Thomas Kallevik

Optimisation of cost and emissions of an EV parking lot within a Zero Emission Neighbourhood by utilising demand response programs, PV and an external battery

Master's thesis in Energy and Environmental Engineering

Supervisor: Hossein Farahmand

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Abstract

In the near future, the world must rapidly reduce the emission of greenhouse gases to cope with the human-made climate crisis, and to meet international agreements. As the energy sector is a significant emitter, reduction in this field will be crucial. In this transition, renewable, non-dispatchable energy sources will replace non-renewable and dispatchable energy sources. Through a literature review, it was a clear need for more flexible end-users. In addition, the literature research presented a development where the electric vehicle will play an essential role in the energy sector as they will contribute to an increase in the need for energy. However, electric vehicles can also provide flexibility to the system. Another result from the literature review was that the installation of solar power is increasing rapidly, and could play an important role in the current energy transition. Based on these findings, this master thesis had a goal of using demand response programs to maximise profit for users within a Zero Emission Neighbourhood. In order to do this, bidirectional vehicle-to-grid, solar panels and external batteries were used. In addition, the model had a goal of minimising CO_2-emissions, and investigate the flexibility within the system.

The proposed model was based on previous work done in the field. Two-step stochastic programming was used to develop the model, where the first step was the decisions made in the day-ahead market, while the second step was during the time of operation. The model made ten different scenarios with a stochastic arrival time, departure time and initial state of charge (soc) for each electric vehicle. In this research, the soc departure was modelled with two different minimum limits, one for when the car departs and one for when it is present in the parking lot. This was to ensure the desired departure soc for the user. The departure soc was also made flexible, so the activated reserves by the system operator could be met.

The research found that implementing solar panels, an external battery and minimisation of CO_2-emissions to a system with bidirectional charging would increase the daily result by 24.57€/day compared to a system with only bidirectional charging. The preferred demand response program was time-of-use, and it saved 1.15€/day compared to

the fixed-rate tariff. There is a need for better designed demand response programs where it is easier to react and adjust to the given signals. With soc departure at 70%, the system is close to net zero emission. Furthermore, the system showed an ability to be flexible, but today's balancing market is not favouring systems like the proposed system. The potential for a Zero Emission Neighbourhood to be flexible is significant, and therefore it needs better suited markets.

Sammendrag

I de kommende årene må verden drastisk redusere utslipp av drivhusgasser for å møte menneskeskapte klimaendringer, og internasjonale avtaler. Det er store utslipp knyttet til energisektoren, og av den grunn vil kutt her være helt avgjørende. I denne overgangen skal fornybare energikilder erstatte ikke-fornybare energikilder. Gjennom et litteratursøk var det et klart behov for mer fleksible sluttbrukere. Litteratursøket presenterte også en utvikling hvor elektriske biler spiller en sentral rolle i energisektoren ettersom de vil stå for en økt etterspørsel etter energi. På en annen side kan elektriske biler også tilby fleksibilitet. Gjennom litteratursøket ble det også stadfestet at solceller øker raskt, og vil være en naturlig del av overgangen til fornybar energi. Basert på disse funnene hadde denne masteroppgaven som mål å bruke ulike nettariffer for å maksimere profitt for brukerne av et nullutslippsnabolag. For å gjøre dette ble det implementert toveis kjøretøy-til-nett, solceller og et batteri. I tillegg hadde modellen et mål om å minimere utslipp av CO_2. Fleksibiliteten til system ble også utforsket.

Den foreslåtte modellen var basert på tidligere arbeid gjort på området. For å utvikle modellen ble det brukt stokastisk programmering til å lage en to-stegs modell. Det første steget i modellen var beslutningen som ble tatt i spotpris-markedet, mens det neste steget var i driftstimen. Modellen utviklet ti forskjellige senarioer med en stokastisk ankomsttid, avgangstid og start state of charge (soc) for hver enkelt elektrisk bil. I denne forskningen var avgangs socen modellert med to forskjellige minimumskrav, en for når bilen forlater og en for når den står parkert. Dette var for å ivareta den ønskede avgangs socen for brukeren. Socen var også modellert med en fleksibilitet slik at modellen kunne nå de aktiverte reservene fra systemoperatøren.

Oppgaven fant ut at en implementering av solceller, batteri og minimering av CO_2-utslipp i et system med toveis ladning ga en daglig økning av resultatet med 24.57 €/dag sammenliknet med et system med bare toveis ladning. Nettariffen som var å foretrekke var tidsavhengig energiledd som sparte systemet for 1.15€/dag sammenliknet med en

konstant tariff. Med en avgangs soc på 70% er systemet nært å ha netto null utslipp av CO_2. Systemet viste også en evne til å være fleksiblet, men dagens balansemarkeder passer ikke til slike systemer. Potensialet for at et nullutslippsnabolag kan være fleksibelt er stor, og derfor trengs det bedre egnede markeder.

Preface

This master thesis was written the fall of 2019 at the Department of Electric Power Engineering at the Norwegian University of Science and Technology. The idea for this master came up after working with flexibility in my specialization project, and the idea of making use of electric vehicles and smart solutions in addition to involving regular customers is something I am passionate about. It has been an important principle in this work to include the users as I genuinely believe that the future energy system and smart solution are dependent on their willingness to involve. This master thesis was written in cooperation with the FME research centre on Zero Emission Neighbourhood in Smart cities. The work has been exciting and challenging, and it will be interesting to follow this field in the future.

I want to thank my supervisor Hossein Farahmand who has allowed me to discover this exciting field and for all of our good conversations and discussions about smart energy systems. I would also like to thank my co-supervisor Kasper Emil Thorvaldsen. This master thesis would not have been the same without his input on the content, our discussions and the support on Python and Pyomo. I would also like to thank the people in Reguleringsmyndigheten for Energi in section Regulering av nett-tjenester at NVE for giving me feedback and interesting discussion during the period, and also for introducing me to this topic in the first place.

I also wish to thank my parents for supporting me through the last five years, and especially during my last period with the master thesis. In the end, I would like to thank Sigrid. Thank you for all the motivational and supportive talks. This master thesis would not have been the same without you.

Table of Contents

List of Tables

List of Figures

Abbreviations

AC	=	Alternating current
ACOPF	=	Alternating current Optimal Power Flow
DC	=	Direct current
DRP	=	Demand response program
DEP	=	Departure
DER	=	Distributed energy sources
DSO	=	Distribution system operator
EU	=	European Union
EV	=	Electric vehicle
FCR	=	Frequency Containment Reserves
Flex	=	Flexibility
FR	=	Fixed-rate tariff
I/C	=	Interruptible/Curtailable tariff
LP	=	Linear programming
mFRR	=	manual Frequency Restoration Reserves
MILP	=	Mixed Integer Linear Programming
MINLP	=	Mixed Integer Non-Linear Programming
NLP	=	Non-linear programming
NO2	=	Price area in the south of Norway
NVE	=	The Norwegian Water Resources and Energy Directorate
PEV	=	Plug in electric vehicle
PL	=	Parking lot
PV	=	Photovoltaic
S or Sys	=	System
SO	=	System operator
SOC	=	State of charge

TOU	=	Time-of-use tariff
TSO	=	Transmission system operator
V2G	=	Vehicle-to-grid
V2H	=	Vehicle-to-home
V2V	=	Vehicle-to-vehicle
ZEB	=	Zero Emission Building
ZEN	=	Zero Emission Neighbourhood

Chapter 1

Introduction

1.1 Background

The world is facing a significant challenge with the human-made climate crisis, and a rapid change is needed to prevent further damage. The international society has set common goals of reducing emissions through the Paris agreement (United Nations (2018)). In addition to the Paris agreement, the European Union (European Union (2014)) has a goal on reducing emissions with at least 40% compared to 1990 values within 2030. A large amount of the emissions in the world come from the production of electricity, both through the actual production, and the extraction of for instance coal, gas and nuclear materials. The overall goal is to phase out non-renewable energy sources from the energy-mix and exchange it with renewable energy sources. In other words, coal and gas will be replaced by hydro, wind, solar, hydrogen and other renewable energy sources. Since 2009, the price for solar panels has dropped with 80% according to Osborne (2016), and it is expected to decrease with 59% by 2025 compared to 2015 levels. It is natural to think that solar power will play an essential role in the future energy mix. Renewable sources are often unregulated which means the power must be used as it is produced. This will require the power system to handle more unregulated power in the coming years. Coal plants and nuclear plants have been providing security in the grid with aids like frequency control, voltage control and power balance in the power system, and this will be lost with this energy transition. Renewable energy systems are often smaller and located less central compared to today's energy sources. This will also increase the need for flexibility.

To cope with the challenge of increased emissions a Zero Emission Neighbourhood can be crucial as it has an overall goal to have zero emission of greenhouse gases for the whole neighbourhood.

Over the last years, the sale of electric vehicles has rapidly increased. In Norway, Skotland et al. (2016) states that electric vehicles alone will stand for an increased need for energy at 4TWh/yr. At the same time, Volkswagen has stated that they will stop the production of fossil fuel cars (NTB (2018)). This shows that electric vehicles can play a crucial part in peoples lives and the overall energy picture in the near future.

1.2 Contribution

The goal for this master thesis is to use bidirectional vehicle-to-grid charging of electric vehicles, solar panels and an external battery to minimise CO_2-emissions for a Zero Emission Neighbourhood consisting of houses. In addition the model has a goal to maximise profit for electric vehicle users by exploiting different demand response programs. The ability for the system to be flexible will also be examined. The basis for the model in this thesis will be work done by Shafie-Khah et al. (2016). Their model maximises profit for a parking lot operator by using bidirectional vehicle-to-grid. In order to maximise profit they make use of the difference in cost between hours for different demand response programs. To reach the goals for this research, the model will be further developed with an external battery and solar panels. In addition the model will be adjusted to fit within the scope of the thesis, and minimisation of CO_2-emissions will be added to the objective function. As the demand response programs are used to get people to behave in a certain way, it is crucial to check whether a system like this responds in the right way. This thesis will compare the different demand response programs in the search for an optimal program for the user, the grid operator and a future with reduced levels of greenhouse gas emissions.

