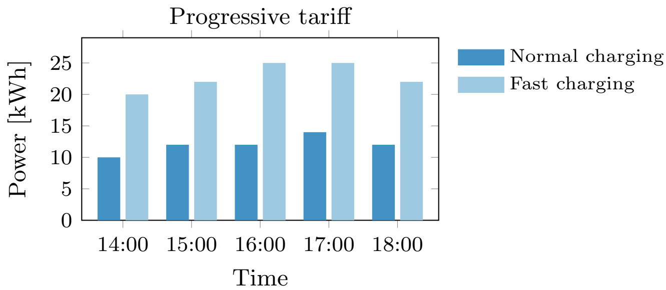

Figure 4.5: Excerpt of a possible price list for a progressive tariff.

The proposed framework for the progressive day-ahead tariff is illustrated in figure 4.6. Once a day, the price list for the next day is published. The procedure of how these prices are found is illustrated in figure 4.6 and explained below:

1. In the forecast model, several operations are done:

   - Based on the expected baseline consumption in the households, and expected grid conditions, the expected grid capacity available for charging each hour the next day, CAP_t is estimated and sent to the price model. As for the price model of alternative one, only one grid component and its respective capacity is considered, but the model can be expanded to include several grid components.
   - Based on historical data and given initial prices, $P_t^{0,norm}$ and $P_t^{0,fast}$, the forecast model estimates the initial charging demand, $Q_{h,t}^{0,norm}$ and $Q_{h,t}^{0,fast}$ for each household. This is sent to the price model.
   - The relevant price elasticity matrices, $E_{t,t'}^{norm}$ and $E_{t,t'}^{fast}$, are sent to the price model.

2. If the sum of the estimated demand for every household found in the previous step, for some time period exceeds the grid capacity, then the model finds new prices, p_t^{norm} and p_t^{fast}, and new expected demand, $q_{h,t}^{norm}$ and $q_{h,t}^{fast}$, which satisfies the grid conditions. p_t^{norm} and p_t^{fast} are published to the EV

users, while $q_{h,t}^{norm}$, $q_{h,t}^{fast}$, p_t^{norm} and p_t^{fast} is sent back to the forecast model for subsequent comparison.

3. Lastly, after one day, the actual demands $Q_{h,t}^{actual,norm}$ and $Q_{h,t}^{actual,fast}$ from all households is sent back to the forecast model. $Q_{h,t}^{actual,norm}$ and $Q_{h,t}^{actual,fast}$ are compared to $q_{h,t}^{norm}$ and $q_{h,t}^{fast}$ in order to improve the forecast model.

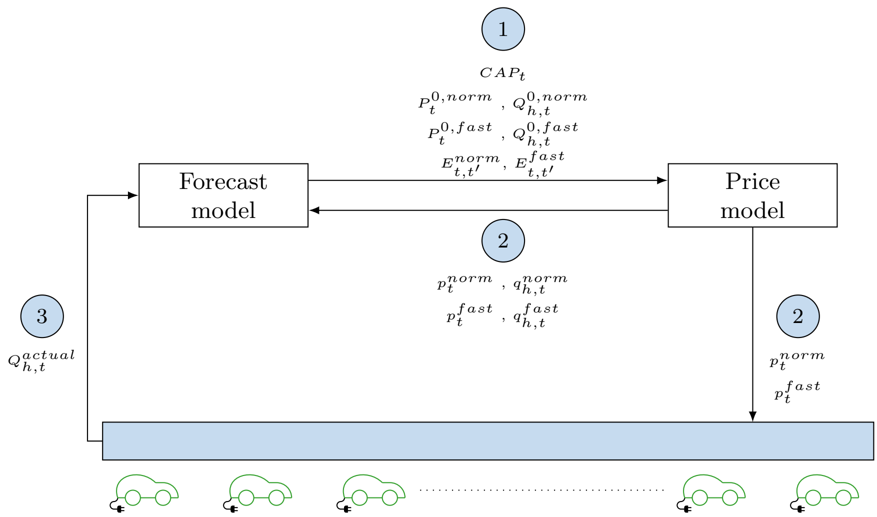

Figure 4.6: Schematic representation of the progressive purpose based day-ahead tariff.

4.6.2 Mathematical Model

4.6.3 Definition of sets, parameters and variables

Indexes	
h	Household.
t	Time period.
Sets	
H	Set of households.
T	Set of time periods.
Parameters	
$Q^{0,norm}_{h,t}$	Initial forecasted demand for normal charging for household h, in time period t.
$Q^{0,fast}_{h,t}$	Initial forecasted demand for fast charging for household t, in time period t.
$Q^{norm,max}$	Maximum demand for normal charging.
$Q^{fast,max}$	Maximum demand for fast charging.
$P^{0,norm}_{t}$	Initial price for normal charging in time period t.
$P^{0,fast}_{t}$	Initial price for fast charging in time period t.
$P^{min,norm}$	Minimum price for normal charging.
CAP_t	Remaining capacity of grid component in time period t.
$\epsilon^{norm}_{t,t'}$	Elasticity coefficient describing the percentage change in demand related to price level 1 in time period t, as a result of a percentage change in demand of normal charging t'.
$\epsilon^{fast}_{t,t'}$	Elasticity coefficient describing the percentage change in demand of fast charging in time period t, as a result of a percentage change in price in time period t'.
Variables	
p^{norm}_{t}	New price for normal charging in time period t.
p^{fast}_{t}	New price for fast charging in time period t.
$q^{norm}_{h,t}$	New estimated demand for normal charging in household h, in time period t.
$q^{fast}_{h,t}$	New estimated demand for fast charging in household h in time period t.
$\delta_{h,t}$	Binary variable which gets the value 0 if $q^{norm}_{h,t}$ reaches $Q^{norm,max}$, else the value is 1.

Standard objective function

The standard objective function is formulated as

$$minimize \sum_{h\in H}\Big|\sum_{t\in T}\big((Q^{0,norm}_{h,t}+Q^{0,fast}_{h,t})-(q^{norm}_{h,t}+q^{fast}_{h,t})\big)\Big|. \tag{4.6}$$

The objective of the model is to minimize the absolute difference of the the sum of the original demand, $Q^{0,norm}_{h,t}+Q^{0,fast}_{h,t}$, for every household h and the sum of the new estimated demand, $q_{h,t}^{norm} + q_{h,t}^{fast}$, for every household h. The authors believe the objective function will contribute to *shift* demand instead of only *reducing* demand.

Constraints

Constraint 4.7 restricts the total new estimated demand in a time period t to be less than the capacity in the same time period.

$$\sum_{h \in H} (q_{h,t}^{norm} + q_{h,t}^{fast}) \leq CAP_t, \qquad t \in T. \tag{4.7}$$

Equation 4.8 and 4.9 restricts $q_{h,t}^{norm}$ and $q_{h,t}^{fast}$ to be less than the quantity the price levels apply for.

$$q_{h,t}^{norm} \leq Q^{norm,max}, \qquad h \in H, t \in T, \tag{4.8}$$

$$q_{h,t}^{fast} \leq Q^{fast,max}, \qquad h \in H, t \in T. \tag{4.9}$$

Equation 4.10 and 4.11 ensures that $q_{h,t}^{fast}$ only can be positive if $q_{h,t}^{norm}$ is greater than or equal to $Q^{norm,max}$. The restrictions ensures that whenever the demand for normal charging is less than $Q^{norm,max}$, than there is no demand for fast charging.

$$q_{h,t}^{norm} \geq Q^{norm,max} \delta_{h,t}, \qquad h \in H, t \in T, \tag{4.10}$$

$$q_{h,t}^{fast} \leq Q^{fast,max} \delta_{h,t}, \qquad h \in H, t \in T. \tag{4.11}$$

The equalities 4.12 and 4.13 express the percentage change in demand related to a price level due to a percentage change of the price in that price level, both in the current time period and every other time periods.

$$q_{h,t}^{norm} - Q_{h,t}^{0,norm} = \sum_{t' \in T} \frac{Q_{h,t}^{0,norm}}{P_{t'}^{0,norm}} \epsilon_{t,t'}^{norm} (p_{t'}^{norm} - P_{t'}^{0,norm}), \qquad h \in H, t \in T, \tag{4.12}$$

$$q_{h,t}^{fast} - Q_{h,t}^{0,fast} = \sum_{t' \in T} \frac{Q_{h,t}^{0,fast}}{P_{t'}^{0,fast}} \epsilon_{t,t'}^{fast} (p_{t'}^{fast} - P_{t'}^{0,fast}), \qquad h \in H, t \in T. \tag{4.13}$$

Lastly, the price of fast charging must be greater than, or equal to, the price of normal charging, and the price of normal charging must be greater than or equal to 0. This is expressed in equation 4.14 and 4.15, respectively.

$$p_t^{fast} \geq p_t^{norm}, \qquad t \in T, \tag{4.14}$$

$$p_t^{norm} \geq P^{min,norm}, \qquad t \in T. \tag{4.15}$$

Discussion of price model

The objective function of this price model is the same as for price model alternative one. Hence, the same discussion regarding the properties of the objective function and potential other objective functions also applies for this model.

The implication of having equality 4.12 and 4.13 in a price model where it is desired to move load from time periods with high demand to a time period with less demand, are the same for this price model as the alternative one price model. In many situations it can be unreasonable to assume that no matter how much the price of a good decreases, a consumer would not buy it only because its initial demand was zero for a given price. The solution of solving this problem that is proposed in section 4.5.2 also applies for this model.

The spatial resolution for this price model is also important, as a low spatial resolution requires every EV user to respond to the same price signals. The proposal of restrictions saying that whenever initial forecasted demand for normal charging, $q_{h,t}^{norm}$, is equal to $Q^{norm,max}$, and initial forecasted demand for fast charging, $q_{h,t}^{fast}$, is equal to $Q^{fast,max}$ the demand for this household is only sensitive to price *increments*, and whenever the initial forecasted demand for normal charging or fast charging is zero, the demand for normal charging and fast charging for this household is only sensitive to price *reductions*, also applies for this price model.

Unlike the alternative one price model, this model does not utilize new information to re-optimize the prices. Instead the model always price demand exceeding normal charging by at least as much as the price for normal charging. The benefit of this is that the model needs to compile only once before the planning horizon. The drawback is that the model does not have the advantage of being able to utilize new information, and hence it might be needed to add a "capacity-buffer" when finding the new prices, to ensure that the demand never exceed grid capacity. This is not efficient from a socio-economic perspective. Considering that this model does not re-optimize as the alternative one price model, and that the price list is created in advance of for a whole day, uncertainty of price elasticities could affect the performance of this model more negatively than the alternative one price model.

There are drawbacks with dividing the demand for EV charging into two groups, fast and normal charging. In a situation with much capacity it would be desired to lower the price for fast charging in one period to shift consumption to this period. However, because of the restriction saying that p_t^{fast} always should be larger than p_t^{norm}, the price for fast charging could not be less than p_t^{norm}. To allow for enough load shifting to this period, the p_t^{norm} would have to be lowered, but that would be infeasible as the $q_{h,t}^{norm}$ then would exceed $Q^{norm,max}$. To find a feasible solution, the model presented here would move loads to other time periods or reduce the demand. To mitigate this problem, a restriction could be added, stating that when $Q_{h,t}^{0,norm}$ is equal to $Q^{norm,max}$, $q_{h,t}^{norm}$ could only react to price increases, not price reductions.

4.6.4 Numerical example

In order to illustrate how the model presented in section 4.5.2 finds the optimal prices for the T next time periods to solve a congestion problem, the model was tested on fictitious EV users in a fictitious network. In the numerical example it was assumed that when every household in a time period demanded normal charging, the grid capacity, CAP_t was never exceeded by this demand. However, the demand for fast charging in addition to normal charging could violate the grid restrictions. Hence, it was only desired to shift the fast charging to other time periods when needed, thus p_t^{norm} was set to be 10 øre/kWh for every time period, while the model tried to find the optimal price for fast charging, p_t^{fast}.

The input data used in the numerical example

In the numerical example, the model created a price list for the four following time periods, which in this thesis were regarded as hours. The price list consisted of a price for normal charging, p_t^{norm}, and a price for fast charging, p_t^{fast}. The remaining capacity, CAP_t, the initial prices, $P_t^{0,norm}$ and $P_t^{0,fast}$, the initial forecasted demand, $Q_{h,t}^{norm}$ and $Q_{h,t}^{fast}$, the elasticity coefficients, $\epsilon_{t,t'}^{norm}$ and $\epsilon_{t,t'}^{fast}$, were all fictitious data created by the authors, and the data used is listed in table 4.8, 4.9, 4.10, 4.11, 4.12, 4.13 and 4.14. The model was implemented and run in Xpress 7.7.

	t=1	**t=2**	**t=3**	**t=4**
CAP_t	28	28	28	28

Table 4.8: The capacity for every time period, used in the numerical example.

	t=1	**t=2**	**t=3**	**t=4**
$P_t^{0,norm}$	10	10	10	10

Table 4.9: The initial prices for normal charging for every time period, used in the numerical example.

The total demand was 107 kWh. Given this demand and the prices, the total cost for all the households for normal EV charging would be 8,00 NOK and the cost for fast charging would be 5,40 NOK. Hence, the total sum for EV charging would be 13,40 NOK.

	t=1	t=2	t=3	t=4
$P_t^{0,fast}$	20	20	20	20

Table 4.10: The initial prices for fast charging used in the numerical example for every time period.

$Q_{h,t}^{0,norm}$	t=1	t=2	t=3	t=4
Household 1	4	4	4	4
Household 2	4	4	4	4
Household 3	4	4	4	4
Household 4	4	4	4	4
Household 5	4	4	4	4

Table 4.11: The initial forescasted demand for normal charging for the different households in the different time periods, used in the numerical example, given the prices in table 4.9.

$Q_{h,t}^{0,fast}$	t=1	t=2	t=3	t=4
Household 1	4	2	1	1
Household 2	1	1	1	1
Household 3	1	1	1	1
Household 4	1	1	1	1
Household 5	4	1	1	1

Table 4.12: The initial forecasted demand for fast charging for the different households in the different time periods, used in the numerical example, given the price in table 4.10.

The elasticity matrices used in the numerical example are shown in table 4.13 and 4.14. Both matrices were loss less, as discussed in section 4.5.3. It was assumed that the EV users were more sensitive to price changes affecting fast charging than normal charging. Hence, the absolute value of the elasticity coefficients, $\epsilon_{t,t'}^{fast}$, in the elasticity matrix for fast charging was greater than for normal charging.

$E_{t,t'}^{norm}$	t=1	t=2	t=3	t=4
t=1	-0,15	0,07	0,05	0,03
t=2	0,07	-0,15	0,05	0,03
t=3	0,05	0,07	-0,15	0,03
t=4	0,03	0,05	0,07	-0,15

Table 4.13: The price elasticities for normal charging, used in the numerical example.

Results

The new optimal prices for normal charging and fast charging are listed in figure 4.15 and 4.16 respectively.

$E_{t,t'}^{fast}$	**t=1**	**t=2**	**t=3**	**t=4**
t=1	-0,50	0,25	0,15	0,10
t=2	0,25	-0,50	0,15	0,10
t=3	0,25	0,25	-0,50	0,10
t=4	0,10	0,15	0,25	-0,50

Table 4.14: The price elasticities for fast charging, used in the numerical example.

	t=1	**t=2**	**t=3**	**t=4**
p_t^{norm}	10,00	10,00	10,00	10,00

Table 4.15: The new optimal prices for normal charging for every time period.

	t=1	**t=2**	**t=3**	**t=4**
p_t^{fast}	26,16	10,00	25,01	13,75

Table 4.16: The new optimal prices for fast charging for every time period.

The new estimated demand for every household for normal charging and fast charging in every time period, is listed in table 4.17 and 4.18 respectively.