This master thesis will start by presenting the literature review done as a part of the author's specialization project. Further on, in chapter 3, the relevant theory for is presented.

Chapter 4 shows the model used in this master thesis. In chapter 5 the case study used is presented. The results are presented and discussed in chapter 6 before they are further discussed in chapter 7. Chapter 8 gives the conclusion for the work done. In chapter 9 possible future work is presented.

Chapter 2

Literature review

In order to find a relevant, useful and interesting research question, a broad and in-depth study of the relevant topics has been done. In this section, the relevant research on electric vehicles, vehicle-to-grid, microgrids, Zero Emission Neighbourhoods and optimisation is presented. This work was done as the author's specialization project during the spring of 2019. The paragraph about the research done by Shafie-Khah et al. (2016) in section 2.4 and 2.5 has been added in conjunction with the work done in this master thesis. The rest of the content in this chapter has only been through linguistic changes and changes done to better fit with the scope of the master thesis.

2.1 Flexibility

Renewable energy is seen as an essential factor in the work of reaching climate goals on reducing emission. This is also why the implementation of these energy sources is crucial. With this implementation, more power will have a higher uncertainty compared to, for instance, planned power production at a coal plant. This will require more customers to be flexible. Flexibility in terms of power consumption and consumer flexibility, mentioned here, is the ability to adapt to the needs in the grid. This means that the actors can give the system operator the flexibility needed for the actual challenge the operator faces. This will give the system operator the chance to operate the system more efficient and safe.

The TSO (transmission system operator) in Norway, Statnett, says that with more unregulated power, the system will be harder to operate efficiently and safely (Krigstad et al. (2018)). One solution would be to build the grid more robust on places with congestion. This is not efficient as the grid can, according to Statnetts report by Krigstad et al. (2018), use the resources connected to the grid more efficient with flexibility. Flexibility could be used for many services in the grid. According to Tan et al. (2016), the electric vehicle can be used as a flexible load, and this will be shown further on. Tan et al. (2016) suggest different flexibility services provided to the grid, such as prevent power grid overloading, minimise emission, peak shaving, frequency control, maintain voltage level, maximise profit and renewable energy intermittent. These services can also be given by other flexible loads, such as heat in an office building or flexibility in a process in the industry.

An added value of flexibility into the system is the ability to use power more efficient and reduce the investments in the grid. It also allows the ambitious plans for renewable energy to take place and to feed this into the grid. From 1990, the electricity generation in Europe has, according to Eurostat (2014), increased by 27%, and flexibility can also be used to cope with this challenge. According to figure 2.1 almost half of the energy generation in the EU comes from combustible fuels while 26% comes from nuclear, that means almost 75% from resources the EU has a goal to either reduce or remove over the coming years. With this in mind, and with the goals of emission reduction over the coming years, more renewable energy will be fed into the grid, and thus more flexibility is needed.

According to figure 2.1 a lot of the electricity generation in Europe is based on combustion fuels or nuclear. These are, to an extent, generation units that can be regulated which also means they will provide flexibility and stability to the system operator. The loss of these flexible sources is one of the significant challenges when moving towards a renewable energy mix.

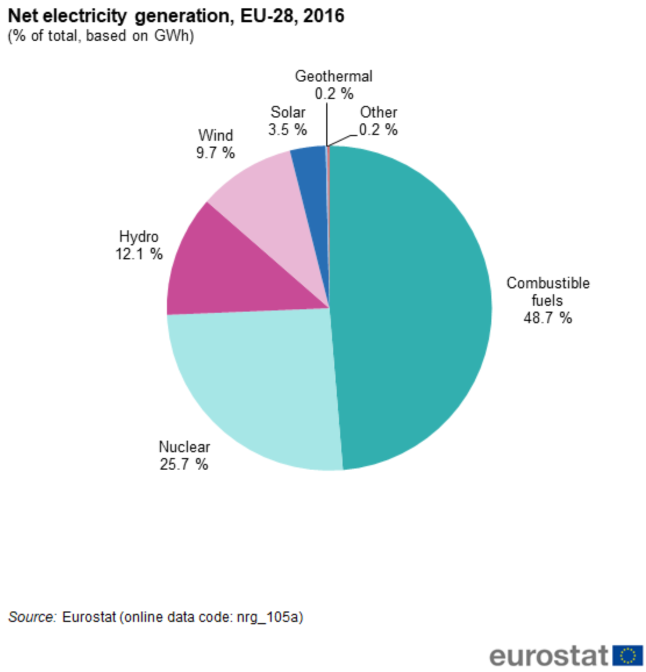

Figure 2.1: Net electricity generation in the EU in 2016 (Eurostat (2014)).

Flexibility is not always present where it is needed. Hydropower, for instance, is helpful for flexibility and frequency control within the transmission grid. However, for congested spots in the distribution grid, hydropower can not help in the same way as other loads could. This is why both in Norway and in Europe, flexibility further down in the system is a mentioned possibility. With a smarter grid and with smart meters, it would be easier to implement more flexible loads, but the question is still, how it can be implemented, used and regulated.

2.1.1 Energy storage

There are several ways to store energy and provide the grid with flexibility. For instance, pump water storage where water is pumped back into the reservoir. Another solution is hydrogen storage of energy. Here electricity produces H_2-gas and store it before it is converted into electricity again. The most important energy storage system is probably batteries. NVE state in a report by Henden et al. (2017) why batteries will play a crucial role in the future grid. The report points to the ancillary services that the system operator will need in order to operate the grid. Batteries are cheap, which is an advantage meaning that a regular customer can buy a battery or an electric vehicle and trade flexibility. It also makes the user more self-sustained with energy.

Another vital difference between, for instance, pump storage and a battery are that a battery can be connected into the grid behind a congested transformer. That means it can be implemented precisely where the flexibility is needed and not on the other side of the country, which can be the case for pump storage. This will give the system operator and especially DSOs (distribution system operator) the chance to get lower operating cost in the grid, and also give them more control in local areas. The fact that a battery provides more local control also gives the DSO more control over the implementation of renewable energy fed into the distribution grid. Renewable energy into the distribution grid could give congestion problems. However, a battery can be used to regulate the grid and the congested equipment.

2.2 Microgrids

Ton and Smith (2012) defined a microgrid as:

Definition 2.1. *...a group of interconnected loads and distributed energy resources within clearly defined electrical boundaries that acts as a single controllable entity with respect to the grid. A microgrid can connect and disconnect from the grid to enable it to operate in both grid-connected or island- mode. (Ton and Smith (2012))*

This definition means that a microgrid can be regarded as an individual grid within an area. The microgrid can either be connected to the main grid or operated in island mode. If it is operated in island mode, both consumption and generation happen within the microgrid.

Microgrids will allow regular customers to produce and sell its power and could also take some load off critical equipment in the main grid. This could also be an efficient way to make infrastructure for people in countries that do not have access to electricity at the moment. A paper from Zhu et al. (2015) states that the development of microgrids in

China will be crucial for the implementation of renewable energy sources in rural areas. Moreover, it will be used to solve air pollution and climate challenges. As China is one of the largest economies in the world, and the worlds most populated country, their action on climate changes will make a huge impact. It is assumed, according to the paper by Zhu et al. (2015), that microgrid will play a role in the transition from fossil fuels over to renewable energy sources.

2.2.1 Zero Emission Neigbourhoods

Zero Emission Neighbourhood (ZEN) is a special type of microgrid. The Norwegian Research Centre on ZEN has defined in their annual 2018 report what a ZEN is (Woods Ruth, Remøe Katinka Sætersdal , Hestnes Anne Grete (2018)):

Definition 2.2. *...it is defined as a group of interconnected buildings with associated infrastructure, located within a confined geographical area, aiming at reducing its direct and indirect greenhouse gas (GHG) emissions towards zero. Life cycle assessment (LCA) is used to estimate the potential environmental impacts of a product or service system throughout its life cycle. The methodology was initially developed and used for zero emission buildings. We have now expanded it to include zero emission neighbourhoods (ZENs).*

In addition to this definition, Sørensen and Jiang (2017) stated that a smart electric vehicle system could contribute to balancing the energy and power in a ZEN. This means that the electric vehicle could potentially play a crucial role to fulfil the goal in a ZEN.

For this project with a particular focus on electric vehicles, it means all the electric vehicles within the confined geographical area. The electric vehicles should be connected in a way that makes it possible to regard all the electric vehicles within the area as one parking lot. In a ZEN the electric vehicles can minimise the cost for the buildings both in regards to energy and capacity tariffs. It can also provide flexibility within the area when considering expanding or upgrading the grid and investment contributions for the user can be lowered. In the long run, it can also provide the grid with certain ancillary functions, as mentioned earlier. Electric vehicles can play a crucial role in reaching the goals for a ZEN on reducing greenhouse gases.

2.3 Electric vehicle

The background of many countries and car producers to invest heavily in electric vehicles (EV) as our primary mode of cars is driven by several factors. In Norway for instance, changing the combustion engine to electrical engine for the transportation sector, will according to a report from NVE by Heen and Fandrem (2017) reduce the total emission by six million tons CO_2 each year or 10% of all emissions in Norway. This is because the electrical engine has better efficiency as well as the electricity in Norway is based mostly on clean, renewable energy (Energifakta (2019)). Another area where an electric vehicle could be beneficial for the environment is in urban areas, as electric vehicles do not emit particles like NO_X. This will result in a more healthy local environment. An issue when integrating electric vehicles into the grid is that it could cause bottlenecks in the grid, as the drawn capacity can be higher than the capacity in a given line or transformer. According to another report by NVE by Skotland et al. (2016), they point at the fact that electric vehicles alone will increase the need of electricity in Norway with $4\ \frac{TWh}{year}$ or 3% of the total electricity consumption in Norway.

An electric vehicle differs from a regular car by the fact that the engine is an electrical motor and the fuel is electricity. Electric vehicles have been around since the 19th century but did not take off until the 21st century with the introduction of the hybrid Toyota Prius and the electric vehicle Tesla (Matulka (2014)). The international energy agency's global electric vehicle overlook for 2018 (OECD/IEA (2018)) stated that the world in 2017 for the first time passed 1 million units sold worldwide. This is a 54% increase compared with 2016. This number is likely to increase, and for instance, in China, the share of electric vehicles in the fleet was 2.2% in 2017 according to the overlook. China also has an increase in wealth for the Chinese people, which means that more people are lifted to the middle class, which will lead to the ability to buy a car. Based on the trend from the international energy agency's overlook, electric vehicles will most likely have a significant impact on the energy picture and the grid worldwide in the near future. Over the coming years, several agreements have made it mandatory to reduce climate gas emissions. In this transition, electric vehicles could play a crucial role. Volkswagen, a big car-producer from Germany, has stated that they will stop the production of fossil cars (NTB (2018)), and other companies are likely to follow.

2.3.1 Challenges

According to a report from the Institute Institute for energy research (2018), there will be challenges with implementing electric vehicles into the grid as they could increase the capacity needed at certain times. In this research, the grid in Texas, USA was investigated, and they found that just 60 000 cars charging simultaneously would threaten the grid. Heen and Fandrem (2017) and the institute Institute for energy research (2018) state that one challenge could be that the congestion happens further down in the grid, behind certain transformers and lines. At the same time, both mentioned, on a general level, that the grid should be able to take on the load as it is projected now. It is important to notice that some of the studies are looking at electric buses, ferries and oversized loads in addition. These loads will impact the grid, especially since they are individually charging at a much higher capacity than electric vehicles, and often in rural areas.

As seen, the implementation of electric vehicles can congest the grid. Paradoxically electric vehicles can also solve this problem through flexibility. This means that electric vehicles actively can be used to efficiently and safely operate the grid. By optimising the electric vehicle charging pattern and use the battery as a source of energy, electric vehicles could participate in grid operation.

2.3.2 Government interaction

Another background information it is vital to have when looking at the implementation of electric vehicles, why it has happened, and how the future will look like, is how the governments have intervened. In Norway, for instance, electric vehicle users will get cheaper parking, fuel, ferries, taxes and the chance to drive in bus lanes during rush hour (Norsk Elbilforening (2019)). The increase in electric vehicles worldwide also shows that other states have done similar things to stimulate for more electric vehicles, and mostly economic incentives are used (Kvalheim (2018)). The policy from the government will influence how many people acquire electric vehicles.

2.3.3 Electric vehicle implementation in Norway

NVE looked into the challenge of increased need of capacity for the electric transport sector in their report by Heen and Fandrem (2017) and analysed how the Norwegian grid would tackle this. One thing the researchers found was that initially, if the charging patterns seen today continues, they will be able to implement electric vehicles easier because they charge mostly during the night and not during peak hours. Although, due to the increased use of electricity in other sectors, the amount of overloaded transformers is at least 10% in several parts of Norway. Figure 2.2 shows the percentage of the overloaded transformers (y-axis) in each area in Norway (x-axis). They have also divided between those they planned to change within 2030 either way (red) and those they need to change due to the increased capacity (blue).

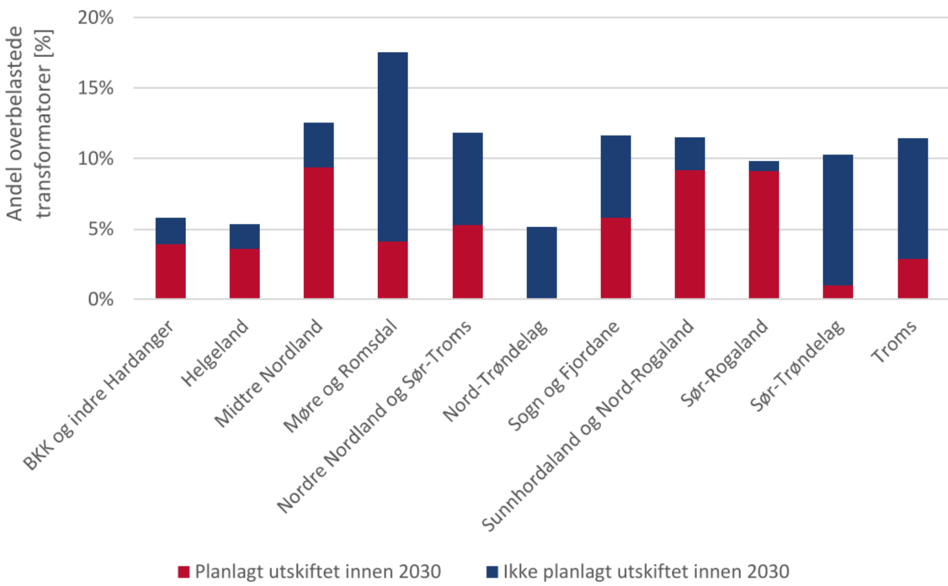

Figure 2.2: Overloaded transformers in Norway in 2030 (Heen and Fandrem (2017))

NVE asked the Norwegian TSO, Statnett, about the integration of electric vehicles into the grid, and they concluded that they would most likely have the capacity. When it comes to the DSOs around Norway, they did calculations and found that some of their transformers and equipment in the distribution grid would need replacement. Some of these are going to be changed regardless of electric vehicles, while some components need replacement due to electric vehicle integration and the transition to an electric transportation sector. The number of congested transformers and lines will be dependent on how much the capacity of each household will increase. If they increase their usage with 5kW, approximately 10% of the equipment will be overloaded. The DSOs have not looked into the voltage quality and how that will be affected, and in Norway with long distances that could be a factor. Not all DSO has made reliability analysis, which can also contribute to inaccurate results. More analysis of the Norwegian grid on a distribution grid level needs to be done to see the implications of implementing electric vehicles and other modes of transportation into the grid. Future work will have to estimate every transformer in the distribution grid, how many vehicles each transformer will handle, and in case of a fault, whether the $n-1$ requirement is fulfilled.

Another challenge NVE (Heen and Fandrem (2017)) points at is the increase in fast chargers over the coming years. They estimate that the numbers of fast chargers will increase with 7 000 in Norway before 2030. The challenge with the fast chargers will mainly be capacity as they will be responsible for a higher instantaneous capacity in the grid. Fast chargers will be necessary for the transition to electric vehicles as the users will demand to have the vehicle ready charged faster, and the car to follow their premises and not vice versa. Due to the capacity limits on peoples houses, and the price of installing fast chargers, they are most likely to be installed at stations. It is also essential to think about how the demography in Norway is, as in other countries, and that is long distances between urban areas where no one lives. The grid in those places is weaker, which means it cannot necessarily provide fast chargers with the demanded capacity. This could be a problem if the cars in these countries will consist of solely electric vehicles in the future. The problem can also come up in the cities, but one solution proposed by Valle (2018) to this challenge, and even for more rural areas, is to connect the chargers directly to the high-voltage grid. Another solution is batteries in connection with the chargers. This is a solution that has already been used to charge ferries in Norway, for instance, the ferry called "Ampere" (Stensvold (2015)), and also in some parking lots for electric vehicles.

Olivella-Rosell et al. (2015) tried to simulate an area for electric vehicles in Barcelona, Spain. Their model included social patterns, charging time, and where it was charged in their optimisation model. They also looked at the part the DSO in Norway did not look at, the voltage quality. They concluded that the distribution grid in Barcelona did manage electric vehicles and that voltage was within its allowed limits. One discussion is that the grid will naturally be stronger in the city centres with a more meshed grid than more rural areas where they might not have the same flexibility and grid strength.

2.4 Vehicle-to-grid

Wagner (2013) defines the goal of vehicle-to-grid (V2G) as ”...aims to optimise the way we transport, use and produce electricity by turning electric cars into ‘virtualpower plants’.”. Electric vehicles have, in other words, the potential to assist the grid with ancillary functions with being a dispatchable generator. This could be frequency control, voltage control, peak shaving, reactive power compensation or support for renewable energy. Tan et al. (2016) looked into how the user could be a resource for the grid both through unidirectional and bidirectional power flow. Vehicle-to-grid could be part of the solution to the capacity challenge that comes with the electrification of, for instance, the transportation sector. Vehicle-to-grid will require several changes to be implemented. Then it is both the actual physical equipment needed at home such as chargers, but also the communication system used by the system operator. The communication system is crucial for the communication between the end-user, the system operator and for instance, an aggregator.

Tomić and Kempton (2007) points at the fact that it is not enough to have flexibility provided by just one single electric vehicle owner. Today in some countries, like Norway, the limit on taking part in the balancing market is having at least a 1 MW load available. Tomić and Kempton (2007) suggests that either it should be fleets of electric vehicles, like they looked at, or/and aggregators who can manage the load and trade with the system operator or sell in the market. Tomić and Kempton (2007) found a net profit up to two million dollars over a year for having 252 Toyotas available for flexibility through up- and down-regulation with vehicle-to-grid. They also found that with a fleet of electric vehicles, the flexibility provider will have a net profit for both unidirectional and bidirectional electricity flow. Tomić and Kempton (2007) also points at the capacity on lines into neighbourhoods or buildings as a capacity problem to fully take advantage of the services provided by vehicle-to-grid, this is also supported by a report from NVE by Henden et al. (2017).

Shafie-Khah et al. (2016) simulated a parking lot of 1000 spaces. The aim for the aggregator was to maximise profit for the parking lot by exploit different demand response programs and bidirectional charging of electric vehicles. They divided the different demand response programs into price-based programs and incentive-based programs. In their study, they assumed that the EV owner left with the soc they needed. They looked at soc combined and not for the given EVs, which mean that one assumes that all of the EV owners will act in the same way. Which also reflect in them using the same aggregated factor of soc for every time step. They had for the different demand response programs a profit from just above 900 \$/day to around 1200 \$/day. The optimal solution was to have a certain share in different demand response programs. They also got a high profit with only time-of-use. A future discussion is whether the optimal demand response program in terms of profit is the most effective for operating the grid.