$q_{h,t}^{norm}$	**t=1**	**t=2**	**t=3**	**t=4**
Household 1	4,00	4,00	4,00	4,00
Household 2	4,00	4,00	4,00	4,00
Household 3	4,00	4,00	4,00	4,00
Household 4	4,00	4,00	4,00	4,00
Household 5	4,00	4,00	4,00	4,00

Table 4.17: The new estimated demand for normal charging for the different households in the different time periods, given the new prices in table 4.15.

$q_{h,t}^{fast}$	**t=1**	**t=2**	**t=3**	**t=4**
Household 1	2,909	2,667	0,765	1,175
Household 2	0,727	1,333	0,765	1,175
Household 3	0,727	1,333	0,765	1,175
Household 4	0,727	1,333	0,765	1,175
Household 5	2,909	1,333	0,765	1,175

Table 4.18: The new estimated demand for fast charging for the different households in the different time periods, given the new prices in table 4.16.

The new estimated total demand was 105,70 kWh. Given the quantities in table 4.17 and 4.18 and the new prices, the total cost for all the households for normal

EV charging would be 8,00 NOK and the cost for fast charging would 5,14 NOK. Hence, the total sum for EV charging would be 13,14 NOK.

How the new estimated demand was feasible regarding grid capacity is shown in figure 4.7.

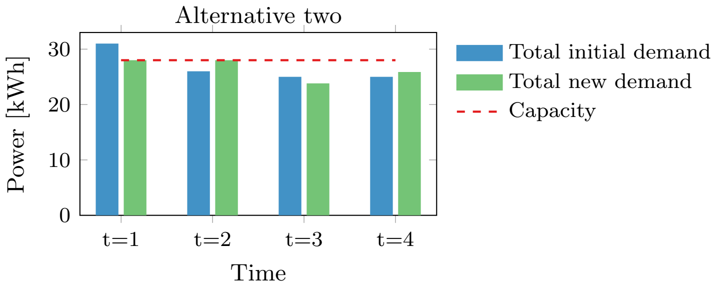

Figure 4.7: Initial and new demand for the alternative two price model.

Discussion

As seen in figure 4.7, the new estimated demand was feasible regarding grid capacity. However, the total demand was reduced by 1,3 kWh instead of only being shifted. Hence, as for the numerical example for the alternative one price model, although the elasticity matrices were supposed to be loss less, the new total estimated demand was a little less than the initial forecasted demand. The reason for this is the same as discussed in section 4.5.3.

The total cost of the EV charging was reduced from 13,5 to 13,14 NOK. The total cost of the EV users depends on how much load is being placed in the different time periods. For other initial data, the EV users would might have had to pay more for the EV charging. As discussed in section 4.5.3, in a simplistic world, as long as the excess amount paid by the consumers for EV charging during a longer time period, does not exceed the marginal cost of increasing grid capacity, the consumers will be better of by being exposed to price signals from this model compared to the situation where the DSO reinforces the grid.

In order to avoid the problem where $Q^0_{h,t}$ is zero, and thus demand is price insensitive, the authors chose initial demands to always be greater than zero also in this numerical example. This also solved the problem of not being able to reduce demand of household which has initial estimated demand to more than zero when some other households has zero demand. The initial forecasted demand for fast charging for every household was set to less than $Q^{fast,max}$ in time periods where any other household had initial forecasted demand less than $Q^{fast,max}$. This was done in order to avoid a situation where the demand for the households with initial demand less than P_t^{max} could not be increased, as the demand for the household with initial forecasted demand equal to $Q^{fast,max}$, could not be increased.

4.7 Concluding Remarks Regarding Price Models for EV charging

Spatial & temporal resolution

Both the level of spatial and temporal resolution affects how well the grid is utilized, and from a socio-economic perspective, unnecessary price signals causing underutilization is not preferable. If the temporal resolution is low, the duration of the price signal is longer than what is necessary, possibly leading to underutilization of the grid in periods where there is no expected congestion. Low spatial resolution can also lead to underutilization, as too many consumers react to a price signal when congestion is expected, although it is not necessary from a grid perspective that all of these consumers reduce their consumption. Ideally, each customer should receive a specific price signal, reflecting how their consumption is affecting the grid conditions. However, this is a difficult task, as it is not straight forward to identify what causes grid problems. Additionally, high spatial resolution of price signals may violate with consumers' perception of fairness. On one hand, it is desired to achieve cost causality (Pérez-Arriaga and Smeers, 2003), meaning that the user must pay the cost he incurs on the network. On the other hand, it may be perceived as unfair that two consumers with the same consumption patterns in the same distribution grid receive different prices, due to differences in local grid capacities.

The price models presented in this thesis can be evaluated under the assumption that the spatial resolution is low and the temporal resolution is high. The alternative one price model will then account for the expected load each consumer incurs on the grid, as the DSO can give the consumer a price list which will take the consumer's expected demand into account. However, as the price per kWh is equal for all consumers within a predetermined area, all consumers (also those with a low and unproblematic demand) will be punished with a higher cost for each kWh. The alternative two price model is not as good as the first model when it comes to cost causality, as the DSO does not receive any information regarding each consumer's load. However, because the tariff is progressive, it ensures that consumers who demands fast charging will pay more per kWh than those who only wants normal charging, something that indirectly ensures that consumers with problematic demands are punished more.

Predictability and the avalanche effect

A price model which provides the consumers with predictability regarding prices, makes it easier for the consumers to plan their consumption, and hence shifting load instead of reducing load. However, the trade-off is that when many consumers plan their consumption for several time periods ahead, a simultaneous response to a low price signal can lead to an avalanche effect, causing new peak loads. The alternative one price model can contribute to the avalanche among the consumers which receives the same price list. However, the fact that the model re-optimizes when new information is received, reduces the avalanche effect, as new consumers can receive other price lists which gives them incentives to shift loads to other time periods than the consumer which was given another price list. The alternative two price model is at risk of causing an avalanche effect by posting the price list the day ahead. However, the price model reduce the effect of the avalanche effect by ensuring a smoother consumption, by pricing fast charging higher than normal charging. For both price models, if the spatial resolution is high, the avalanche effect can be reduced by giving different price lists to different consumers. The trade-off between predictability and the avalanche effect is important to evaluate when creating a price model.

Socio-economic effectiveness

As discussed in section 2.6 and 3.4, a regulated monopolist should set the price of a good where the demand curve intersects the marginal cost curve. However, if there is a capacity problem in the grid, the price must be set higher to ensure that the demand does not exceed the capacity. In this situation a dead weight loss occurs, which can be seen as a socio-economic loss. When utilizing price models, the price must be increased in time periods with expected congestion in order to ensure that the capacity is not exceeded. However, from a socio-economic point of view it is beneficial that the grid is utilized as much as possible. Hence, the regulated monopolist should not set prices which causes underutilization. Thus, in order to ensure that load is shifted instead of reduced, the price in time periods with no expected congestion can be decreased below marginal cost to ensure that the demand from congested time periods is moved to these time periods. However, the price the consumers pay in the time periods with no expected congestion will not reflect the marginal cost of utilizing the grid in these time periods. It is possible to regard the excess amount paid by the consumers in congested time periods, as a cost coverage of the fact that in other time periods the price is set below marginal cost.

Further, said in a simplified way, the use of price signals is only socio-economic optimal compared to reinforcements of the grid as long as the socio-economic cost of using price signals is less than the socio-economic cost of reinforcing the grid. Moreover, if the consumers do not respond to price signals as their demand is rather constant regardless of price, and the total marginal willingness to pay for transmission of electricity surpasses the long run marginal investment cost, the electricity grid should be reinforced instead of using price signals. In situations where the grid infrastructure is good, and only a transmission line is needed to be replaced in order to solve a capacity problem, the marginal cost of replacing this line is relatively low, and price signals reflecting the marginal investment costs will have little effect. The DSO should take the above mentioned aspects into account when deciding *if* a price model sending price signals should be used, and also when deciding *which* price model should be used. The price model chosen should be the price model which is most socio-economic efficient, and it should only be used if it is more socio-economic efficient than the alternative of reinforcing the grid. As mentioned, the alternative one price model will be better suited for pricing congestion only when there is congestion, as the model re-optimizes when new information is received. This will ensure that the dead weight loss of using this model is less than for the progressive purpose based day-ahead tariff which do not re-optimize and have to set prices for several time periods ahead without utilizing new information. Hence, the alternative one price model seems more socio-economic optimal. However, the simplicity of the alternative two model makes it easier to implement, and it can be easier for the consumers to understand the model and plan the consumption, which can contribute to load *shifting* instead of *reduction*.

Demand response in practice

It is natural that the DSO sets the prices for electricity transmission. Hence it can be reasonable to assume that the DSO manage the price model which uses price signals in order to utilize demand response to prevent grid congestion. However, demand response can also be used for many other purposes, for instance as a tool for balancing the power production and consumption. In this case, it can be more natural that a third party is responsible for extracting the flexibility potential from EV users through pricing, and selling flexibility services to the DSO to alleviate congestion. For the price models suggested in this chapter the prices must be communicated to the consumers. For the alternative one price model, information regarding if an EV is connected (alternatively the total load in the area) must be sent to the operator. As this model re-optimizes, the communication frequency is much higher than for the alternative two price model, and it can be more difficult for the consumer to understand it. It is crucial for the success of a price model that the consumers participate and reveal their flexibility potential. In order to ensure this, it is important that the consumers understand the price models, and that perhaps educational signals, as discussed in section 2.4.1, are sent to the consumer in order to make the consumer aware of how it's consumption affects the grid and his transmission costs. If the consumers have embedded algorithms able to control their electricity usage, utilizing demand response will be easier, as it requires little from the consumer itself. Additionally, it can reduce the consumer's cost of grid tariffs. However, if it should be optional for the EV user to be exposed for a purpose based tariff, even greater economic incentives might be needed to ensure participation.

Uncertainties related to indirect control

No matter how good a price model is, indirect control of EVs can never guarantee a 100 % certainty when it comes to avoiding bottlenecks in the electricity grid. Consequently, the DSO should consider to combine indirect control with other alternatives, for instance direct disconnection of power intensive appliances. Indirect control of EV charging can also be combined with direct control of EV charging, as will be discussed in the following chapters.

To summarize this section: It is not socio-economic optimal that the consumers have to change their consumption pattern and reduce demand when it is not necessary. Hence, a price model which ensures high utilization of the grid should be chosen. Further, in order to ensure that consumers have to adapt their demand only when needed, a price model with high temporal and spatial resolution is required. However, high temporal resolution can be demanding for the consumers, as they must adhere to constantly changing prices, and high spatial resolution can be perceived as unfair. Moreover, predictability of prices for the consumers can contribute to load shifting instead of load reduction. Nonetheless, predictability in prices can increase the avalanche effect. The balancing of these aspects is necessary. Lastly, a price model utilizing price signals to affect demand, should only be introduced if this is more socio-economic efficient than reinforcing the grid, and it must be recognized that a indirect control model of EVs never can ensure a 100 % guarantee of avoiding congestion.

Part III

Direct Control

In this part of the thesis, a direct control model for EV charging is proposed. The authors have been focusing on predictability for the EV user regarding prices and charging time, when developing the model. The model can be operated by a DSO, or for instance an aggregator. In the first chapter of this part, chapter 5, relevant work for creating a direct control charging model for EVs are discussed, followed by a proposal of a model that fits the Norwegian distribution grid. In chapter 6, a case study will be presented, along with the results from testing the model.

CHAPTER 5

Proposal of a Direct Control Model for EV Charging

In this chapter, a direct control model for EV charging is proposed. It is assumed that the party operating the model has full information regarding grid conditions within a substation. The direct control model is intended to be used in combination with price signals. The price signals should give the EV users incentives to offer flexibility by being connected to the charging point for a longer time period than what is minimum required for the EV to reach the desired BSOC. The authors have emphasized predictability for the EV users when developing the model. The predictability concerns how much the charging will cost, and when the EV charging will be completed. The model can be operated by the DSO itself, or by a third party, as soon as AMI is installed. This chapter starts with a problem description, before a review of relevant work is given. In the last part of this chapter, the mathematical model for the direct control of EV charging will be presented, followed by a discussion of the model properties.

5.1 Problem Description

A high penetration of EVs can cause a serious strain on the distribution system. To avoid high investment costs, and a grid which is underutilized most of the day, technology and incentives are needed to reduce EV charging during the existing peak hours. In this part of the thesis, the main focus is on the *technology* and how to utilize the potential of AMI to create a model which ensures that energy consumption is spread more evenly throughout the day. Controlling EV charging directly can contribute to reduced peak loads by automatically coordinating the charging of the EVs, so that the grid capacity is never exceeded. The coordination of the charging can be solved by creating an optimization model, which has been done in this thesis.

5.2 Related Work

Pieltain Fernández et al. (2011) propose an extensive approach for evaluating how different levels of EV penetration affects distribution network investments, as well as energy losses in the grid. The obtained results show that investment costs can increase by up to 19 %, compared to the actual distribution network investment cost when there are no EVs, depending on the charging strategy chosen. Energy losses can increase by up to 40 % in off-peak hours for a scenario where 60 % of the vehicles are EVs. In urban areas, where there is a high load density, the required investment is highest. By using different charging strategies, up to 60 - 70 % of the incremental investment costs can be avoided. The article does not propose a charging strategy for minimizing the cost of upgrading the distribution network, it assumes that different charging strategies provides different “simultaneity factors”, which is the probability of the EVs charging simultaneously.

Deilami et al. (2011) propose a direct charging control strategy for multiple EVs in smart grid. The strategy is a real-time smart load management control strategy, which is based on real-time minimization of total cost of generating the energy, plus the energy loss in the grid. The model includes the grid capacity restriction, and also a priority of which EVs to charge. This is relevant for the problem description in this thesis, however the model is based on the existence of a retailer, or a third party operating in the electricity market, and it tries to reduce the cost of the retailer/third party. The need for a retailer or a third party operating in the electricity market makes the composition of actors involved in the problem relatively complex, and very good communication systems are required. Moreover, the model does not ensure predictability for the EV users regarding cost and charging time.

Wu et al. (2012) have designed a minimum-cost load scheduling algorithm. Similar to Deilami et al. (2011), the existence of a third-party operating in the electricity market is needed in order to integrate the charging strategy. The third-party has a contract with the EV owner that stipulates that charging will only occur during off-peak hours, e.g., from 10 PM to 7 AM, since the wholesale electricity price is low in this period. What is interesting about this model is that the EV owners receive a reduced electricity price in return of relinquish control of their battery state of charge (BSOC). This solution could be used as an inspiration for finding a way of ensuring participation in direct control charging programs. However, only charging the EVs during night does not necessarily give the best utilization of the electricity grid.

Rezaei et al. (2014) describe a direct “packetized” strategy for EV charging, where in time limited periods, the EV charging is requested and approved/disapproved. The model prioritize the EVs which need urgent charging. As long as there is no congestion in the grid, every plugged in EV will be charged. When there is congestion, the EVs which need urgent charging are prioritized. The advantage of this model is that it does not require that EVs report driving patterns (as the

EV users only send requests), in contrast to many other models, and therefore the EV owners privacy is preserved. The disadvantage of this model is that it does not provide the EV user with predictability regarding when the EV will be fully charged. Similar to Deilami et al. (2011) and Wu et al. (2012), the existence of a third-party operating in the electricity market is needed to integrate the charging strategy.

Richardson et al. (2012) demonstrate how better utilization of the existing network can be accomplished by controlling the rate the EV is charged by. The model maximizes total power delivered to the EVs, while operating within the limits of the network, and it prioritizes charging of EVs with low BSOC. This model will be possible to integrate as soon as AMI is installed, as it does not require an aggregator operating in the electricity market. However, the model does not provide the EV users with predictability of when the EV will be fully charged.