2.4.1 Local Vehicle-to-grid

Mohseni et al. (2017) planned a microgrid based on day-ahead prices with homes containing energy storage, photovoltaic cells and electric vehicles. In this microgrid bidirectional electricity flow was possible, and they used both vehicle-to-grid and home. Mouli et al. (2017) also used vehicle-to-grid and photovoltaic cells to minimise cost for charging the electric vehicles. They both reduced the cost, which shows that using electric vehicles in local systems and not on the main grid level could be cost beneficial. This could also be more realistic in a shorter time horizon based on the challenges already introduced for vehicle-to-grid. It is also interesting to look into an aggregated electric vehicle parking lot, where several electric vehicles are connected together.

2.4.2 Challenges with Vehicle-to-grid

An issue with vehicle-to-grid that is widely covered in research is the degradation of the battery in the electric vehicles. The reason behind this concern is the increase of cycles the battery is charged and discharged with vehicle-to-grid. Siegfried et al. (2016) has compared two different articles where one of them suggests that batteries undergo degradation and the other one suggests that they do not undergo faster degradation given that the system operator discharge and charge the battery according to the producer's advice. These contradictory solutions show that more research needs to be done in this area. What is interesting for this literature review is to look at whether it is still profitable to have vehicle-to-grid with battery degradation. Tomić and Kempton (2007) had battery degradation as a fixed cost in their study. They got a profit even with battery degradation.

One solution that both Tan et al. (2016) and Tomić and Kempton (2007) looked at is unidirectional vehicle-to-grid. The system operator can charge the battery, but not discharge it. The degradation will naturally be lower, and it will be a smart charging system where the ancillary functions will be limited compared to bidirectional charging. Battery degradation is important for further studies as it could impact the lifetime of the battery significantly, and the cost of degradation and other costs can never exceed the net profit. Then the incentive to connect the electric vehicle to vehicle-to-grid/home/vehicle will be limited. It should also take into account the improvement of the batteries in electric vehicles when trying to suggest how it will look like in the future.

One of the challenges with making a new market for flexibility is a situation where the system operator and the financial market have different outcomes and needs. If a new marketplace for flexibility is made, the possibility for selling and buying flexibility in an area where the flexibility is not needed will be present. The solution to this will be a situation where only actors behind congested equipment can participate and sell their flexibility.

2.4.3 Price system

Krigstad et al. (2018) states that, over the coming years, the difference between high and low prices in the market will increase. Due to this, the profit for an energy storage system will have the possibility to increase as the system can store energy from low price periods to high price periods. Figure 2.3 shows the difference in price throughout a given day. These numbers are the system price in the Nordic area from 03.01.2019. This indicates that there are already differences within a day that could suggest a profit if the charging is planned and optimised. As seen from figure 2.4 the prices are likely higher during winter compared to summer in the Nordic areas. This is due to the seasonal changes in the Nordic climate. The consumption of electricity is higher in the winter compared to the summer due to heating. An electric vehicle will have the scope and optimisation in regards to price over a day and not between seasons. This is because an electric vehicle will most likely be used as a car every day, and are not able to store energy between seasons.

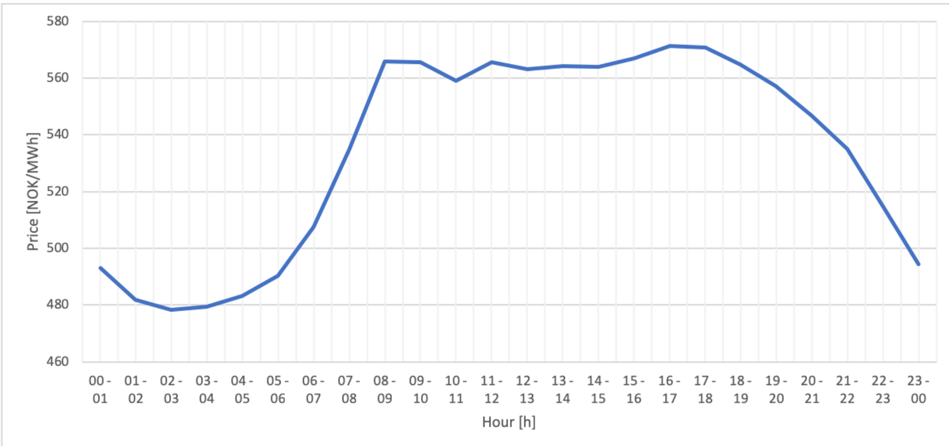

Figure 2.3: System price 03.01.2019 (Nord Pool Spot (2019))

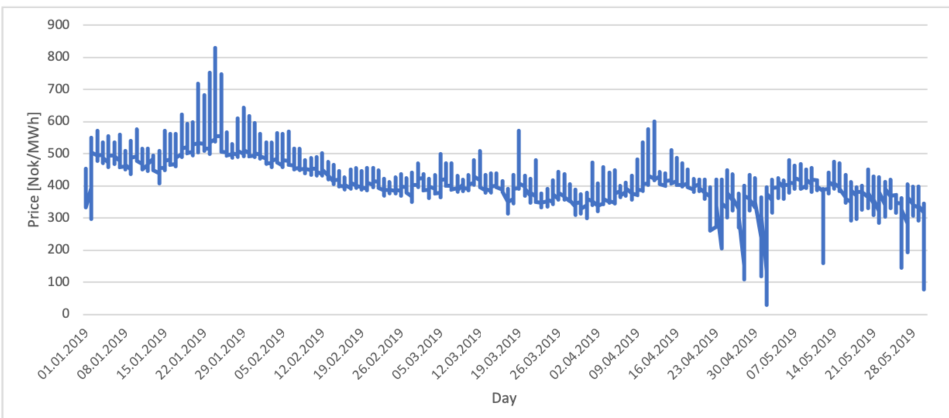

Figure 2.4: System price from 01.01.2019 to 30.05.2019 (Nord Pool Spot (2019))

2.4.4 Non-technical challenges

To make vehicle-to-grid successful users are needed, and it is a lot of social factors that need to be taken into consideration. It does not matter if the technical solution is perfect, or the market is efficient if the users are not willing to be flexible. Tan et al. (2016) points at social barriers being the main obstacle for the implementation of vehicle-to-grid. There are several aspects of this challenge; it is not just whether or not it is a net profit. Several papers point at range anxiety as a serious challenge, as well as battery degradation. Range anxiety means that the driver is afraid of the battery being empty either when the driver is supposed to drive or when driving. It is necessary to implement this into the optimisation problem with a minimum soc (state of charge) level, or times when the electric vehicle needs to be charged at a specific soc. According to Tomić and Kempton (2007), at least 90% of the cars are parked during peak hours where vehicle-to-grid will be of good use. Even though the vehicle is parked, the user must still be convinced that they will most likely not use the car, and if they need, they will have minimum soc. The anxiety is also when the user is afraid that there is not enough power if anything unexpected comes up.

Junker et al. (2018) made a dynamic function called ”Flexibility function” where they quantify the user's flexibility. With this function, the system operator can control the flexibility with penalty signals; this could be price, CO_2 or other signals. Then the system operator can put an index on the actual user that says something about how flexible they are, or in other words, how they will react to signals. Then the system operator can quantify the user's flexibility, and they would get the relevant people to participate with flexibility. These signals and their result also shows how important the economic aspect is. The regular user will join in based on an economic incentive. In the end, the user needs to have a net profit. The degradation of the battery and the investment cost for a charger must be included. Incentives through a new market or tariffs could also be a way to change the user's behaviour.

2.5 optimisation approaches

There are different optimisation techniques, depending on what kind of input present, and the goal for the optimisation. The difficulty with electric vehicles and other variables that depends on human behaviour is that it is stochastic and nonlinear, and it could be hard to find accurate input data. Many papers have used different techniques to optimise electric vehicles scenarios, both in connection to the grid, via a vehicle-to-grid solution and in terms of charging patterns.

Tan et al. (2016) went through some different optimisation approaches. First, both linear programming and quadratic programming are well known and widely used approaches. They will require a linear set of equations to be solved; this could be inaccurate if the system is hard to linearize. For nonlinear programming (NLP) or mixed integer nonlinear programming (MINLP), there is no linearity requirement present, but the computation can be hard due to complex variables. Further on, there is Lagrangian relaxation, but this method could have difficulty obtaining the feasible solution in large systems. There is also a chance of solving electric vehicle problems with artificial intelligence.

Tan et al. (2016) suggests using a genetic algorithm or particle swarm optimisation to solve vehicle-to-grid problems. The reason behind the use of these solutions is that they are able, by an iteration process, to find global optimum within the allowed solutions obtained. These methods also require less computation time, which often can be a challenge within power grid optimisations.

Zakariazadeh et al. (2014) proposed a model to charge and discharge electric vehicles within a local distribution grid. This model considered both the economic and technical aspects. This paper uses MINLP, but due to long computation time, they divided their problem into one main problem and one subproblem. The technique used is called Benders decomposition, where they are making cuts to reach an optimal solution. The main problem is a mixed integer linear problem (MILP), and the subproblem is an NLP. This problem also has a multi-objective function, which both minimises cost and minimises emission. Here mainly constraints on charging and discharging, and power limits were implemented.

A paper by Mohseni et al. (2017) used MILP to optimise the energy consumption of household appliances within a microgrid. The energy consumption was based on a Set of Sequential Uninterruptible Energy Phases (SSUEP), and the data was applied to the day-ahead energy framework to react on time-based prices. The objective function had a goal of reducing the cost of supplying the residents in the microgrid. The main appliances they had in their microgrid was battery energy storage, an electric vehicle with vehicle-to-grid and solar panels. The constraints for the electric vehicles were physical constraints put on charging, discharging and power limits.

Mouli et al. (2017) looked into optimising the charging of electric vehicles from solar panels at an office building. Their objective function wanted to minimise the cost of electric vehicle charging, feeding solar power into the grid and offering reserves to the system operator. They used MILP and the branch-and-bound approach to solve this problem. They also used stochastic programming to plan the EV, due to electric vehicle charging being dynamic and uncertain. The constraints on electric vehicles in this study was mainly on soc, discharge and charge of electric vehicles.

Igualada et al. (2014) used MILP to minimise cost for a residential microgrid that contained renewable energy sources and vehicle-to-grid. It also included the behaviour of the electric vehicle owner in the model. The constraints they used for the electric vehicle model was especially on charging, discharging and soc. They also included a constraint on range anxiety. The objective function minimised cost between the microgrid and the main grid.

Another algorithm, the ACOPF (AC optimal power flow) was used by Zaferanlouei et al. (2016) to simulate electric vehicles in a grid with renewable energy. Their objective function was to minimise the cost of energy taken from the upstream grid, hence optimal scheduling of electric vehicle charging pattern. Their constraints on electric vehicles were on the battery, charging, discharging and soc. Their study also simulated a parking lot containing 50 electric vehicles.

Olivella-Rosell et al. (2015) used a different approach when their research tried to figure out the impact of charging electric vehicles in Barcelona had on the distribution grid. The problem worked with stochastic variables and used Monte Carlo simulation in order to emulate the parameters. The method used in this paper was Agent-Based Modeling and

Simulation, and they solved the problem by the Newton-Raphson method. This method gave the researches the chance to divide the EV owners into individuals. It also allowed for having flexible systems and represent social interactions. Those social factors are among others, the number of trips, types of electric vehicles, distance and velocity.

Shafie-Khah et al. (2016) used stochastic programming to reflect the uncertainty in the real-life system. They divided into two stages, one in the day-ahead market, and one within the balancing market. They used a truncated Gaussian distribution to determine the initial soc, arrival time and departure time. The problem was modelled as a MILP and solved with CPLEX12.

Both Olivella-Rosell et al. (2015) and Shafie-Khah et al. (2016) is modelling the uncertainty of user behaviour. Since their behaviour is uncertain, it is a strength to include this in the model. In order to reflect the different scenarios and uncertainty Shafie-Khah et al. (2016) use stochastic programming. This is also the optimisation method which will be used in this thesis. Since this research is looking at a Zero Emission Neighbourhood with houses, the user behaviour is essential to estimate as this could influence the final result.

Chapter 3

Theory

In this section, relevant theory for the research is presented and explained. First stochastic modelling, the optimisation method used in this research is presented. Further on the different demand response programs is explained. Zero Emission Neighbourhood is presented and explained in order to understand better how electric vehicles, solar panels and battery can play a role. Some aspects of electric vehicles, batteries, solar panels and CO_2-emission are also included. Relevant definitions, regulations and laws are also mentioned in this chapter.

3.1 Stochastic modelling

In the real world, one has to consider uncertainty in order to get a result that reflects the actual outcome. In stochastic programming, the optimisation is carried out in several stages with several scenarios. Here, different scenarios are designed and based on the information in each stage and then a decision can be made. This means that in stochastic programming, uncertainty is taken into consideration through different scenarios and stages. There are different numbers of stages based on the flow of information in the problem. For instance, there is a two stage model, where the two different stages are called here-and-now and wait-and-see. Here-and-now is the first stage where there exist different scenarios and several outcomes, and then it makes a decision based on the limited information present.

In the second stage, later in time, the wait-and-see stage comes in. Here the outcomes are known, and a decision is now made based on that. This means that there will not be any scenarios and uncertainty in this stage as there was in here-and-now. A general model of a stochastic problem is shown below.

$$\begin{aligned} \min c^T x + E_\xi Q(x, \xi) \\ Ax = b \\ x \geq 0 \end{aligned}$$

$$\begin{aligned} Q(x, \xi) = \min q^T y \\ Wy = h(s) - T(s)x \\ y_s \geq 0 \end{aligned}$$

The above expression is a general model for a two stage stochastic model collected from Birge and Louveaux (2011). Here x denotes the first stage decision, the here-and-now decision. ξ denotes the parameters that are uncertain in the model and is what changes based on the scenarios. y is the second stage decision, or in other words the wait-and-see decision. $Q(x, \xi)$ is the equation for what one can do in stage two in the problem. The E_ξ is the expected value of each scenario with its probability to happen.

One important aspect when designing a stochastic problem is to choose the parameters considered uncertain correctly. This is important in order to reflect the uncertainty present in the problem and to get the most realistic results possible.

When designing a stochastic problem, the non-anticipativity constraints are needed to ensure that the same parameters are used until there is a change in stage; in other words, there exists new information. These constraints will also ensure that the decision is made solely on the information in the previous and present stage and not future stages.

3.2 Demand response programs in electricity markets

With more renewable power injected into the grid and higher electricity consumption, demand response programs will play a crucial role in order to get the end-users to adapt to the needs for the grid. Albadi and El-Saadany (2008) defines demand response as ”the changes in electricity usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time.”. There are two ways to get end-users to change their consumption in order to meet the demand in the grid; incentive-based- and price-based programs. The different programs have different sub-programs and will be used with different needs in the grid. According to Albadi and El-Saadany (2008) there are three different ways an end-user can respond. The first is to adjust power consumption during peak periods. In this response, the end-user will not move the consumption to other periods; this alternative will result in loss of comfort. This could, for instance, be turning off the heater during high peak and allow a lower temperature at home. The second alternative moves power consumption from peak periods to low-peak periods. This could be a dishwasher or charging of the electric vehicle. The last alternative is on-site generation of power, where electricity is produced on-site during peak periods, for instance, a diesel generator.

3.2.1 Grid tariffs

In connection to the grid, the demand response programs must be understood as the grid tariffs. The price of electricity in, for instance, Norway is divided into two parts. First, it is the system price or market price paid to the power supplier. The second part is the grid tariff paid to the grid operator (Norwegian Energy Regulatory Authority (2019a)). The grid tariff is meant to cover the cost of operating the grid for the system operator. This part is regulated by the Norwegian Energy Regulatory Authority to ensure that the grid is operated safely and optimally both economically and physically. Another difference between the two parts of the electricity price is that the market price is paid to a power supplier operating in a perfect market, while the grid operators are operating in a monopolistic market. The operating grid costs are, for instance, losses in the grid, but the highest cost for the system operator is the maintenance and investments in the grid. The reason for the tariffs to potentially have a structure different from a fixed-rate is to make the customer behave according to the needs for the grid. It is essential to stimulate behaviour as it can reduce both the operational costs within the grid, but also the investments. This is also why demand response programs are mentioned together with flexibility. The programs can contribute to lowering the investments in the grid, and the design of the future grid tariff will be important in light of the upcoming challenges mentioned earlier.

3.2.2 Incentive-based programs

Incentive-based programs can be divided into classical and market-based programs. When a customer receives a fixed bill credit or discount rate for their participation in a program, it is called a classical incentive-based program. On the other hand, when a customer is rewarded for performance depending on how much the load is reduced during a critical period, it is called a market-based incentive program (Albadi and El-Saadany (2008)). With the Direct control the operator can, on short notice, shut down equipment equivalent to what the customer is compensated for. In Interruptible/Curtailable (I/C) programs, the customer is asked to reduce on beforehand. If the customer cannot meet the demand the operator asks for the customer will receive a penalty. If the customer, for instance, participates with its water heater, the customer is compensated for the amount they offer in both programs. If the operator wants to shut it off, they will shut it off without the ability to withstand in the direct-control program, which can be critical for the bacterial level in the heater. Then the I/C program is better as the customer can take the penalty if they need hot water, or it is getting under its predefined level. Furthermore, the demand bidding is a program where the customer places their bid in the wholesale market. If the bid is accepted, they need to adjust their load to the value of the bid, or they will face penalties. Capacity market programs will give the customer a day-ahead notice on load reduction.

3.2.3 Price-based programs

Price-based programs are based on reflecting the cost of electricity prices with dynamic pricing rates. The aim of implementing these dynamic pricing systems is to give the end-user an incentive to shift its consumption from peak-hours to off-peak hours (Albadi and

El-Saadany (2008)). Time-of-use is divided into off-peak and peak hours and will give a permanent price-signal. Critical-peak pricing can be used on the top of time-of-use rates in order to reflect critical periods or critical days for a limited time. Extreme-day-critical-peak pricing can be used for a whole day, and this could be the case if there is critical equipment out of service or cold/hot days. Price-based programs will encourage the end-user to either adjust some consumption and move it to other hours, or change the comfort and reduce consumption.

3.2.4 Capacity price

The Norwegian Water Resources and Energy Directorate (NVE) are currently in the process of changing the tariff in Norway and shift it towards using capacity rather than energy. This is to try to reflect the actual cost in the grid better, as well as giving the incentive to reduce the load during critical hours as seen in the models above. In their hearing from Hansen et al. (2017), they point towards three different models. The energy-based program time-of-use is the first one, and this model has already been discussed. The two last ones are the capacity-based programs measured tariff and subscribed tariff.

Measured capacity

This model measures the highest peak on the capacity for the end-user during a period, and the end-user pays for this top. The model is described in figure 3.1. This figure shows the highest peak for 24 hours, but measured tariff could also be the highest peak in an hour or highest peak over a month. They all have in common that the highest peak is used as the basis for the compensation. Measured tariff is commonly used in Norway for customers with consumption over $100000 kWh/yr$ according to the hearing report from NVE (Hansen et al. (2017)). For this model to work, it needs the right time span. The most common today is the highest peak over a month. This model gives the end-users less incentive to reduce its consumption if the peak comes the first day in the month, even though that is hard to know. Some users have their highest peak when the grid is stable, and hence they pay for something the grid can tackle. According to NVE, it was hard for the testers to understand how they could reduce their consumption with this model.

The time-of-use can also be mixed into this model where peaks during peak hours will cost more than peaks during off-peak hours. On the other hand, this will also increase its complexity.