Ager-Hanssen and Myhre (2014) describe a direct control model for EV charging, where the objective is to maximize charging power to the connected EVs, while operating within the grid limitations. When the EV is connected to a charger, the only information provided to the charging operator is whether or not the EV user requires urgent charging. In the objective function, the charging of EVs is prioritized based on the choice of charging type (urgent/non-urgent), BSOC and the time since the EV was connected. The authors propose that urgent charging should cost more than non-urgent charging, giving the EV user incentives to only choose urgent charging when it is absolutely necessary. The disadvantage of this model is that the EV user can not be guaranteed to have the desired BSOC when disconnecting, as no departure time is registered by the operator. The advantage is that it requires little information about the EV user.

Sundstrom and Binding (2012) propose a direct control model for EV charging where each EV is given an individual charging plan which satisfies the EV user's requirements, while avoiding that the aggregated EV charging cause distribution grid congestion. An aggregator, which in the article is referred to as the *charging service provider* (CSP), controls the charging and calculates the individual charging schedules, while the retailer and the DSO can influence the charging schedules. The CSP sends a description of available flexibility of the EV users in the fleet, and the retailer sends back a preferred charging curve. The CSP then tries to optimize the charging in order to follow the preferred charging curve as close as possible. After solving the optimization problem the CSP sends its desired charging plan to the DSO, and if it does not cause any grid violations, the charging schedule can be carried out. If the charging schedule causes grid violations, the DSO sends restrictions regarding charging power to the CSP, and the CSP must solve the optimization problem again. The authors propose that the CSP receives a share of the increased profit of the retailer as a result of the extra flexibility. A benefit with this model is that it gives incentives for the aggregator (CSP) to provide direct control of EV charging as it receives some of the retailer's increased profit. A drawback is that this type of framework requires a lot of communication between the CSP and the retailer, and the CSP and the DSO, making it challenging to implement and operate.

5.3 Model Description

The model created is handling the charging of EVs within a substation. It is usually the transformer in a substation which is the limiting component in the grid concerning power output[1]. It is not necessary that the party operating the model controls every household within the substation, as long as it can receive information concerning the households it does not control, and use this in the model. The restrictions of the grid are at four different levels, as illustrated in figure 5.1. The first level is the maximum power in the charging point the EV is connected to. The second level is the maximum power in the main fuse. The charging power of the EV plus the non-flexible power demand of the household (the baseline), cannot exceed this limit. The results of the model in Ager-Hanssen and Myhre (2014) showed that the main fuse was never the limiting grid component, hence this restriction is not included in the model in this thesis. The third level is the transmission line the households are connected to. A transmission line can for instance cover 5-6 households, and the total current used in all of these households, cannot exceed the maximum current the transmission line can carry. The last level is the substation. The power output of all the households (and other units in the substation using power), cannot exceed the maximum power output from the substation. It is important to notice that although every household is operating within the capacity of the transmission line capacity, the capacity in the substation can still be exceeded. Hence, it is not enough to only have restrictions saying that the maximum power in the transmission lines can not be exceeded. The restriction of the substation is also necessary.

The authors of this thesis have created a direct control model for EV charging suited for the Norwegian distribution grid. As mentioned in the introduction of this chapter, the control model is intended to be utilized in coordination with price signals. However, unlike many other charging control models, for instance Rezaei et al. (2014), the objective of the model in this thesis is not to minimize the charging cost of each vehicle, or to minimize the total purchase cost needed to charge the EVs, as it is in Deilami et al. (2011). The amount the EV users pay for the charging depends on the amount of energy needed in order to have the desired BSOC when disconnecting, how long the EV will be connected, and the price list. For instance, if the EV can stay connected to the charging point for six hours, but only needs to charge three hours with maximum charging power to reach the desired BSOC, the price the EV users pay is the price in the three cheapest hours out of the six hours in the price list. This gives the EV users incentives to offer flexibility by being connected for a longer time period than needed to receive the desired BSOC. Even if the objective function was to minimize the charging costs, the cost for each EV could not be cheaper than the price they receive from this

[1]Information given orally by Anders Kvam, TrønderEnergi Nett

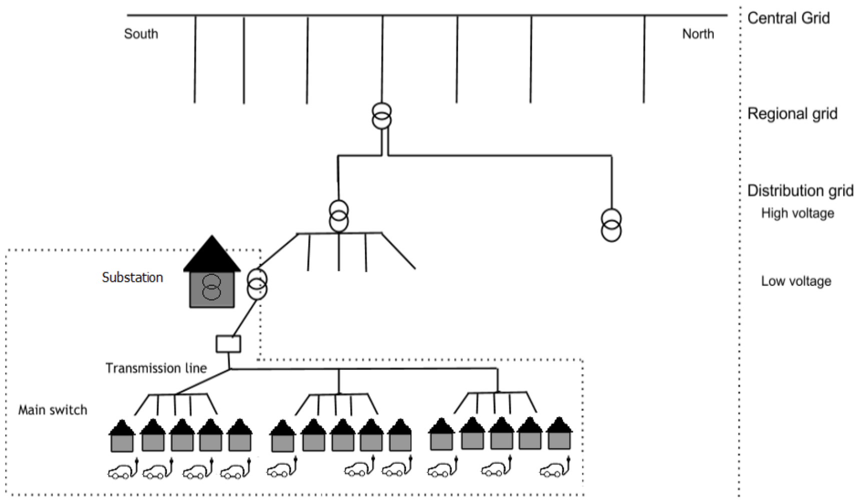

Figure 5.1: Illustration of the Norwegian Grid. The network within a substation is inside the dotted area.

price model. The objective of the model is instead to maximize the total charging power, while operating within the limitations of the grid. This can contribute to a correction of miscalculations in the price model, and make sure that the EVs are charged as fast as possible, given the condition of the grid. Further, the authors believe that EV users value predictability, hence the model guarantees that the EV has the desired BSOC when disconnecting. The model can be operated by the DSO or a third party.

An example of how the EV users can offer flexibility, and which prices they are exposed to, is shown in figure 5.2. In this example, there is an EV who needs two hours of charging with E (the maximum power in the charging point) to reach the desired BSOC. Two alternatives are considered: Alternative one - to stay connected for three time periods (hence providing one hour of flexibility), or alternative two - to stay connected for five periods (providing three hours of flexibility). In both alternative one and two, the EV user will be exposed to the two cheapest hours within the connection period; P_1 and P_3. However, in order to give an incentive to provide flexibility, hence choosing alternative two instead of alternative one, the EV user must receive a flexibility compensation F for every time period she is connected exceeding the minimum connection time. F can be a fixed compensation, or it can vary with the demand for flexibility. In this case, the cost of alternative one would be $P_1 \cdot E + P_3 \cdot E - F$ while the cost of alternative two would be $P_1 \cdot E + P_3 \cdot E - 3 \cdot F$. Hence, if it is possible for the EV user to stay connected for five, instead of three, time periods, the total cost will be less, giving incentives to the EV user to provide true information. This way of pricing the EV charging gives the EV user the possibility of deciding when the EV should have the desired

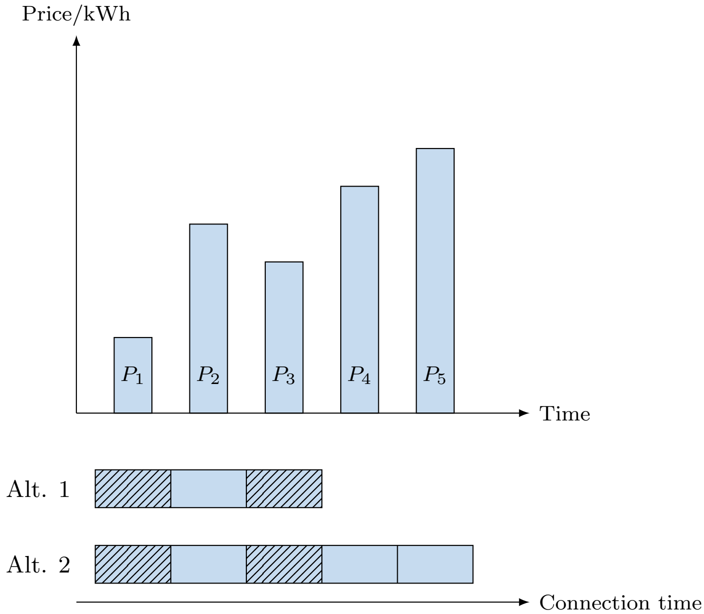

Figure 5.2: Illustration of which prices an EV user who needs two hours of charging will be exposed to, for two alternative connection periods.

BSOC (the EV user's selection is affected indirectly through prices). Hence, when price signals is combined with the direct control model, the EV user is given more predictability than the model proposed in Ager-Hanssen and Myhre (2014) did, as the EV user is guaranteed to have the desired BSOC at the disconnection time.

The model's objective is to decide the power each EV is charged with in the next time period. It is assumed that the charging power can vary continuously between zero and the maximum power in the charging point. Hence, there is no integer requirement, which is beneficial for the solution speed of the model. Every time the model compiles, it receives new input, and it is assumed that this input is constant over the next time period. The model also emphasize that EVs with low BSOC and/or EVs which have a short time until disconnecting, should be prioritized compared to EVs which have high a BSOC and/or have a longer time until disconnecting. When the EV connects to the charging point, information regarding desired BSOC, current BSOC, and for how long the EV will be connected, is collected. Information about the grid conditions and the baseline is also received as an input. The information exchange between the Direct Control Operator (DCO), and the EV/EV user is illustrated in figure 5.3. First, the DCO sends a price list to the EV/EV user with the total cost of the charging given different connection times and given desired BSOCs. Then, the EV user gives the DCO information about the desired BSOC, and when the EV will be disconnected. The first two steps only happens when the EV connects, and not for every time period. Lastly, for every time period, the DCO utilizes the information received from the EV user to find the optimal charging power for this EV, given the baseline and other connected EVs.

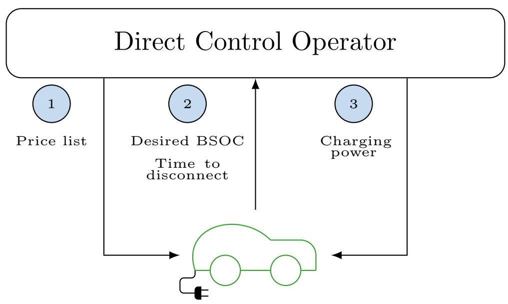

Figure 5.3: Illustration of information flow between the operator of the charging control model and the EV owner.

5.4 Mathematical Model

5.4.1 Definition of sets, parameters and variables

Indexes

h	Household.
t	Transmission line.

Sets

H	Set of households.
T	Set of transmission lines.
H^t	Set of households in transmission line t.

Parameters

$BSOC_h$	$BSOC$ for the EV connected to the charging point in household h.
$BSOC_h^{desired}$	The desired $BSOC$, given by the EV user, for the EV connected to the charging point in household h.
P_h^{max}	Maximum power output in the charging point in household h.
P_t^{max}	Maximum power the transmission line t can tolerate.
$P^{S,max}$	Maximum power output in the substation.
B_t	Total baseline in transmission line t.
C_h	1 if the EV is connected to the charging point in household h and needs charging, 0 else.
D_h	Remaining time periods before the EV disconnects from the charging point in household h.
P_h^{min}	The minimum power the EV in the charging point in household h must be charged with in this time period to be guaranteed the desired $BSOC$ at the time of disconnection.
W_h	Priority coefficient for the EV connected to the charging point in household h, expressing the ratio between the remaining energy needed for charging the battery to the desired level and the maximum charging power, and the time to disconnect.

Variables

p_h	The charging power of the EV connected to the charging point in household h.

5.4.2 Standard objective function

The standard objective function, z, is formulated as

$$z = W_h \cdot C_h \sum_{h \in C} \left(p_h - \left(\frac{p_h}{P_h^{max}}\right)^2\right), \tag{5.1}$$

where

$$W_h = \Big(\frac{\frac{BSOC_h^{desired} - BSOC_h}{P_h^{max}}}{D_h} \Big). \tag{5.2}$$

For each time period, the objective of the charging model is to maximize the power delivered to the connected EVs, subject to the network constraints and the user preferences.

The priority coefficient, W_h, ensures that EVs with low BSOC compared to the desired BSOC relative to the time to disconnect (this is referred to as poor *properties*), are prioritized compared to EVs with higher BSOC compared to the desired BSOC relative to the time to disconnect. The *smoothing term* $\big(\frac{p_h}{P_h^{max}}\big)^2$ should contribute to a distributional effect, meaning that it is preferable to charge for instance two similar EVs with 50 % charging power, than only one of these EVs with a 100 % charging power. The authors believe that a smoother charging curve is preferable for the EV battery's durability. It should be mentioned that the smoothing term only ensures the distributional effect up to a certain value of the charging power, and it should be adapted for different use, but for the purpose of this thesis, with charging powers only up to 8 kW, the smoothing term has the effect the authors wants. The parameter C_h makes sure that only EVs which are connected and need charging (meaning they do not have the desired BSOC yet), can be charged.

5.4.3 Constraints

The charging power, p_h, can not exceed the maximum charging power, P_h^{max}, in the charging point in household h, and if the EV does not need charging it should be set to zero. This is stated in the following constraint:

$$p_h \leq P_h^{max} \cdot C_h, \qquad h \in H. \tag{5.3}$$

Constraint 5.4 expresses that the charging power, p_h, must be greater than the minimum charging power, P_h^{min}, required in the current time period in order to guarantee that the EV will have the desired BSOC when disconnecting. P_h^{min} does only have a value if it is absolutely necessary that the EV is charged with a given power in this time period in order to achieve the desired BSOC at the disconnection time. P_h^{min} is calculated between every iteration of the model.

$$p_h \geq P_h^{min} \cdot C_h, \qquad h \in H. \tag{5.4}$$

The sum of all the power outputs for EVs connected to a charging point in transmission line t, plus the total baseline in the line, cannot exceed the maximum power the transmission line can tolerate, P_t^{max}:

$$\sum_{h \in H^t} p_h + B_t \leq P_t^{max}, \qquad t \in T. \tag{5.5}$$

Next, the total power output for all the EVs connected to a charging point in the substation, plus the total baseline, cannot exceed the maximum power delivered by the substation, P^S_{max}:

$$\sum_{h \in H} p_h + \sum_{t \in T} B_t \leq P^{S,max}. \tag{5.6}$$

Lastly, the charging power, p_h, must be greater than, or equal to, zero for every EV connected to a charging point:

$$p_h \geq 0, \qquad h \in H. \tag{5.7}$$

5.5 Discussion

The mathematical model presented in section 5.4 has the benefit of ensuring predictability for the EV users, while requiring relatively little communication between the actors. If the DSO operates the charging control itself, two way communication is only needed in the time step where the EV connects to the charging point, and after this, only one-way communication is required.

The purpose of the priority coefficient, W_h, in the objective function of the model, is to ensure that the EVs with the poorest properties (low BSOC compared to the desired BSOC, and a short time to disconnect) is prioritized. The authors believe that when there is a problem with congestion in the grid, and not every EV can be charged with maximum charging power, it is beneficial that the EVs with the most critical properties is prioritized. Further, when the properties of an EV becomes critical, such that P_h^{min} has a value, this EV should always be charged at P_h^{min}. In the objective function of the direct control model in Ager-Hanssen and Myhre (2014), thre was *two* priority terms, one comparing BSOC the required BSOC, and one handling the time to disconnect. In this thesis however, this is represented in one term, as the authors believe that it is the remaining required BSOC *relative* to the time to disconnect, which is important to prioritize.

In situations with very high power output in the grid, it might not be possible to charge every EV which needs to be charged at P_h^{min} in order to have $BSOC_h^{desired}$ when disconnecting. A restriction could be added, saying that when this is not possible, P_h^{min} should be set to 0 for every EV, and then the EVs are prioritized based on the value of the priority coefficient, W_h. As a result, in some situations, the desired BSOC will not be reached when the EV disconnects.