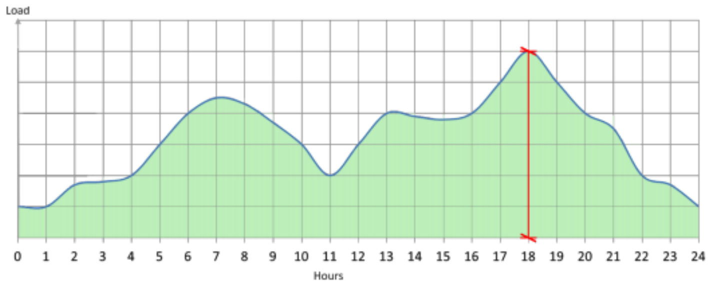

Figure 3.1: Demand response program measured capacity (Karlsen (2018)).

Subscribed capacity

Subscribed capacity will work similarly to cellphone, insurance or internet-access subscriptions. The end-user will subscribe to a certain capacity and will be charged if this limit is exceeded according to figure 3.2. The red arrows show the consumption over the subscription limit. This model will give the end-user an incentive to reduce total simultaneous capacity usage. One solution could also be to combine a time-of-use model with subscribed capacity. In this way, over-consumption can be more expensive in the hours where the grid needs a reduction in capacity and will be less expensive in the hours where the grid do not need this flexibility. This will make the model more complex, but on the other hand, it will reduce the socio-economic loss as one do not have as strong incentive in the off-peak hours as in the peak hours to reduce capacity. One challenge with this model is that it can be hard for the end-user to react on signals and choose the best possible subscription limit. This is because, in a model like this, it will be beneficial to overconsume some hours. If the end-user is left with capacity in every hour, the limit should have been lower. The challenge for the end-user is then to know how much it is beneficial to overconsume. One solution to this challenge could be to use the data collected in the smart meters to suggest a limit based on the consumption over the previous years.

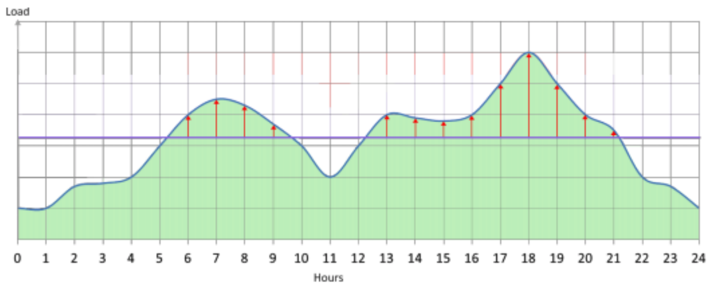

Figure 3.2: Demand response program subscribed capacity (Karlsen (2018))

3.3 Zero Emission Neighbourhood

An overall goal for a Zero Emission Building (ZEB) is to have "zero emission of greenhouse gases related to their production, operation and demolition" Dokka et al. (2013). There are several guidelines on how a Zero Emission Building should be defined. Dokka et al. (2013) states some of these guidelines in their work on a definition. First, it is the system boundaries; local renewable energy should be produced on-site. For the CO_2 calculation for electricity, the emission factor for a European average should be used. There are several other guidelines, but they fall on the side of this thesis.

Based on the mentioned definition by Woods Ruth, Remøe Katinka Sætersdal , Hestnes Anne Grete (2018), a Zero Emission Neighbourhood is several Zero Emission Buildings combined with the same overall goal. This will make the whole neighbourhood a part of the system boundaries. The buildings can then interact to fulfil the neighbourhoods overall goal, which is to have zero emission of greenhouse gases. Zero Emission Neighbourhood can play a crucial part on the road towards an emission-free society, and to reach climate goals. These neighbourhoods can create awareness for its inhabitants on climate change as the end-user will have to be more conscious of the usage of energy, and when to use it. When talking about a parking lot within a Zero Emission Neighbourhood, or solar panels, it is essential to mention that they do not need to be physically next to one another. In a neighbourhood, the parking lot and the solar panels can be connected to the individual houses as long as they are technically connected and within the system boundaries. This means that the goal of reducing emission for the neighbourhood means looking at the net emission for the system, or the houses and equipment combined.

As mentioned, the goal for a Zero Emission Neighbourhood is to have zero emission of greenhouse gases and hence also CO_2. Solar panels, electric vehicles and the external battery can be used as tools to reduce emission from the neighbourhood. When measuring the CO_2-footprint from the energy used in the neighbourhood, the source of energy is crucial. The difference between coal and solar power in terms of CO_2-footprint will be huge, and that is why the electricity mix is important. It has become easier to find the emissions in the grid as the flows in the transmission grid is known, and the energy sources within an area are known. Based on these flows, a CO_2-footprint can be estimated in an area. With energy storage systems like electric vehicles and batteries, the power used in the neighbourhood can be bought in hours with low CO_2-footprint and consumed in an hour with high emission. Solar panels could also play an important role as they will produce renewable emission-free energy which can be consumed in the neighbourhood or sold to the grid. If the energy is sold to the grid, it will help with lowering the CO_2-footprint for the energy in the grid.

3.4 CO_2-emission

Carbon dioxide or CO_2 for short is a gas that is released, for instance in combustion. CO_2 is a greenhouse gas, which means it is a gas that contributes to global warming by trapping heat inside the atmosphere (United States Environmental Protection Agency (2019)). The international agreements mentioned earlier are concerned about the increase in emission of CO_2 and have as a goal to reduce the emission. CO_2-footprint means the amount of emissions emitted per produced unit. For the case with energy generation, it means how much emission that is released in the generation of one unit energy. This can be useful when different energy sources are compared.

In order to reduce emissions, the EU introduced in 2005 a system for emission quotas called EU Emission Trading System (European Commission (2019)). This system gives every country a quota of CO_2 they can emit. If the country does not want to cut emissions or it is cheaper to reduce somewhere else the country/company can buy quotas from others. The number of quotas decreases every year. Then the overall CO_2-emission within the

European Union (together with Iceland, Liechtenstein and Norway) is reduced, and it is cut at the most cost-effective place. The trading system covers only 45% of the emission in these countries. The emissions within this system will be 43% lower in 2030 compared to 2005 levels. Based on these quotas, it is possible to set a price on the emission of CO_2.

3.5 Existing regulation for on-site generation

If there are on-site generation, for instance, in a Zero Emission Neighbourhood, the neighbourhood can be regarded as a prosumer. A prosumer is an end-user that produces energy for their use, and in some hours inject the excess power into the grid (Norwegin Energy Regulatory Authority (2019b)). This definition and program make it possible for end-users like a regular household to have solar power, wind turbines or other sources of energy at home. In Norway the production limit on taking part in this program is 100kW (Lovdata (2019)). If this limit is exceeded, the customer will be regarded as a producer, and other laws will apply. In Norway, the grid operator is forced to connect the prosumer up to the maximum capacity installed in the house of the prosumer. If the prosumer wants to install a higher production capacity than this limit, the prosumer can pay connection charges as long as the total installed capacity is never higher than 100 kW. The surplus energy can be sold to a power supplier. According to Norwegian law, the customer will not pay tariffs when injecting power to the grid. The customer will also contribute to lower losses in the grid, and hence the energy losses in the tariff will be paid to the customer when injecting power to the grid (Norgesnett (2019)).

3.6 Batteries

Batteries are used to store energy, and they are used in, for instance, electric vehicles, but can also stand alone, either at home or connected to the grid. For the last years, lithium-ion cells have been the preferred alternative in the market (Newman et al. (2003)). A concern with batteries, both in vehicles and stand-alone is degradation. It has been shown that lithium-ion cells undergo degradation (Siegfried et al. (2016)). Degradation means that its capacity reduces as the battery is charged and discharged. The system can degrade in two ways, capacity fade, which means the range, and power fade which is the limitation of power capability.

Another element within a system containing a battery is the converter. The converter converts the power within the battery from DC to AC if it is discharged, and from AC to DC if the battery is charged, given that the battery is connected to an AC-system. If the battery is connected directly to the PV-system or an electric vehicle, it only needs to adjust the voltage (Masters (2005)). The loss of power happens both when charging and discharging, and can often be equal to around 90% efficiency. This gives an overall efficiency for a battery at around 81% (Masters (2005)).

3.7 Electric vehicle

An electric vehicle is a vehicle with an engine running on electrical power. As seen earlier on, it has been an increase in sold units worldwide, and it is expected to continue to grow. As mentioned the battery in an electric vehicle will undergo degradation with charging and discharging. It is also a need for a converter in the same way it is needed for the batteries.

3.7.1 Vehicle-to-grid

Vehicle-to-grid means that power can flow both from the grid to the electric vehicle and the other way around. Vehicle-to-grid can be defined by both unidirectional- and bidirectional charging (Tan et al. (2016)). With unidirectional charging, the energy can only flow from the grid to the electric vehicle, while the bidirectional flow allows the energy to flow both ways. This means that the different techniques can provide the grid with different services since bidirectional also allows for feeding power back into the grid. Some of the different services for these charging techniques are shown in figure 3.3.

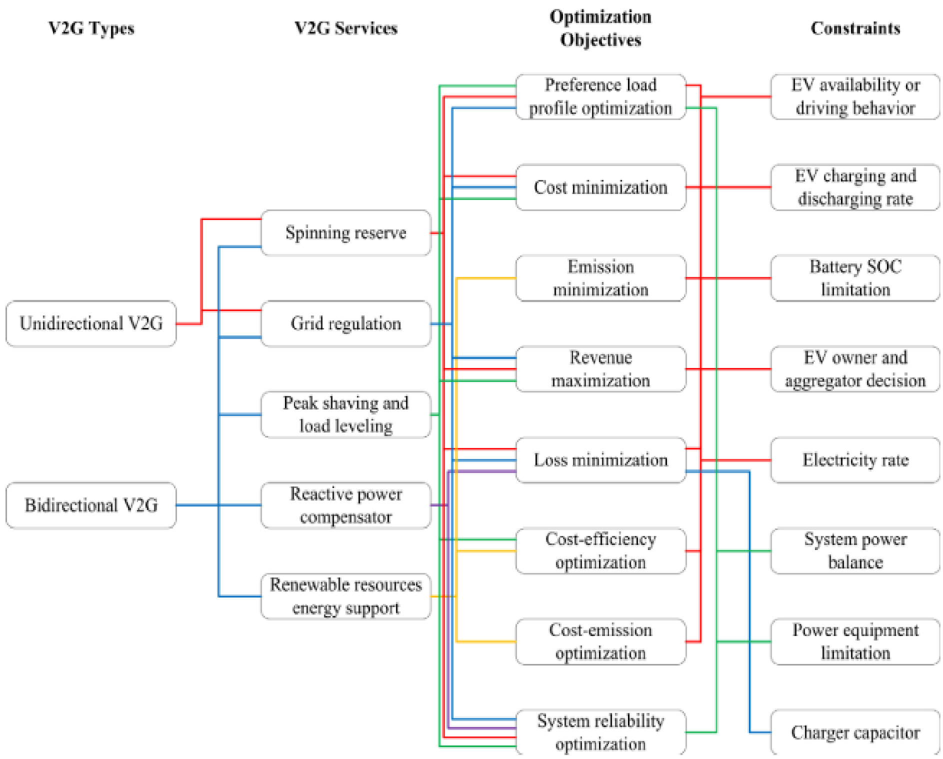

Figure 3.3: Flowchart of the different approaches for each vehicle-to-grid services (Tan et al. (2016)).

3.8 Photovoltaic power

Photovoltaic (PV) systems are using sunlight to convert solar radiation into electrical energy. As written in the introduction, PV-systems have significantly decreased its installation costs over the past ten years, and it is assumed that they will continue to drop towards 2025. A PV-system can either be connected to the grid like a solar park or be off-grid as seen on cabins in Norway. Since the solar panels produce DC power, there will be a need for converters if the panels are connected to an AC source or the grid. This means that there will be a loss of energy in the converter that converts DC to AC. If the panels are connected straight to a DC source, then this kind of converter is not needed. There might be a need for transforming the voltage (Masters (2005)).

Solar panels are only able to utilise a certain amount of radiation from the sun. This means that only a percentage of sunlight can be converted into electrical energy. Most solar panels produced today have an efficiency between 15%-20% (Aggarwal (2019)).

3.9 Connection charges

Grid operators in Norway are required to offer a grid connection to all end-users in Norway (Norwegin Energy Regulatory Authority (2019a)). If the customer is not connected to the grid from before or the customer wants a higher installed capacity, the grid operator should cover the expansion partly by charging the end-user, and this charge is called connection charges. It is not allowed to charge more than what the customer is asking for. This means that if a line is upgraded with 10kW and the customer asked for 1kW, the grid operator can maximum charge the end-user 10% of the costs (Lovdata (2019)). The grid company can not charge the customer if there is capacity within the grid, and connection charges can neither be retroactive. If this should be seen in connection with prosumers, there is a first-come-first-served principal at the moment. If the upgrade is within the capacity for an end-user, the grid operator can not charge for the upgrade, as the end-user has the right to connect up to its maximum capacity.

3.10 Balancing markets

In Norway, there are different reserve markets to handle imbalances in the grid. The responsible in this market, and to activate bids is the Norweigan TSO, Statnett. The different balancing markets are explained by figure 3.4. The markets discussed in this research are the Frequency Containment Reserves (FCR) and manual Frequency Restoration Reserves (mFRR) markets. The first market is the market for FCR, which is the first reaction to a unbalance in the grid. The interaction in this market happens either as weekly bids or as day-ahead bids (Statnett (2019c)). The clearing of the weekly market happens before the clearing of the electricity spot market, while the clearing of day-ahead happens after the electricity spot, as seen in figure 3.4. If the bid is accepted, the user will be compensated equal to the bid and the amount that was accepted. Statnett can discriminate in this market, and choose bids higher than the clearing price if there are reasons based on the operation of the system. If a user is not able to deliver the promised amount, Statnett has the authority to ban the user from the market (Statnett (2019c)). The lowest bid possible is 1MW which excludes all smaller customers that are not aggregated.

Another balancing market in Norway is the mFRR, which is the tertiary response for unbalances in the grid (Statnett (2019b)). In this market, the bids can either be for a period of time, an hour or a 15 minute period. The lowest possible quantum in this market is 10MW; in other words, it is harder to participate in this market for smaller consumers compared to the FCR market. The bids will be accepted in the same way as for FCR, and if the user is not able to deliver the flexibility, it can be banned from this market as well. It will be considered breaking Norwegian law not to be able to deliver the promised amount in the balancing markets.

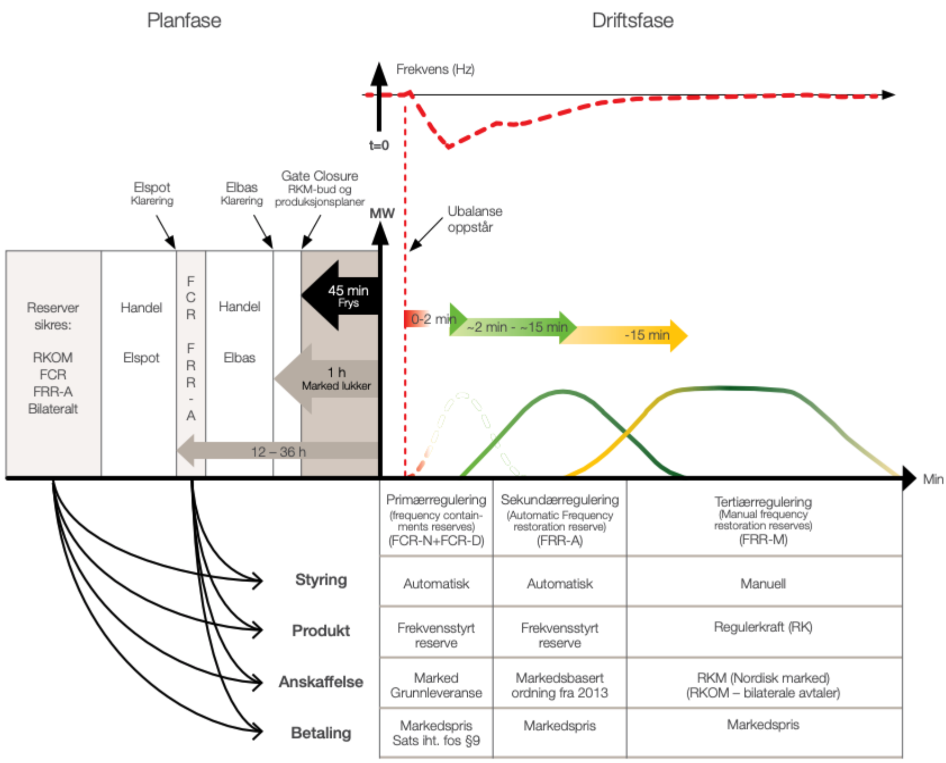

Figure 3.4: Different balancing services for the system operator in Norway (Statnett (2017)).

Chapter 4

Model

This chapter presents the model used and developed in order to minimise CO_2-emissions for a Zero Emission Neighbourhood, as well as maximise profit for the users. The model is making use of bidirectional vehicle-to-grid for a parking lot consisting of electric vehicles, an external battery, solar panels and different demand response programs, to reach its desired goals. First, the original model used by Shafie-Khah et al. (2016) will be presented. This model can also be found in Appendix C. Afterwards, the complete model developed in this project is presented. The complete proposed model can be found in Appendix A.

Figure 4.1 shows the complete system in the model developed. The point where the parking lot, solar panels, the external battery and external grid meet is referred to as the system in this thesis.

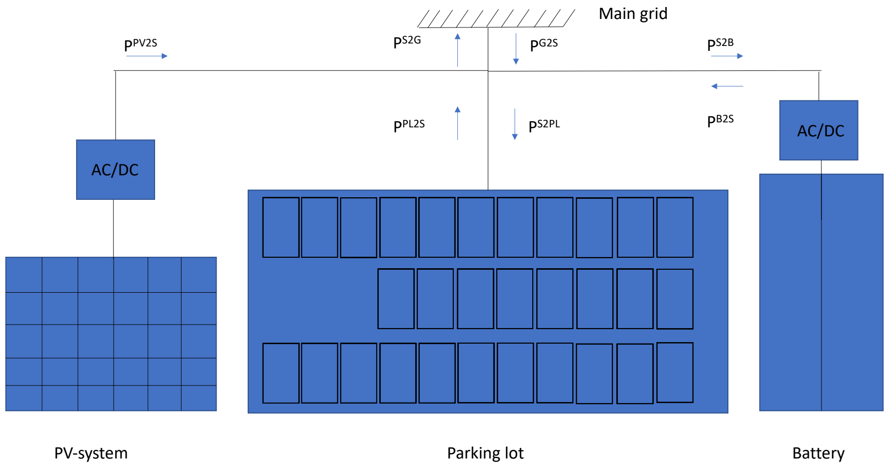

Figure 4.1: The proposed system with solar panels, electric vehicles and a battery in connection with the grid.

4.1 Original model

This section will go through the model presented in the paper by Shafie-Khah et al. (2016) named "Optimal Behavior of Electric Vehicle Parking Lots as Demand Response Aggregation Agents". The mathematical model formulation is presented in Appendix C. The main goal for this paper is to maximise profit for a parking lot operator by using bidirectional charging and different demand response programs.

The reason for choosing this paper as a basis was mainly its strengths on uncertain parameters. As seen in equation C.31, C.32 and C.34 the initial soc, arrival time and departure time for the different electric vehicles are given as truncated Gaussian distributions. As the behaviour of the users is highly stochastic, a distribution like this can make the outcome more similar to a real-life scenario. The fact that this model also has bidirectional vehicle-to-grid and make use of the charging both ways also makes the model more attractive to a Zero Emission Neighbourhood where the overall goal is zero emission.