The model proposed in Ager-Hanssen and Myhre (2014) had the drawback of prioritizing to charge one EV at 100 % charging power instead of charging two EVs with similar properties at 50 % charging power if there was limited grid capacity. This resulted in a situation where the charging power for each EV was fluctuating from P_h^{max} in one time period, to 0 in the next time period, as the properties changed. The authors think it should be avoided that the charging power fluctuates this way, hence the "smoothing"-term, $\left(\frac{p_h}{P_h^{max}}\right)^2$, is used in the objective function. Up to a certain charging power (which for this smoothing term is larger than P_h^{max} in every charging point, h), it is beneficial to charge several EVs with the same properties at a lower charging power, than to charge *one* EV at the highest possible charging power. However, it should be mentioned that for other charging powers than what have been used in the test cases for this model, other types of smoothing term must be used. It is beyond the scope of this thesis to find the optimal smoothing term. The drawback with this smoothing term, is that the EVs with the largest maximum power in the charging point will be prioritized over EVs with lower maximum power in the charging point, although they have an identical priority coefficient, W_h. The reason for this is that the value of $\left(\frac{p_h}{P_h^{max}}\right)^2$ is relatively lower for the EVs with high P_h^{max}, although this EV charges with the same charging power as an other EV with lower P_h^{max}. This can probably be justified by the fact that the EVs with a higher installed charging power in a charging point, has paid for this upgrade, and hence it is reasonable that these EVs are prioritized compared to the EVs which have not paid for a higher charging power. However, from a grid perspective it is not beneficial to reward EV users which upgrades their charging point, as this will cause even higher peak loads.

One last thing that should be mentioned is that the way the prioritizing coefficient, W_h, is formulated now, there will be a problem running the model for the time periods where the time to disconnect, D_h, for some EV is zero. When running the model the authors have solved this by dividing by $D_h + 1$ instead of D_h. As D_h is never less than zero, it will never be necessary to have a denominator equal to zero. Additionally, as 1 is added to D_h for every EV, it will not affect the prioritization among the EVs.

CHAPTER 6

Case Study

To reveal the potential of the model presented in chapter 5.4, the model was tested on a fictitious network with fictitious households and EV users. The authors were interested in analyzing how controlled charging, both indirect and direct, would affect the EV users and the grid, compared to a situation with uncontrolled charging. This chapter starts by giving an overview of the input data used in the model, and the different scenarios the model has been tested for. Then, the results of the different scenarios are presented, followed by a discussion of the results.

6.1 The Input Data Used in the Case Study

The test case simulated 24 hours. Each time period was set to 15 minutes, hence the model compiled 96 times with new input. In the test case, different EV user profiles were created by the authors, and used in the test case. Additionally, a baseline for each household was created. Network restrictions set by the authors were also used as an input. The network consisted of one transformer, three transmission lines, and ten households within each transmission line. The model was implemented and run in Xpress 7.7.

6.1.1 EV user profiles

To simulate EV users, four different EV user profiles was created. Two types of EVs were assumed; Tesla and Volkswagen e-Golf. These EV types were used in the test case in order to have an EV with high maximum BSOC, and an EV with a lower maximum BSOC, respectively. These EV types were further characterized by a driving pattern. The available battery capacity of the Tesla was 80 kWh, and the household of the Tesla-owner was assumed to have 8 kW as maximum power in the charging point, while the e-Golf's battery capacity was 24 kWh, and the maximum charging power was assumed to be 4 kW. It was assumed that the households which had an EV, either had the EV as the only car (first car), or as a supplement to a petrol car (thus the EV was a second car). Depending on whether the EV was the first or second car of a household, it was assumed that the driving pattern differed. It was assumed that when an EV connected to the charging point, the desired BSOC when disconnecting was provided by the EV user to the DCO. If the EV then needed to be charged with maximum power in the charging point in every time period to reach this desired BSOC by disconnection time, that EV provided no flexibility. On the other hand, the EV provided flexibility if it didn't have to be charged at maximum power in all remaining time periods to reach the desired BSOC. For instance, if the maximum power in the charging point was 8 kW, and the EV would be connected for 3 hours and needed 16 kWh before disconnecting, the EV user would provide 1 hour of flexibility. An overview of the EV user profiles is given in table 6.1, and explained below.

Whenever the EV was a household's first car, the BSOC when arriving from work was assumed to be 40 kWh (50%) and 10 kWh (42%), for the Tesla and the e-Golf respectively. It was assumed that these types of EV users drove their EV in the afternoon, and in the first connection period, the Tesla required a BSOC of 56 kWh (providing 1 hour of flexibility) while the e-Golf required 22 kWh (providing no flexibility). While driving in the evening, the energy usage was 20 kWh for the Tesla and 12 kWh for the e-Golf. In the second connection period, it was assumed that both the Tesla and the e-Golf wanted to be fully charged by the next morning, hence, they provided 4,5 hours and 6,5 hours of flexibility, respectively (given that the charging needs were fulfilled in the first connection period).

		Tesla		**e-Golf**	
		1st car	*2nd car*	*1st car*	*2nd car*
	Battery size	80 kWh	24 kWh	80 kWh	24 kWh
	Max Power in Chargepoint	8 kW	4 kW	8 kW	4 kW
1st connection period	Time	16:00-19:00	16:30-07:30	17:00-20:00	17:30-08:30
	BSOC	40 kWh	30 kWh	10 kWh	5 kWh
	Required BSOC when disconnecting	56 kWh	80 kWh	22 kWh	24 kWh
	Flexibility offered	1 h	8,75 h	0 h	10,25 h
	Energy used between 1st and 2nd connection period	20 kWh	N/A	12 kWh	N/A
2nd connection period	Time	21:00-07:00	N/A	22:00-08:00	N/A
	BSOC[1]	36 kWh		10 KWh	
	Required BSOC when disconnecting	80 kWh		24 kWh	
	Flexibility offered[1]	4,5 h		6,5 h	

Table 6.1: Overview of the EV user profiles used in the case study.

[1]given that the charging needs were fulfilled in the first connection period

On the other hand, if the EV was the household's second car, the BSOC was assumed to be 30 kWh (37%) for the Tesla and 5 kWh (21%) for the e-Golf when connecting in the afternoon. It was assumed that these users did not use their EV during the afternoon, and as they both required the EV to be fully charged by the next morning, the Tesla provided 8,75 hours of flexibility, while the e-Golf provided 10,25 hours of flexibility.

6.1.2 The household's baseline

In this case study, it was assumed that the total load in a household, excluding EV charging, made up the *baseline*. To determine the aggregated baseline within each transmission line, a profile regarding typical power output in a Norwegian household was used as a forecast of the power output throughout the day (Sintef, 2014). The baseline used in the test case is illustrated in figure 6.1. The graph in figure 6.1 illustrates the average hourly power output in Norwegian homes for a weekday during winter.

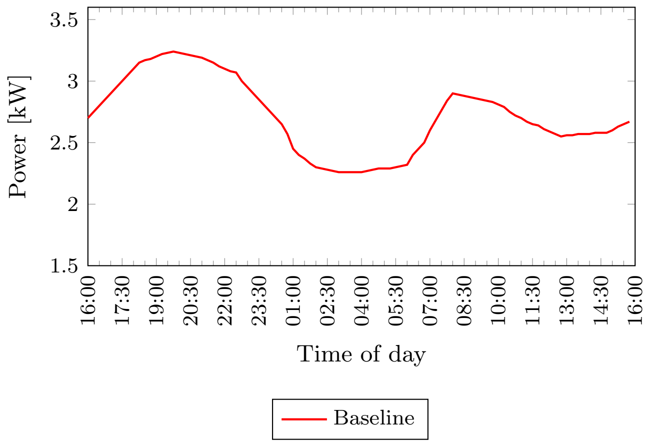

Figure 6.1: Illustration of the average baseline in Norwegian households a weekday during winter.

The reader should be aware of three things. First, since the graph illustrates the average power output during an hour, it does not capture the peaks that occur when for instance a household uses its induction stove for some minutes. As a result, there could be some periods of the day where even more load should be moved than the result of the model proposed. Secondly, it was assumed that the baseline did not include charging of EVs, so every time period an EV in a household was charged, this power output would come in addition to the baseline. The last thing one should be aware of is the assumption that the owners of Teslas on average had a 20 % higher power output than the owners of Volkswagen e-Golf, resulting in a lifted baseline illustrated in figure 6.2. This was an assumption made by the authors, because it was expected that the owners of EVs like Teslas, had a higher comfort level and larger homes which needed more power.

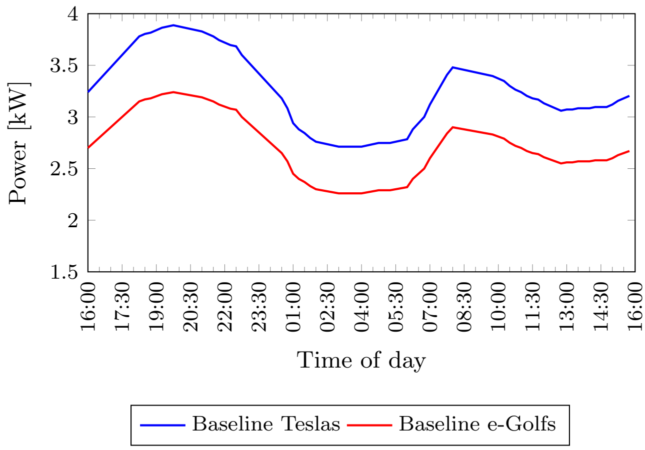

Figure 6.2: Illustration of the baseline for e-Golf owners (bottom most), and Tesla owners (topmost).

6.1.3 The Network

The network which was used in the test case was dimensioned as realistic as possible regarding the power capacities in the different parts of the distribution grid. Characteristics of the distribution grid operated by Hafslund was used[2]. Hafslund is the DSO in Oslo, Akershus and Østfold. It was assumed that there were 10 households within each transmission line. The transmission lines normally have a maximum current of 80-350A. In the transmission lines in this test case, the maximum current was set to 282A, hence the transmission lines had a maximum power of 65 kW assuming that the voltage was stable at 230 V. It was assumed single phase voltage within the transformer, hence the relation between power (P), current (I) and voltage (U) was as in equation 6.1:

$$P = U \cdot I \tag{6.1}$$

The substation limit was set to 175 kW. The network restrictions are summarized in table 6.2, and the grid levels are illustrated in figure 6.3.

The reader should notice that the maximum power in each grid level was chosen in order to reveal the potential of the model.

[2]The characteristics of the grid was sent from Hafslund to the authors by mail.

Grid Level	Maximum Power
Substation	175 kW
Transmission Lines	65 kW
Charging Point	4/8 kW

Table 6.2: The network restrictions used in the case study.

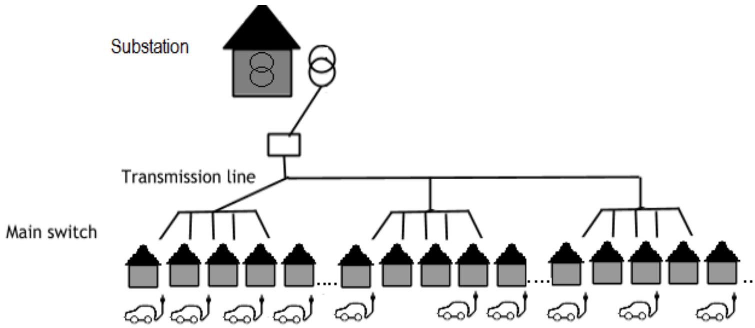

Figure 6.3: Illustration of the network used in the case study.

6.1.4 The price list used in the case study

It was assumed that a time-varying price list affected the EV users' choice of desired BSOC and connection time, both when controlled directly and indirectly. In both cases, the resulting choices were as shown in table 6.1. The price list used in the case study, is illustrated in figure 6.4.

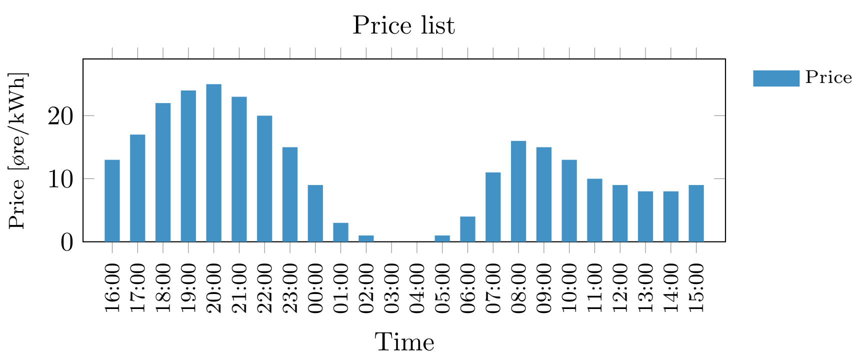

Figure 6.4: The price list used in the case study.

6.1.5 Scenario description

To illustrate the grid impact with different control methods of EV charging, four scenarios was studied:

- Uncontrolled charging
  - 30 EVs
- Controlled charging
  - 30 EVs direct control
  - 30 EVs indirect control
  - 15 EVs direct control, and 15 EVs indirect control

For all the scenarios, it was assumed that all households within the network had an EV, hence the network consisted of 30 EVs. What varied in the different scenarios was *how* the charging of these EVs was controlled.

Uncontrolled charging, also known as "dumb charging", was regarded as the situation where the charging was not controlled by any automatic algorithms. The charging started when the EV user plugged in the EV, and lasted until the EV was fully charged, or disconnected. It was assumed that these EV users did not respond to price signals.

In the case of controlled charging, the model presented in section 5.4 was first tested on the scenario with 30 EVs controlled directly. Here, the aim was to examine if the test network could accommodate this number of EVs, and also investigate to what degree the EV users were affected by the DCO controlling the EV charging. When an EV was controlled indirectly, it was assumed that the EV had an embedded algorithm, placing the charging in the cheapest hours, as long as the EV user's choices were fulfilled. It was tested how 30 indirectly controlled EVs would affect the grid. For the scenario with 15 directly controlled EVs and 15 indirectly controlled EVs, it was interesting to see if the directly controlled EVs could rectify the avalanche effect that could occur when some of the EVs were indirectly controlled. The distribution of EV user profiles in the different transmission lines is illustrated in figure 6.5, where the scenarios with 30 EVs is shown. In the scenario with 15 EVs controlled directly and 15 EVs controlled indirectly, there was an equal share of the different EV user profiles in the transmission line. Hence if there were two Tesla 1st cars in the line, one of them was directly controlled and the other one was indirectly controlled.

6.2 Results

In this section, the results from the test case are presented. The scenarios with direct control were run in Xpress 7.7, while the scenarios with uncontrolled charging was calculated manually. For the scenarios with 30 and 15 indirectly controlled

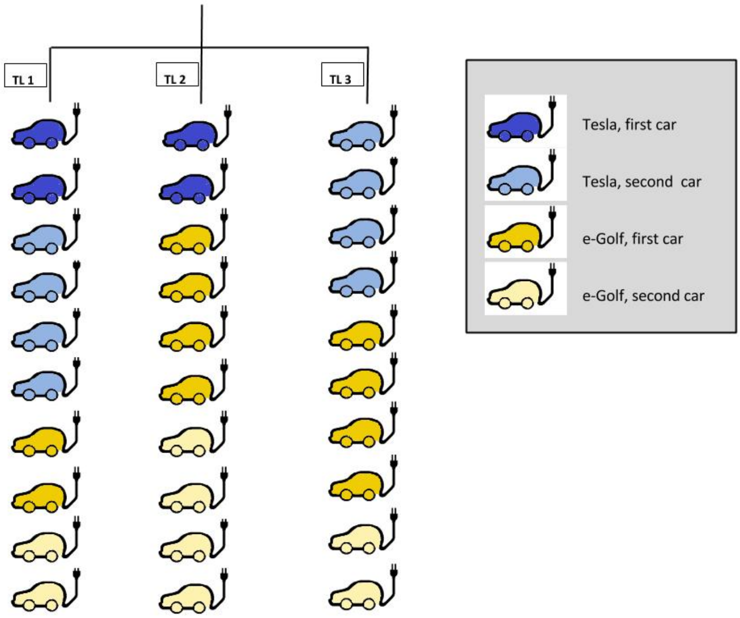

Figure 6.5: Overview of the distribution of EV user profiles in the three transmission lines in the 30 EV scenarios.

EVs, the authors calculated where the charging would be placed, given the price list in section 6.1.4 and the EV user profiles in table 6.1.

6.2.1 Aggregated load curves

Uncontrolled Charging

Figure 6.6 and 6.7 show the total power demand in the substation and in transmission line one respectively, with uncontrolled charging of 30 EVs. The arrival times for the different EV users are listed in table 6.1, and it was assumed that the EVs were charged at maximum charging power from the connection time and onwards. It can be seen that in the scenario with 30 uncontrolled EVs, the capacity in the substation was at most exceeded by 96 kW.

When looking at the power demand in transmission line one, the capacity was at most exceeded by 35 kW. The results from transmission line two and three can be found in the appendix, and show similar results.

The results from the uncontrolled charging scenario show that to accommodate a high EV penetration without controlling the charging, the capacity of the transformer as well as the transmission lines would have to be increased.

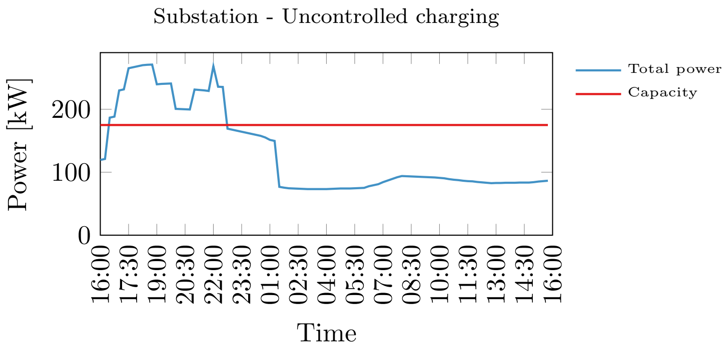

Figure 6.6: The power demand in the substation when the charging was uncontrolled.

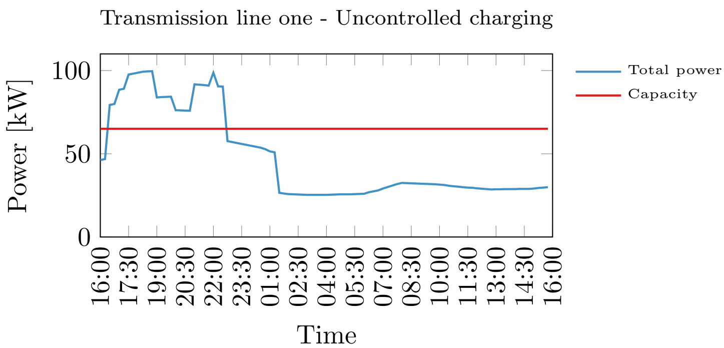

Figure 6.7: The power demand from transmission line one when the charging was uncontrolled.

Direct control

Figure 6.8 illustrates the power demand in the substation when the charging was uncontrolled and directly controlled. When the charging was uncontrolled, there was a total of 374 kWhs overload in the substation. These kWhs were shifted when the charging was directly controlled, hence the substation was never overloaded. Still, the energy use was not reduced, only shifted.

Figure 6.9 illustrates how transmission line one was affected by having 10 EVs within the area it was covering. When the charging was uncontrolled, there was 147 kWhs of overload in the line. When the charging was controlled directly, there was no overload, as the load had been shifted to other time periods. Similar to the situation in the substation, the energy use was not reduced, only shifted.

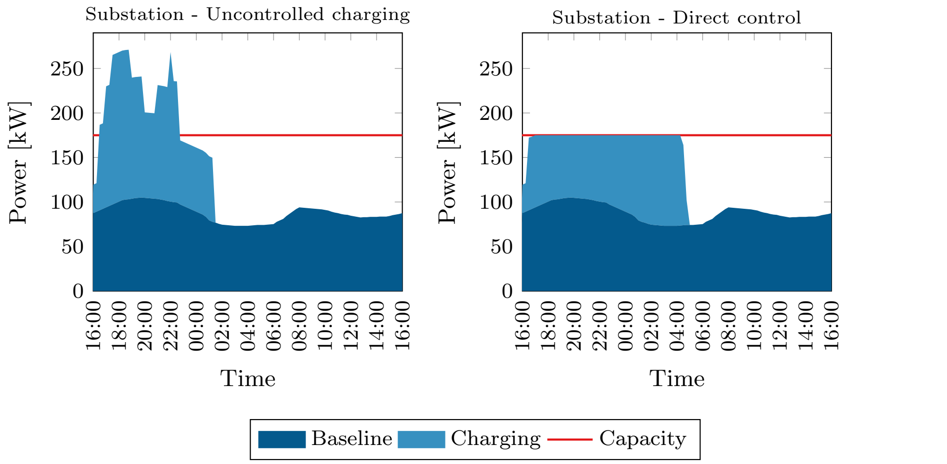

Figure 6.8: The power demand in the substation, when the charging was uncontrolled and controlled directly.

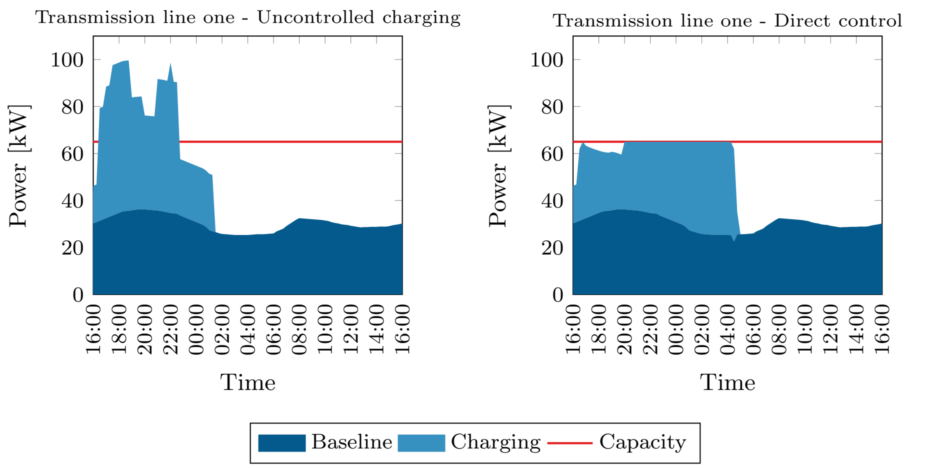

Figure 6.9: The power demand in transmission line one, when the charging was uncontrolled and controlled directly.

Indirect control

When the charging of the EVs was controlled indirectly, the price list which was illustrated in figure 6.4 was sent to the EVs, and it was assumed that an embedded algorithm placed the charging in the cheapest hours. As a result, overload was seen during nighttime. The peak normally seen in the afternoon with uncontrolled charging, was now shifted because several EVs reacted to the same price signal, resulting in an avalanche effect. This is illustrated in figure 6.10. The results from the transmission lines can be found in the appendix.

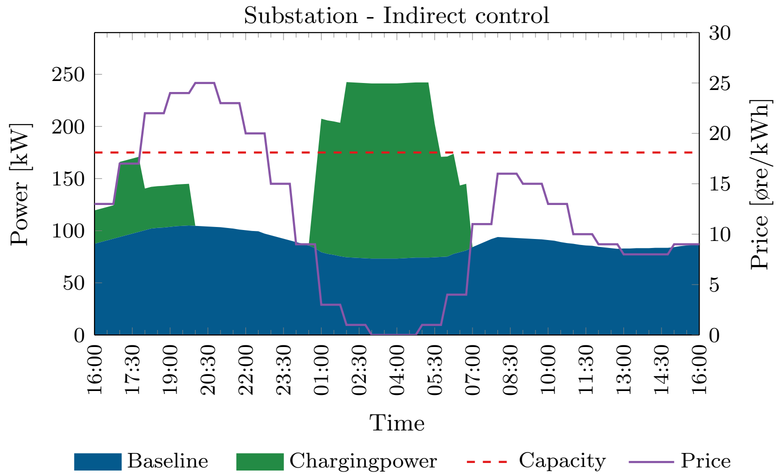

Figure 6.10: The power demand in the substation, when the charging was controlled indirectly through price signals.

Direct and indirect control

In the case study it was also tested how the EVs controlled directly could compensate for an avalanche effect among the indirectly controlled EVs. This was tested with 15 EVs controlled directly, and 15 EVs controlled indirectly. The results for the power demand in the substation is shown in figure 6.11, while the results from the transmission lines can be found in the appendix. It can be seen that whenever there was a demand for charging from the EVs controlled indirectly through price signals, the charging power of the EVs controlled directly was reduced, and the capacity of 175 kW was not exceeded.

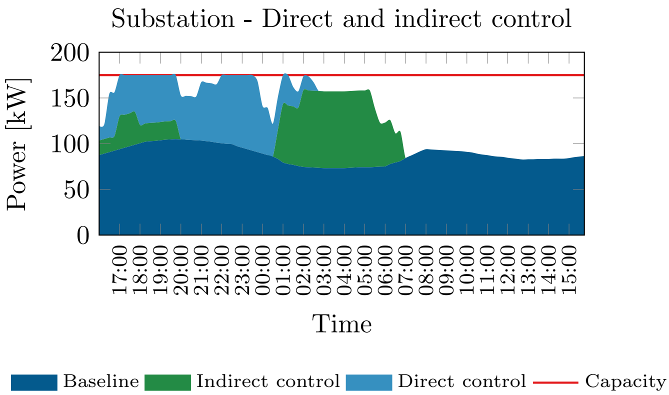

Figure 6.11: The power demand in the substation, when the charging was controlled directly and indirectly.

6.2.2 Individual charging curves

Figure 6.12 shows how the charging power of a directly controlled Tesla 1st car varied, and how the BSOC developed respectively, during the first connection period. Figure 6.13 illustrates the same, but these are the results when the Tesla 1st car was uncontrolled. It can be seen that both EVs had the desired BSOC at the disconnection time (19:00). However, while the uncontrolled EV was charged at P_h^{max} until it reached $BSOC_h^{desired}$, the directly controlled Tesla was charged at P_h^{max} in the beginning of the charging period, but after a while the charging power was reduced to less than 50 % percent of P_h^{max}. However, the directly controlled EV had the desired BSOC when disconnecting, and additionally, it provided flexibility to the DCO.

Distribution of charging among equal EVs

Two aspects regarding the charging of individual EVs should be discussed. First, it is natural that two EVs with identical properties are treated equally within one period (intra periodical fairness). Secondly, it is preferable that the charging power for one EV does not fluctuate too much between periods (inter periodical fluctuations).

The model presented in the project thesis of Ager-Hanssen and Myhre (2014) ranked poorly on both of these aspects. Whenever there was not enough capacity for two EVs to be charged with maximum power in the charging point, the model would "randomly" choose to charge one with maximum power, and the other with the remaining power. In the next time period, the properties would change, so that the model would prioritize the other EV. In figure 6.14, it is illustrated how two initially equal EVs were charged. In the project thesis one can see how initially

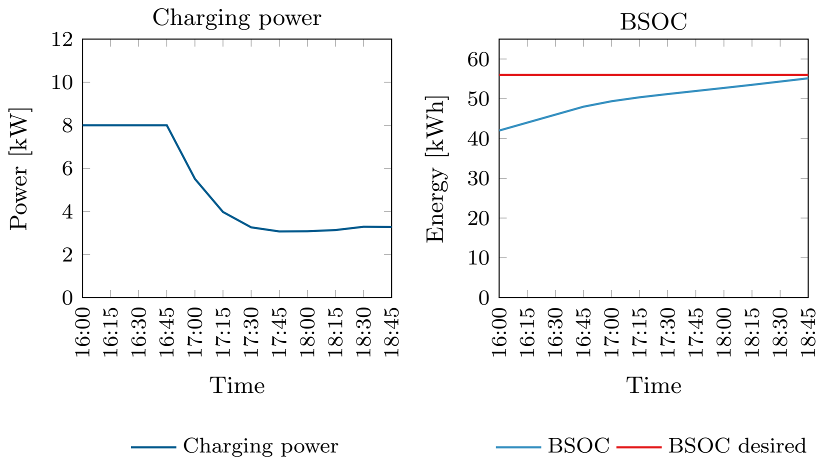

Figure 6.12: Charging power and development of BSOC of a directly controlled Tesla 1st car.

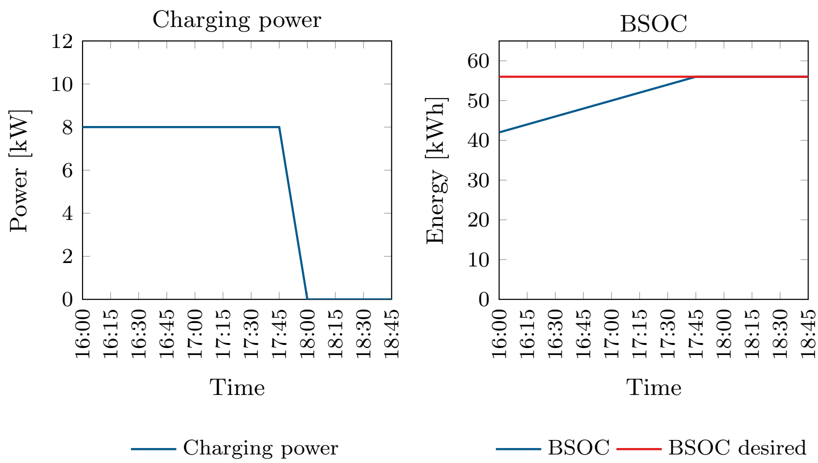

Figure 6.13: Charging power and development of BSOC of an uncontrolled Tesla 1st car.

equal EVs were treated unequally within one time period, and as a side effect, there was a fluctuation of charging power for each EV between time periods.

With the direct control model presented in this thesis, this weakness was taken care of by introducing the smoothing term. The smoothing term made sure that EVs with identical properties were charged with the same power, ensuring intra periodical fairness, as can be seen in figure 6.14. As a side effect, this also lowered the inter periodical fluctuations of the charging power. For instance, when looking

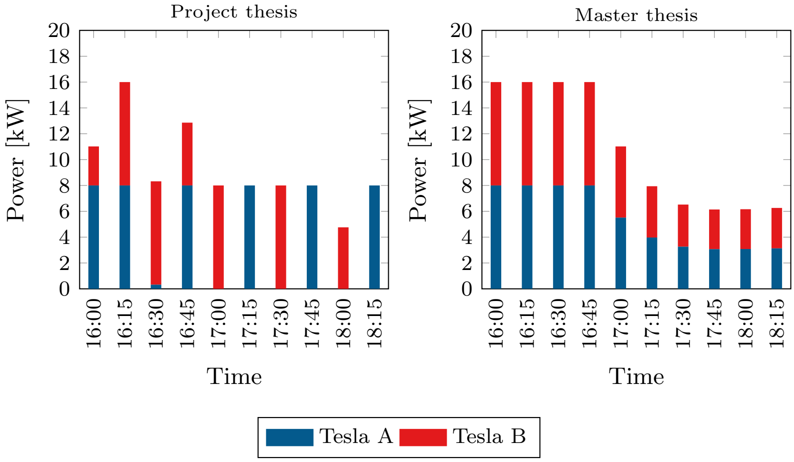

Figure 6.14: Results from the project thesis of Ager-Hanssen and Myhre (2014) and the results from the case study in this thesis, showing how the available charging power was distributed between two initially equal EVs.

at Tesla A in the project thesis, one can see that the charging power fluctuated greatly between time periods. However, in the master thesis, one can see that this was not the case, as the available power was distributed equally intra periodically, avoiding fluctuations inter periodically.

6.2.3 Prioritization

The purpose of the coefficient, W_h, in the objective function, was to prioritize the EVs with poor properties. A high value for W_c meant that the properties of the EV was poor. The aim was that an EV with high value for W_h would be prioritized compared to an EV with lower W_c. When two EVs had the same properties, the smoothing term $\left(\frac{p_h}{P_h^{max}}\right)^2$ should ensure that the remaining capacity for these EVs was distributed fairly among them. Figure 6.15 illustrates how the coefficient W_h ensured that the EV with the worst properties (Tesla 1st car) was prioritized until the properties got relatively better for this EV than for the other EV (Tesla 2nd car) which then was prioritized. It should be mentioned that from 01:30 and the following time periods, it looks like the value of W_h was the same for both Teslas. However, it was slightly higher for the Tesla 2nd car, hence this EV was prioritized.

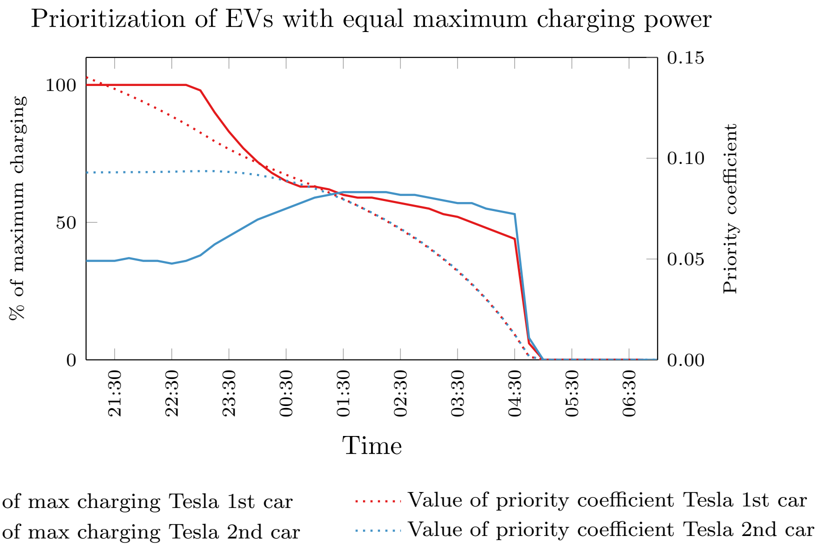

Figure 6.15: Illustration of how the charging power varied, given the priority coefficient for a Tesla first and second car in transmission line one.

As mentioned in section 5.4, there is a drawback with having the smoothing term, $\left(\frac{p_h}{P_h^{max}}\right)^2$, in the objective function. This was illustrated by the results, where a Tesla and an e-golf had the same properties (same value for W_h), but the Tesla was prioritized compared to the e-Golf. This is because the value for $\left(\frac{p_h}{P_h^{max}}\right)^2$ (which counts negatively in the objective function) gets lower for an EV with high P_h^{max}, and hence it is better for the objective function to prioritize the Teslas compared to the e-golfs. This phenomena is illustrated in figure 6.16.

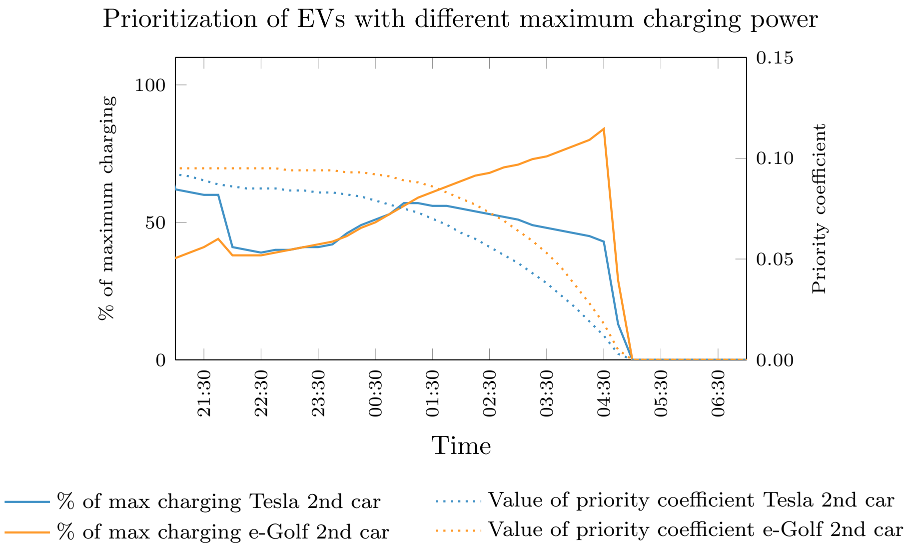

Figure 6.16: Illustration of how the charging power varied, given the priority coefficient for an e-Golf second car and a Tesla second car in transmission line three.

6.3 Discussion

The case study showed that the model presented in section 5.4 could contribute to a lower risk of overloading the grid components, compared to the scenarios where the EVs were uncontrolled or controlled indirectly. When 100% of the EVs were controlled directly, there was never a risk of overloading the components. When some of the EVs were controlled indirectly, it was valuable for the DCO that some EVs were controlled directly, as they could compensate for forecast errors, and thus inaccuracies in the prices sent to the EVs, which could cause the avalanche effect.

If the grid capacity was very limited, a situation where it was not possible to charge every EV by P_h^{min} could occur. This would prevent the EVs from having the desired BSOC when disconnecting. It is necessary to discuss what the DCO should do in this situation. For instance, the DCO could have a local storage available which could be used to serve charging power to the EVs when they needed to be charged at P_h^{min} while the grid was congested. Another opportunity is for the DCO to communicate with the EV users when there is a probability for this situation to occur, and ask is anyone is interested in a compensation by reducing the charging power of these EVs in the relevant time periods.

In the case study, P_h^{min} was calculated between every model iteration. If the sum of all P_h^{min} was greater than the remaining capacity for charging, P_h^{min} was set to 0 for every EV, and the charging was based on the prioritization in the objective function. Further, in the calculation between every time period, it was only checked if it was necessary for the EV to be charged at P_h^{max} in this time period in order to reach $BSOC_h^{desired}$ before disconnecting. Hence, in a situation where it was not necessary for the EV to be charged at P_h^{max}, but for instance at $\frac{P_h^{max}}{2}$, then P_h^{min} would be set to zero. The way P_h^{min} was calculated in the case study, could result in a situation where $BSOC_h$ was not exactly $BSOC_h^{desired}$ when the EV was disconnected. Hence, the EV's $BSOC_h$ could be a little lower than $BSOC_h^{desired}$ when disconnecting. However, in this situation, the EV's $BSOC_h$ would practically be equal to $BSOC_h^{desired}$.

The last thing that should be discussed is the trade off between reality representation and computational effort. It is demanding to have small time periods because this requires the model to compile very often. In the test case, the time periods were set to 15 minutes, and the value of the baseline for the households in the network was taken in as an input in the beginning of every time period, and remained constant throughout this period. 15 minutes is a relatively long period considering what can happen within this period. For instance an induction stove can be used for 5 minutes, resulting in a power output on top of the baseline of approximately 6 kW. This effect is illustrated in figure 6.17. The result can be that in some periods the power output will exceed the capacity. One can imagine that this especially could be a problem for the main fuse, and the results saying that the main fuse is never a binding constraint, is most likely unrealistic.

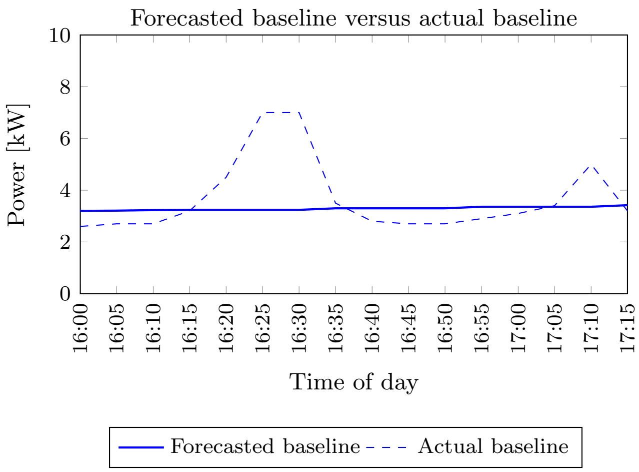

Figure 6.17: Illustration of how the actual baseline could differ from the forecasted baseline.

Part IV

Combination of Control Methods

CHAPTER 7

Combination of Indirect and Direct control methods for EV charging

In this thesis, different control methods for EV charging have been discussed. Chapter 4 discussed different price models suited for EV charging, while chapter 5 and 6 discussed how the EV charging could be controlled directly. The authors believe that these control methods should coexist, and work together, in order to ensure the most optimal utilization of the grid. The purpose of this chapter is to illustrate how indirect and direct control of EV charging can be used in combination.

7.1 Why Price Models Should be Combined with Directly Controlled EV Charging

Chapter 4 proposed two different price models with the aim of reducing peak loads caused by EV charging, without reducing the demand. Although pricing can be a "simple" way to affect the consumption of many consumers, price models can never give 100 % certainty regarding whether the desired quantity of flexibility is provided, and if the flexibility is provided in the desired time periods. Chapter 6 showed how an avalanche effect occurs when many EVs with embedded control algorithms are exposed to the same price signals. However, in combination with some directly controlled EVs, the avalanche effect was reduced considerably. New price models designed to reduce peak loads, give incentives for the consumers to utilize automatic control mechanisms, for instance embedded algorithms in the EV, ensuring the most inexpensive cost of EV charging. When the EV charging is controlled by an embedded algorithm, it is natural to assume that the EV user wants some predictability regarding the EV charging, for instance to be able to state the desired battery level at the disconnection time. To have this form of predictability is also possible when the EV charging is controlled directly. The model proposed in section 5.4, gives the EV user this predictability. Thus, the authors believe that many EV users would be rather indifferent when it comes to choosing between an embedded algorithm in the EV, and direct control charging, as long as not too much information must be given to a second party, and as long as it is just as cheap, or cheaper, to be directly controlled. Educational signals can contribute to participation in a direct control charging program, as information regarding how the EV charging affects the grid, and also the cost of the EV charging, can give the EV user a desire to contribute to a better grid utilization. Having some directly controlled EVs can be of considerable value for a DSO, and also for the consumers in the distribution grid which can avoid having to cover grid reinforcements through its grid tariffs. The next section illustrates how price models can work in combination with directly controlled charging, uncontrolled charging, and charging controlled by an embedded algorithm.

7.2 Schematic Representation of a Combination of Control Methods for EV Charging

Figure 7.1 is a schematic representation of how the authors believe a combination of different control methods for EV charging could appear. In this schematic representation, there are two main system areas, with an interface between them. The first system area is operated by the DSO, and here a forecast, a price model and a direct control model is operated. The prices created in the price model are prices for transmission of electricity, and not electricity itself. The prices can either be power tariffs, or energy tariffs, and it can be targeted only to EVs, or to the entire consumption in a household. It is assumed that only flexible loads react to prices, and here flexible loads are represented by EVs. The prices can be posted in advance by giving the consumers a price list of the prices for the next T time periods, or the prices can be posted real-time (just before the relevant time period). The other system area consists of the EV users, and the charging of the EV. The EV receives information about the prices in different time periods from the DSO. The EV charging can be controlled directly or indirectly, and different information is sent to the DSO depending on the EVs control method.

7.2.1 Description of the schematic representation

In the forecast model, the remaining capacity available for EV charging, CAP_t^{EV}, is forecasted. In order to find the remaining capacity for EV charging, the baseline consisting of inflexible demand must be forcasted. The remaining capacity is found by taking the total grid capacity less the forecasted baseline. Additionally, an initial demand, $Q_{h,t}^0$ is forecasted, given an initial price, P_t^0. The elasticity matrix for each household, $E_{h,t,t'}$ is also estimated in the forecast model. All this information is sent to the price model.

In the price model, if it is expected that the initial prices can cause grid congestion, a price list, p_t, is computed. New feasible quantities, $q_{h,t}$, are estimated, with the

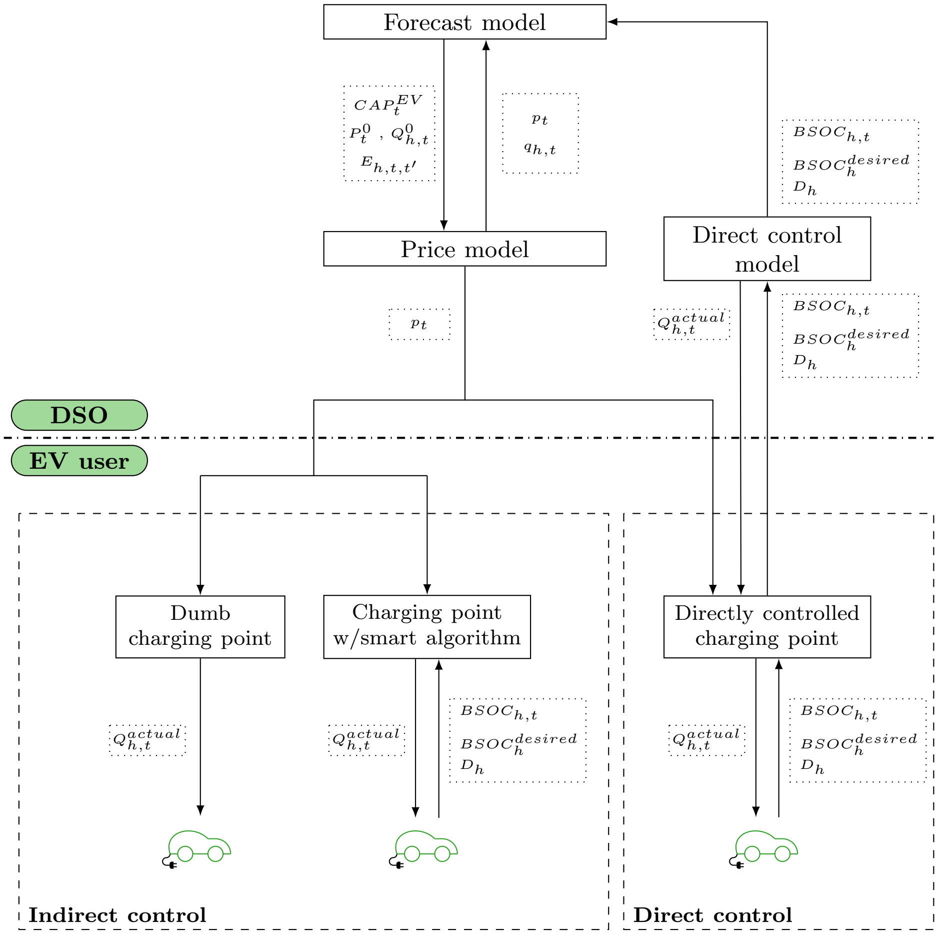

Figure 7.1: Schematic representation of a combination of control methods for EV charging.

aim of shifting demand to periods with excess capacity. The price for each time period in the price list, p_t, can either be published real time for each period (where the price list contains only one element), or the price list can be computed once a day, posting the prices for each time period the following day. Alternatively, it can be a combination of the above mentioned solutions, where a price list for the next T time periods is being updated in each time step.

The EVs which are controlled indirectly are exposed to the prices, p_t. The intelligence in the charging point of these EVs varies. The charging point can either be "dumb", meaning that the EV is charged at the maximum charging power in the charging point as soon as the EV is connected, and the charging continues until the EV is fully charged or disconnected. Or, the charging point can be "smart", meaning that there is an embedded algorithm which detects the battery state of charge at connection time, $BSOC_{h,t}$, and gives the EV user information regarding the prices, p_t. In the case where the prices are decided real time; an *expected* price list can be presented. Based on these prices, the EV user specifies a desired battery state of charge, $BSOC_h^{desired}$, and a point in time, D_h, when he/she wants the EV to have this battery level. The EVs which are controlled directly, are also exposed

to the prices, p_t. I addition, they receive a fixed or variable compensation for every time period they offer flexibility. Based on these prices the EV user specifies a desired battery state of charge, $BSOC_h^{desired}$, and a point in time, D_h, when he/she wants the EV to have this battery level. This information plus the initial battery state of charge, $BSOC_{h,t}$, is sent to the direct control model. This model controls the charging in the time periods the EV is connected, and it ensures that the EV has the desired BSOC at the time of disconnection. The model receives information regarding total load in the relevant grid area, and hence it can utilize the capacity of the grid in the most optimal way.

Lastly, information regarding the choice of $BSOC_h^{desired}$ and D_h of the directly controlled EVs, is sent to the forecast model. Unless the price model is purpose based, where a dedicated meter measures the EV load, information regarding how the indirectly controlled EVs responded to the prices, $Q_{h,t}^{actual}$, can not be observed directly by the forecast model. However, the DSO has information regarding the aggregated consumption in every household, and it can utilize this to estimate how the EV charging took place, as the variations of the baseline throughout a day is relatively constant when comparing different days. The estimation of how the indirectly controlled EVs actually was charged, along with the known $Q_{h,t}^{actual}$ from the directly controlled EVs, can be compared to the estimated demand $q_{h,t}$ given the prices p_t, in order to improve the elasticity matrix, $E_{h,t,t'}$.

7.3 Discussion

The authors believe that price signals are well suited both to control EVs indirectly, as well as ensuring that EVs controlled directly provide the adequate amount of flexibility when needed. Utilizing that some EVs are directly controlled can have a positive effect on the electricity grid, compared to only relying on the response of indirectly controlled EVs, as shown in chapter 5. The actor sending the price signals should consider how the different EVs are charged in order to find the optimal prices.

The schematic representation of how control methods can be combined, illustrated in figure 7.1, has only two actors in the value chain; the DSO and the EV user. It is possible that another actor, for instance an aggregator, can manage some of the operations which in figure 7.1 is managed by the DSO. If an aggregator should control the charging by offering an indirect or direct charging service to EVs, the aggregator would have to be informed by the DSO about the grid conditions. The aggregator could then offer a congestion management service to the DSO and/or offer flexibility to retailers.

CHAPTER 8

Conclusion

Large penetrations of EVs can entail major challenges for the distribution grid. Without controlled charging of EVs, the peak load in the grid increases, which can cause overload of network components. This problem can either be solved in the traditional way where heavy grid investments are made, or innovative and more socio-economic alternatives can be considered.

The main purpose of this thesis has been to help the distribution system operators (DSOs) in Norway to prepare for the increasing EV penetration by introducing possible indirect and direct control methods for EV charging. How to achieve indirect control of EV charging through pricing, and how EV charging can be controlled directly while fulfilling the EV users' preferences, have been the main focus in this thesis. The findings have been used to discuss how these control methods could be used in combination in order to ensure a utilization of the grid which is as socio-economic efficient as possible.

Principles and considerations important for designing optimal grid tariffs suited for the new consumption pattern, were presented and discussed. This was used as a basis for creating two price models for EV charging, both purpose based. The first model was a real-time tariff with fixed price lists, where the aim was to ensure predictability for the EV users regarding prices while still having the ability to utilize real-time information regarding the grid condition. This was achieved by giving different price lists to different EV users, depending on when the EV connected to the charging point. The second model was a progressive day-ahead tariff where the charging power which exceeds what was referred to as normal charging, was charged by a higher price per kWh. The aim of the model was to find the prices for normal and fast charging, as these should vary with changing grid conditions. Furthermore, a direct control model was proposed, which controlled the charging of several EVs within a substation, while giving the EV users predictability regarding the EVs battery state of charge (BSOC) at the disconnection time, as this was specified by the EV user. The model's objective was to charge the EVs with the maximum possible charging power, and to prioritize the EVs with low

BSOC compared to the desired BSOC, relative to the time to disconnect. All of the three models were tested on fictitious networks with fictitious EVs.

The work presented in this thesis demonstrates that the distribution grid could tolerate a high penetration of EVs when the charging is controlled, and still fulfill the EV's charging needs. The high penetration of EVs tested in this thesis would have been problematic for the network if the charging was uncontrolled. Without indirect and/or direct control methods of the EV charging, the distribution grid would have to be reinforced to accommodate the increasing number of EVs and other power intensive appliances. By using price signals to shift EV charging away from existing peak loads, or by directly controlling the EV charging ensuring no grid congestion, investments can be postponed. However, as indirect control methods do not give a 100 % guarantee of avoiding congestion, and as it can be difficult to ensure participation in direct control programs, a combination of the two methods can possibly give the most socio-economic utilization of the grid.

With the introduction of Advanced Metering Infrastructure (AMI), the Norwegian regulator facilitates the use of demand response. The DSOs should consider alternatives to grid reinforcement as this can prevent underutilization of the grid. Price signals can be used to indirectly control the charging of EVs, but also to ensure that an adequate amount of flexibility is offered when the EVs are controlled directly. Pilots should be prioritized, not only for technological solutions, but also for testing how consumers respond to different price signals. Without understanding and engaging the consumers, which are the providers of flexibility, demand response will not succeed.

Bibliography

H.A. Aalami, M. Parsa Moghaddam, and G.R. Yousefi. Demand response modeling considering interruptible/curtailable loads and capacity market programs. *Applied Energy*, 87(1):243 – 250, 2010. URL http://www.sciencedirect.com/science/article/pii/S030626190900244X.

Siri Bruskeland Ager-Hanssen and Siri Olimb Myhre. Controlled charging of electric vehicles - an alternative to grid reinforecements. Project work, Norwegian University of Science and Technology, December 2014.

Changsun Ahn, Chiao-Ting Li, and Huei Peng. Optimal decentralized charging control algorithm for electrified vehicles connected to smart grid. *Journal of Power Sources*, 196(23):10369–10379, 2011.

MH Albadi and EF El-Saadany. Demand response in electricity markets: An overview. In *IEEE Power Engineering Society General Meeting*, volume 2007, pages 1–5, 2007.

D.K.H. Begg, S. Fischer, and R. Dornbusch. *Economics*. McGraw-Hill higher education. McGraw-Hill Higher Education, 2008. ISBN 9780077117870. URL http://books.google.com/books?id=JnBzPwAACAAJ.

Math HJ Bollen. The smart grid: Adapting the power system to new challenges. *Synthesis Lectures on Power Electronics*, 2(1):1–180, 2011.

Claude R. Olsen. Nettstasjon på hvaler første skritt mot smartgrid-integrering, November 2013. URL http://smartgrids.no/nettstasjon-pa-hvaler-forste-skritt-mot-smartgrid-integrering/. Accessed: 01.05.2015.

Controlled Power Company. Power problems and voltage regulator technologies, August 2014. URL http://www.controlledpwr.com/help-regulator-technologies.php. Accessed: 26.04.2015.

R. De Sa Ferreira, L.A. Barroso, P. Rochinha Lino, M.M. Carvalho, and P. Valenzuela. Time-of-use tariff design under uncertainty in price-elasticities of electricity demand: A stochastic optimization approach. *Smart Grid, IEEE Transactions on*, 4(4):2285–2295, Dec 2013.

Sara Deilami, Amir S Masoum, Paul S Moses, and Mohammad AS Masoum. Real-time coordination of plug-in electric vehicle charging in smart grids to minimize power losses and improve voltage profile. *Smart Grid, IEEE Transactions on*, 2 (3):456–467, 2011.

J. Dickert and P. Schegner. Residential load models for network planning purposes. In *Modern Electric Power Systems (MEPS), 2010 Proceedings of the International Symposium*, pages 1–6, Sept 2010.

Direktoratet for Byggkvalitet. § 14-4. energirammer, 2015. URL http://dibk.no/no/BYGGEREGLER/Gjeldende-byggeregler/Veiledning-om-tekniske-krav-til-byggverk/?dxp=/dxp/content/tekniskekrav/14/4/. Accessed: 09.05.2015.

ECON Analyse. Tariffering av energimålte kunder i distribusjonsnettet. Technical report, ECON, 2006. URL http://www.iaea.org/inis/collection/NCLCollectionStore/_Public/38/013/38013644.pdf. Accessed: 10.05.2015.

Energi og Miljøkomiteen. Innstilling fra energi- og miljøkomiteen om norsk klimapolitikk, June 2012. URL https://www.stortinget.no/no/Saker-og-publikasjoner/Publikasjoner/Innstillinger/Stortinget/2011-2012/inns-201112-390/1/#a5. Accessed: 05.05.2015.

Eurelectric. 10 steps to smart grids. Technical report, 2011. URL http://www.eurelectric.org/media/26140/broch.10steps_lr-2011-030-0304-01-e.pdf. Accessed: 10.05.2015.

European Technology Platform SmartGrids. Vision and strategy for europe's electricity networks of the future. Technical report, European Technology Platform SmartGrids, 2006. URL http://ec.europa.eu/research/energy/pdf/smartgrids_en.pdf. Accessed: 02.05.2015.

Ahmad Faruqui and Jennifer Palmer. Dynamic pricing and its discontents. Technical report, The Brattle Group, 2011. URL http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1956020. Accessed: 09.05.2015.

J García-Villalobos, I Zamora, JI San Martín, FJ Asensio, and V Aperribay. Plug-in electric vehicles in electric distribution networks: A review of smart charging approaches. *Renewable and Sustainable Energy Reviews*, 38:717–731, 2014.

Grønn Bil. http://www.gronnbil.no/om-gronn-bil/hovedprosjektet-gronn-bil-article19-140.html, December 2009. URL http://www.gronnbil.no/om-gronn-bil/hovedprosjektet-gronn-bil-article19-140.html. Accessed: 01.06.2015.

Grønn bil. Statistikk, May 2015. URL http://www.gronnbil.no/ladbarebiler/?zr=1&region=0&p=t&lat=70.28946201078232&lng=10.814591473579412&z=3&y=2015&m=3&ct=&ts=y&lang=no_NO&flist=. Accessed: 28.05.2015.

Hafslund Nett. Nettleiepriser. URL https://www.hafslundnett.no/avtaler/nettleiepriser/12283.

Xian He, Nico Keyaerts, Isabel Azevedo, Leonardo Meeus, Leigh Hancher, and Jean-Michel Glachant. How to engage consumers in demand response: a contract perspective. *Utilities Policy*, 27:108–122, 2013.

Kai Heussen, Shi You, Benjamin Biegel, Lars Henrik Hansen, and Katrine B Andersen. Indirect control for demand side management-a conceptual introduction. In *Innovative Smart Grid Technologies (ISGT Europe), 2012 3rd IEEE PES International Conference and Exhibition on*, pages 1–8. IEEE, 2012.

A. Ipakchi and F. Albuyeh. Grid of the future. *Power and Energy Magazine, IEEE*, 7(2):52–62, March 2009.

KANAK. Utvikling av nettariffer i smarte nett. Technical report, EC Group, 2014. URL http://www.energinorge.no/getfile.php/FILER/NYHETER/NETT%20OG%20SYSTEM/2014-02-11%20Utvikling%20av%20tariffer%20i%20smarte%20nett.pdf. Accessed: 09.05.2015.

D.S. Kirschen, G. Strbac, P. Cumperayot, and D. de Paiva Mendes. Factoring the elasticity of demand in electricity prices. *Power Systems, IEEE Transactions on*, 15(2):612–617, May 2000.

K Kostková, L' Omelina, P Kyčina, and P Jamrich. An introduction to load management. *Electric Power Systems Research*, 95:184–191, 2013.

Hong Liu and Shaoyun Ge. Optimization of tou price of electricity based on electric vehicle orderly charge. In *Power and Energy Society General Meeting (PES), 2013 IEEE*, pages 1–5, July 2013.

Amir S Masoum, Sara Deilami, Paul S Moses, and Ahmed Abu-Siada. Impacts of battery charging rates of plug-in electric vehicle on smart grid distribution systems. In *Innovative Smart Grid Technologies Conference Europe (ISGT Europe), 2010 IEEE PES*, pages 1–6. IEEE, 2010.

Miljostatus.no. Utslipp av klimagasser for transport, February 2014. URL http://www.miljostatus.no/Tema/Klima/Klimanorge/Kilder-til-utslipp-av-klimagasser/Transport/. Accessed: 28.05.2015.

Niels Christian Nordentoft. Development of a dso-market on flexibility services. Technical report, iPower Consortium, 2013. URL http://ipower-test2.droppages.com/Publications/WP%203-8%20report.pdf.

NVE. Endring i forskrift 302 om utkoblbart forbruk, June 2009. URL http://www.nve.no/no/Om-NVE/Lover-og-forskrifter/Endring-i-lover-og-forskrifter/Endring-i-forskrift-302-om-utkoblbart-forbruk/. Accessed: 03.04.2015.

NVE. Økonomisk regulering av nettselskap, November 2013. URL http://www.nve.no/no/Kraftmarked/Regulering-av-nettselskapene/Om-beregning-av-inntektsrammer/Kvalitetsincentiver/. Accessed 13.05.2015.

NVE. Om kraftsystemet, August 2013. URL http://www.nve.no/no/Energi1/Kraftsystemet/Kraftsystemdata/Om-kraftsystemet/. Accessed: 10.03.2015.

NVE. Elmarkedstilsynet, January 2013. URL http://www.nve.no/no/Om-NVE/Organisasjon/Elmarkedstilsynet/. Accessed: 21.05.2015.

NVE. Ams - smarte strømmålere, April 2014a. URL http://www.nve.no/ams. Accessed: 13.04.2015.

NVE. Økonomisk regulering av nettselskap, November 2014b. URL http://www.nve.no/no/Kraftmarked/Regulering-av-nettselskapene/. Accessed 13.05.2015.

NVE. Nettleie, 2015a. URL http://www.nve.no/no/Kraftmarked/Forbrukersider/Nettleie1/. Accessed: 09.05.2015.

NVE. Tariffer i distribusjonsnettet, February 2015b. URL http://www.nve.no/no/Kraftmarked/Nettleie1/Beregning-av-nettleie-til-forbruker-husholdning-og-naring/Beregning-av-tariffer-i-distribusjonsnett/. Accessed: 09.05.2015.

NVE. Høring om tariffer for uttak i distribusjonsnettet. Technical report, NVE, 2015. URL http://publikasjoner.nve.no/hoeringsdokument/2015/hoeringsdokument2015_03.pdf.

NVE. NVEs konsepthøring om nye tariffer. From the conference "Effektbaserte tariffer" held by Energi Norge on May 12th 2015, May 2015.

NVE. Anleggsbidrag, February 2015. URL http://www.nve.no/no/kraftmarked/tilknytning/anleggsbidrag/. Accessed 13.05.2015.

Olje- og energidepartementet. Forskrift om økonomisk og teknisk rapportering, inntektsramme for nettvirksomheten og tariffer, January 2015. URL https://lovdata.no/dokument/SF/forskrift/1999-03-11-302?q=%C2%A7+13-1+energiloven#KAPITTEL_5. Accessed 13.05.2015.

Niamh O'Connell, Qiuwei Wu, Jacob Østergaard, Arne Hejde Nielsen, Seung Tae Cha, and Yi Ding. Day-ahead tariffs for the alleviation of distribution grid congestion from electric vehicles. *Electric Power Systems Research*, 92(0):106 – 114, 2012. URL http://www.sciencedirect.com/science/article/pii/S037877961200168X.

Ignacio J Pérez-Arriaga and Yves Smeers. Guidelines on tariff setting. In *Transport pricing of electricity networks*, pages 175–203. Springer, 2003.

Luis Pieltain Fernández, TGS Roman, Rafael Cossent, C Mateo Domingo, and Pablo Frías. Assessment of the impact of plug-in electric vehicles on distribution networks. *Power Systems, IEEE Transactions on*, 26(1):206–213, 2011.

Robert S. Pindyck and Daniel L. Rubenfield. *Microeconomics*. Pearson, 2013.

Regjeringen.no. Overføringsnettet. Technical report, Regjeringen.no, 2008. URL https://www.regjeringen.no/globalassets/upload/oed/pdf_filer/faktaheftet/evfakta08/evfakta08_kap06_no.pdf. Accessed 30.05.2015.

Regjeringen.no. Energiutredningen – verdiskaping, forsyningssikkerhet og miljø, Januar 2012. URL https://www.regjeringen.no/nb/dokumenter/nou-2012-9/id674092/?docId=NOU201220120009000DDDEPIS&q=energiutredningen&navchap=1&ch=5#KAP13-4. Accessed 14.05.2015.

Pooya Rezaei, Jeff Frolik, and Paul DH Hines. Packetized plug-in electric vehicle charge management. *IEEE Trans. Smart Grid*, 5(2):642–650, 2014.

David B Richardson. Electric vehicles and the electric grid: A review of modeling approaches, impacts, and renewable energy integration. *Renewable and Sustainable Energy Reviews*, 19:247–254, 2013.

Peter Richardson, Damian Flynn, and Andrew Keane. Optimal charging of electric vehicles in low-voltage distribution systems. *Power Systems, IEEE Transactions on*, 27(1):268–279, 2012.

Sintef. Remodece, November 2014. URL http://www.sintef.no/SINTEF-Energi-AS/Prosjektarbeid/USELOAD-/REMODECE/. Accessed: 05.11.2014.

Sintef. Strømbrudd til milliarder – er det akseptabelt?, July 2014. URL http://www.sintef.no/SINTEF-Energi/Om-SINTEF-Energi-AS/Xergi/Xergi-2003/Nr-3---november/Strombrudd-til-milliarder-er-det-akseptabelt/. Accessed: 11.04.2015.

Statnett. Bli kjent med nettplan - stor-oslo, 2014. URL http://storoslo.statnett.no/om/. Accessed 01.12.2014.

Olle Sundstrom and Carl Binding. Flexible charging optimization for electric vehicles considering distribution grid constraints. *Smart Grid, IEEE Transactions on*, 3(1):26–37, 2012.

The Norwegian Smartgrid Centre. Om smartgrid, November 2014. URL http://smartgrids.no/senteret/about-smartgrid/. Accessed: 01.03.2015.

THEMA. Prising av overføringskapasitet med ams. Technical report, THEMA Consulting Group, 2013a. URL http://www.thema.no/wp-content/uploads/2015/04/THEMA-rapport-2013-23-Prising_av_overf%C3%B8ringskapasitet_med_AMS1.pdf. Accessed: 09.05.2015.

THEMA. Innkreving av residuale nettkostnader med ams. Technical report, THEMA Consulting Group, 2013b. URL http://www.thema.no/wp-content/uploads/2015/04/THEMA-rapport-2013-22-Innkreving_av_residuale_nettkostnader_med_AMS.pdf.pdf. Accessed: 10.05.2015.

Transportøkonomisk Institutt. Transport og klima - funn og fakta om transportens klimapåvirkning, 2014. URL http://www.tempo2014.no/Transport-og-klima-Cicero-Rapport.pdf. Accessed: 15.05.2015.

Troms Kraft. Fleksibelt forbruk, July 2012. URL http://www.tromskraft.no/naring/nett/fleksibelt. Accessed: 01.06.2015.

United States Environmental Protection Agency. Global greenhouse gas emissions data, September 2013. URL http://www.epa.gov/climatechange/ghgemissions/global.html. Accessed: 28.05.2015.

Naveen Venkatesan, Jignesh Solanki, and Sarika Khushalani Solanki. Residential demand response model and impact on voltage profile and losses of an electric distribution network. *Applied Energy*, 96(0):84 – 91, 2012. URL http://www.sciencedirect.com/science/article/pii/S0306261911008798.

Di Wu, Dionysios C Aliprantis, and Lei Ying. Load scheduling and dispatch for aggregators of plug-in electric vehicles. *Smart Grid, IEEE Transactions on*, 3 (1):368–376, 2012.

Qiuwei Wu. *Grid Integration of Electric Vehicles in Open Electricity Markets*. John Wiley & Sons, 2013.

Fredrik Ygge and Hans Akkermans. *Power load management as a computational market*. Centre for Telematics and Information Technology, 1997.

APPENDIX A

Results from Case Study

A.1 Results - Uncontrolled charging

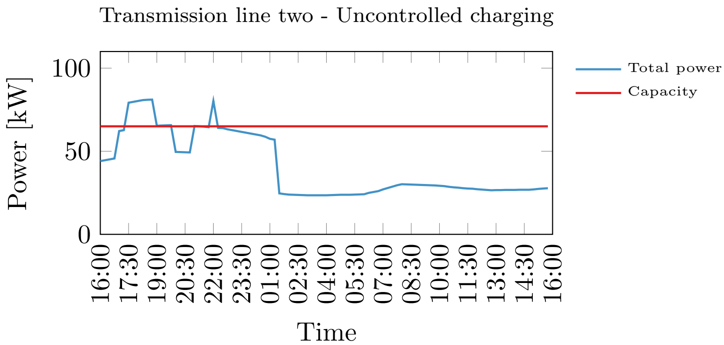

Figure A.1: The power demand in transmission line two when the charging was uncontrolled.

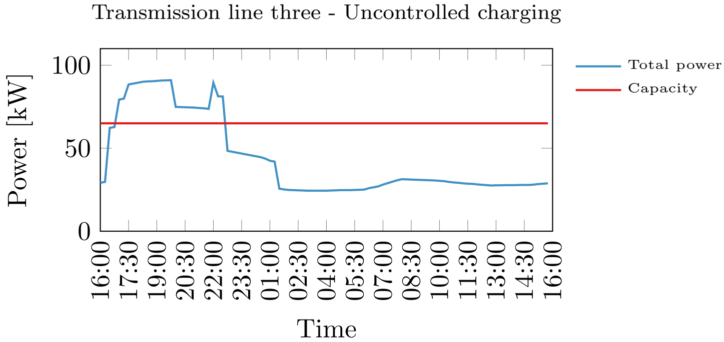

Figure A.2: The power demand in transmission line three when the charging was uncontrolled.

A.2 Results - Controlled charging

A.2.1 Direct control

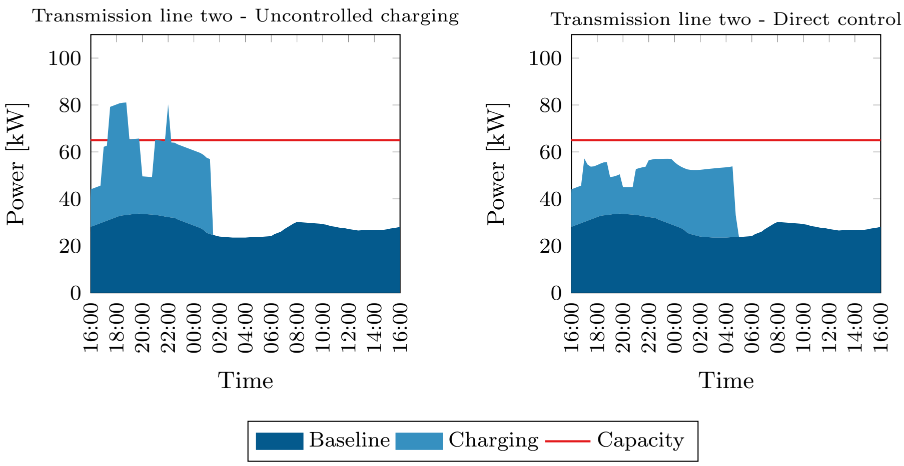

Figure A.3: The power demand in transmission line two, when the charging was uncontrolled and controlled directly.

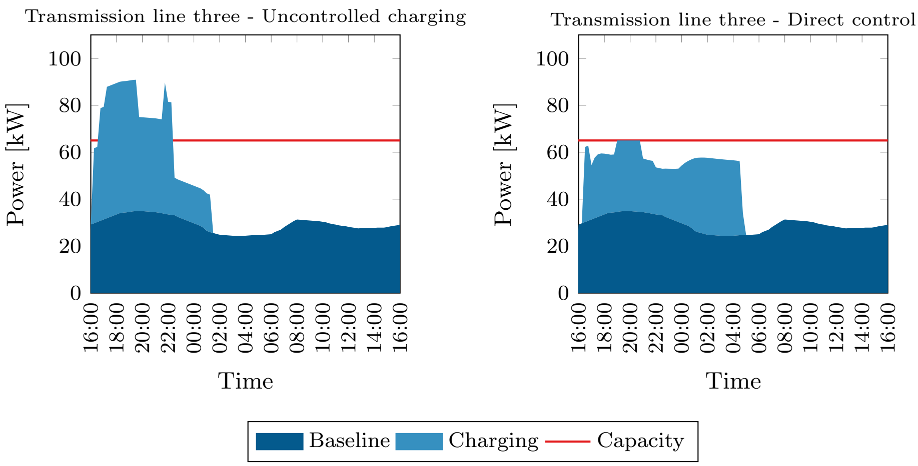

Figure A.4: The power demand in transmission line three, when the charging was uncontrolled and controlled directly.

A.2.2 Indirect control

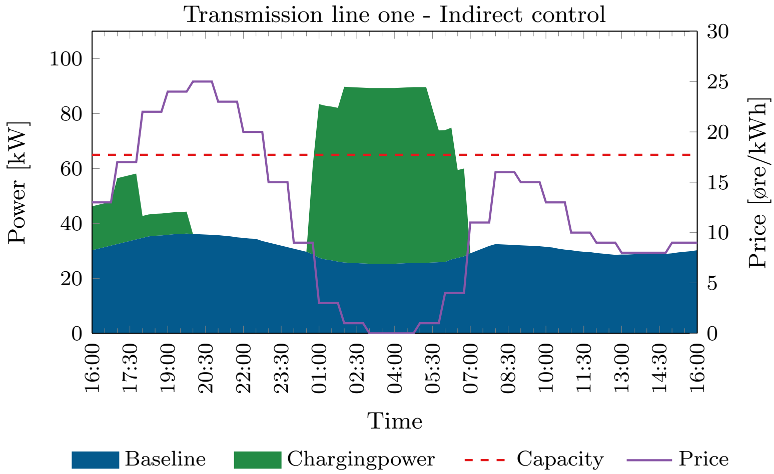

Figure A.5: The power demand in transmission line one, when the charging was controlled indirectly through price signals.

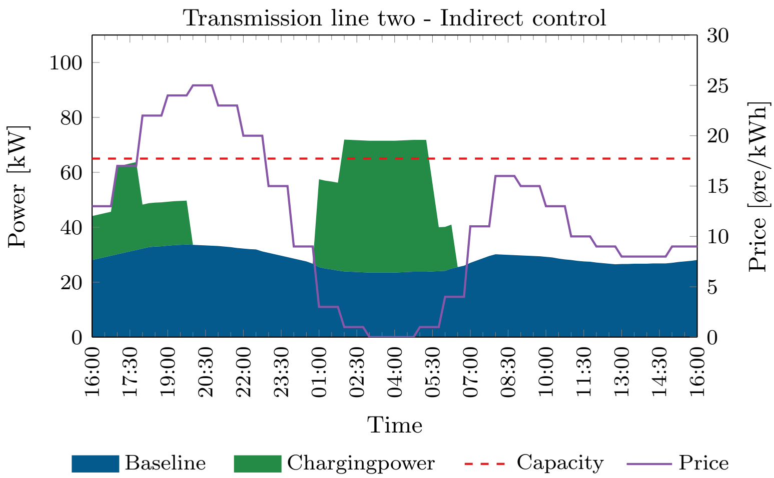

Figure A.6: The power demand in transmission line two, when the charging was controlled indirectly through price signals.

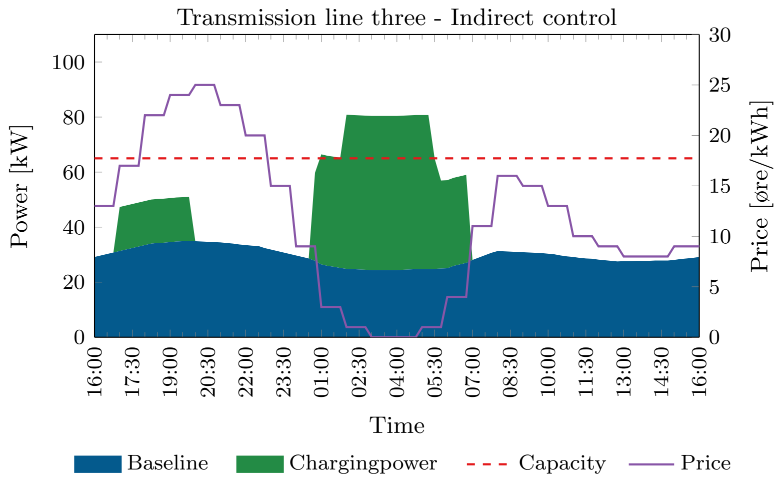

Figure A.7: The power demand in transmission line three, when the charging was controlled indirectly through price signals.

A.2.3 Direct and indirect control

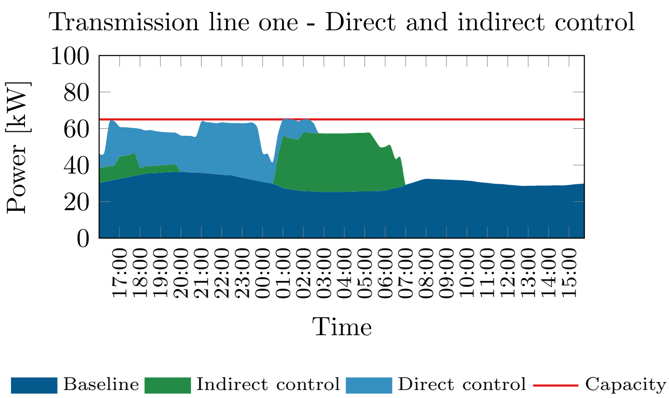

Figure A.8: The power demand in transmission line one, when the charging was controlled directly and indirectly.

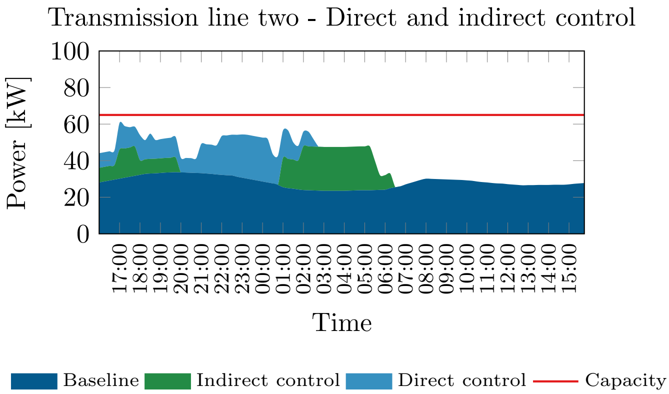

Figure A.9: The power demand in transmission line two, when the charging was controlled directly and indirectly.

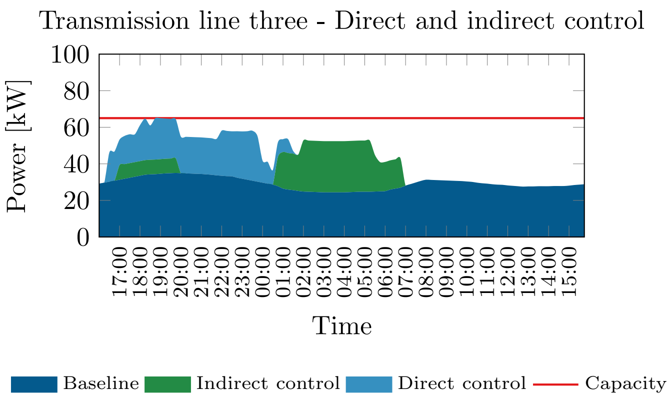

Figure A.10: The power demand in transmission line three, when the charging was controlled directly and indirectly.