Objective function

The objective function in the original model is given in equation C.1. The function consists of two parts. The first part is the here-and-now part which is the first stage in the stochastic problem. The first stage is defined by equation C.2 and C.8, for the income and the cost, respectively. The here-and-now stage is the choice made in the day ahead of the hour of operation and is based on the information available at that time. The income in the here-and-now stage is defined by equations C.3 through C.7. Cost in the here-and-now stage is given by the following equations: C.9, C.10, C.11 and C.12. The other part of the objective function is the wait-and-see part, or the second stage of the objective function. This stage is the decision made in the hour of operation where all the information is present, and the activated energy from the system operator is known. In this part, there is only one term for the income, and it is given in equation C.13. Equations C.15 through C.17 give the costs for the second stage. The mentioned equations are what makes the objective function. The objective function has a goal to maximise profit for a parking lot operator or an aggregator. As the goal for this thesis is to make a model for a Zero Emission Neighbourhood consisting of houses and not a commercial parking lot a change in the objective function is needed. To reflect how a neighbourhood looks, the agenda for the system operator needs to be adjusted to better fit with the goal.

Expressions and constraints

Further on, the constraints and expressions are defined. The first two constraints are given as equation C.18 and C.19. These ensure that there is never more or less than 100% of the aggregated demand response programs involved. Equation C.20 gives the degradation costs for the batteries in the electric vehicles. To ensure that the total rate of charge or discharge never exceeds the limit for the electric vehicles, equation C.21 and C.22 are used. Equation C.23 gives the aggregated soc for the parking lot, while equation C.29 gives its limits. To meet the demands for the inhabitants in the Zero Emission Neighbourhood, there is a need for some adjustments to the equations on the soc to ensure the departure soc for the cars. Equation C.24 gives the arrived soc to the parking lot. The energy provided to the cars is given by equation C.25, while the energy from the cars to the grid is given by equation C.26. These two equations are used to determine the transaction between the parking lot operator and the electric vehicle owners. Equation C.27 show the aggregated energy for the cars as if no energy was interchanged with the grid. The soc limit for each individual car is given by equation C.28. The constraint in equation C.30 gives the limit for how much energy that can be provided to the grid. Equation C.35 gives the initial soc for a car for the hours the car is present in the parking lot. The number of cars present in the parking lot is given by equation C.36, while equation C.37 ensures that the number of cars never exceeds the number of parking spots. At last, the equation to determine the activated reserves in stage two is given as a uniformly distributed function in equation C.38.

4.2 Proposed model

The goal for this research is to use bidirectional charging of electric vehicles, external battery and solar panels to minimise CO_2-emissions for a Zero Emission Neighbourhood. The research also has a goal of maximising profit for the users and explore the flexibility of the system. The combination of using solar panels and a storage facility like an external battery or electric vehicles makes minimisation of emission and maximisation of cost easier. This is because the system is more flexible and can make use of the difference in price and CO_2-footprint between hours. In this section, the work done with developing the model is shown. The complete model is given in Appendix A. As a general comment, the model has been adjusted to operate according to the regulations and laws in Norway; this will be further specified. The model considers the user to be a price taker, in other words it will take the market price and then decide what it wants to do.

4.2.1 Stochastic programming method

The model by Shafie-Khah et al. (2016) used a two-stage stochastic model. This was, based on the information given in the paper, hard to replicate. That is why this project has changed from a two-stage model to a two-step model. The implications are that there will be an optimal scheduling in the first step. Here the different scenarios with different parameters of arrival time, departure time and initial soc will be optimised with an uncertain activation of reserves. The activation of reserves will be assumed in the first step to be within 0-100%. Step two takes in the finalised model from step two and gets the actual activation of reserves from the system operator. Then it is once again optimised, and this will also be the final result for the end-user. The interaction with the grid in step two is given by the interaction in step one and is fixed. The only possible change for the grid flow in step two is the activated reserves. The direction of flow will also be fixed in step two.

4.2.2 Prices

In this research, the regulations on prices in Norway have been used to make the model more realistic. This means that the energy exported back into the grid is compensated with the system price plus the marginal loss as this part becomes negative for prosumers. These are the rules for compensating prosumers in Norway. When buying energy from the grid, the system price for the energy plus the tariff is paid. In the reserve market, it is the same price for providing capacity and getting a penalty for not being able to deliver the activated reserves. That being said, Statnett, the system operator in Norway, has the authority to throw the user out of the market if the demand is not met.

In the work done by Shafie-Khah et al. (2016) they had the same price for the energy provided to the grid and energy drawn from the grid. This price was also dependent on the demand response programs, which gave them different prices for each program, and hence different basis of income. In other words, their model got paid the tariff when selling energy back to the grid.

4.2.3 Sets

In this model, there are four different sets. The first set is the different scenarios, denoted by ω. The next set is the different demand response programs, denoted by i. Some of the possible programs are explained in detail in chapter 3. In set N the different cars involved in the analysis are given, and they are indexed as n. The last set is the different time steps, denoted by t.

The original model by Shafie-Khah et al. (2016) had the participation in each demand response program as a variable, α_i. This allowed them to participate in several demand response programs at once. This possibility is left out of this research. The reason for this is because a percentage participation in each program will make it complex and hard for the end-user to understand. As described earlier, the demand response programs are made to get the user to behave in a certain way. If the program is too complex, it will not serve its purpose, as the users will not know how to behave. For this reason equation C.18 and C.19 from the original model is excluded and α_i is turned into a parameter. The different variables in the model are also dependent on the demand response program in this research, and this was not the case in the work done by Shafie-Khah et al. (2016). This is done to give the different variables the chance to vary based on the different signals and incentives given by the different programs.

4.2.4 Objective function

The objective function in this model has a goal to maximise profit for the system according to the equation A.1 below.

$$\begin{aligned} &\max profit^{Sys} = \\ &[\,\epsilon_{\omega_1} \sum_{t \in T} \sum_{i \in DRPs} \alpha_i \{Income^{HereAndNow}_{\omega,i,t} - Cost^{HereAndNow}_{\omega,i,t}\} \\ &+\epsilon_{\omega_2|\omega_1}[\,\alpha_i\{Income^{WaitAndSee}_{\omega,i,t} - Cost^{WaitAndSee}_{\omega,i,t}\}]\,] \end{aligned} \tag{A.1}$$

The different terms mentioned in equation A.1 are given in the following expressions. They are divided into the two steps for the model. The here-and-now step is the choice it makes the day ahead the hour of operation. The next step, wait-and-see, gives the actual activated energy from the system operator in the hour of operation. The different terms will be explained in detail throughout sections 4.2.5, 4.2.6, 4.2.7, 4.2.8 and 4.2.9 in this chapter.

$$\begin{aligned} &Income^{HereAndNow}_{\omega,i,t} = \\ &Income^{En,S2G}_{\omega,i,t} + Income^{Cap,Res}_{\omega,i,t} + Income^{Inc}_{\omega,i,t} + Income^{\mathrm{CO_2}}_{\omega,i,t} \end{aligned} \tag{A.2}$$

$$\begin{aligned} Cost^{HereAndNow}_{\omega,i,t} &= \\ Cost^{En,G2S}_{\omega,i,t} + Cost^{Deg,PL}_{\omega,i,t} + Cost^{Deg,B}_{\omega,i,t} + Cost^{Fixed}_{i} \\ + Cost^{Pen}_{\omega,i,t} + Cost^{\mathrm{CO_2}}_{\omega,i,t} + Cost^{Pen,\mathrm{CO_2}}_{\omega,i} \end{aligned} \tag{A.3}$$

$$Income^{WaitAndSee}_{\omega,i,t} = Income^{Res,Act}_{\omega,i,t} \tag{A.4}$$

$$\begin{aligned} Cost^{WaitAndSee}_{\omega,i,t} &= \\ Cost^{Deg,Res}_{\omega,i,t} + Cost^{Art,More}_{\omega,i,t} + Cost^{Art,Less}_{\omega,i,t} + Cost^{SOC,flex}_{\omega,i,t} \end{aligned} \tag{A.5}$$

4.2.5 Parking lot

A parking lot with bidirectional charging can minimise emissions and maximise costs in the same way as a battery, by making use of the difference between hours in terms of price for energy and CO_2-footprint. As this model has another scope and agenda than Shafie-Khah et al. (2016) some changes have been made.

The first change to be made is the functions for the arrival time and departure time. Since this research looks at a Zero Emission Neighbourhoods with only houses, the users are more likely to arrive in the afternoon and depart in the morning. Equation A.7, A.8 and A.9 represent these changes. Equation A.6 gives the numbers of cars present in the parking lot at all times.

$$t^{dep}_{\omega,n} = f(x) = f_{TG}(x; \mu_{dep}, \sigma^2_{dep}, (t^{dep,min}, t^{dep,max})) \quad \forall \omega, \forall n \tag{A.7}$$

$$t^{arv}_{\omega,n} = f(x) = f_{TG}(x; \mu_{arv}, \sigma^2_{arv}, (Max\{t^{arv,min}, t^{dep}_{n}\}, t^{arv,max}) \quad \forall \omega, \forall n \tag{A.8}$$

$$t_{\omega,n}^{dep} < t_{\omega,n}^{arv} \quad \forall\omega, \forall n \tag{A.9}$$

$$N_{\omega,t}^{PEV} = N_{\omega,t}^{PEV,arv} - N_{\omega,t}^{PEV,dep} + N_{\omega,t-1}^{PEV} \quad \forall\omega, \forall t \tag{A.6}$$

The stochastic soc arrival for the electric vehicles is given by equation A.11.

$$soc_{\omega,n}^{PEV,ini} = f(x) = f_{TG}(x; \mu_{soc}, \sigma_{soc}^2, (soc^{PEV,min}, soc^{PEV,max})) \quad \forall\omega, \forall n \tag{A.11}$$

In this model a binary parameter has been introduced, $\delta_{\omega,t,n}^{Arv}$. This parameter will make sure that only the actual arriving cars in hour *t* are added to the aggregated soc in equation A.16. In the work by Shafie-Khah et al. (2016) the soc arrival for the cars was equal in all the hours, which will give arriving cars in the hours where no cars are present, and this could lead to imprecise results.

$$soc_{\omega,t}^{arv} = \sum_{n=1}^{N_{\omega,t}} Cap_{n,\omega,t}^{PEV} \times soc_{n,\omega,t}^{PEV,ini} \times \delta_{\omega,t,n}^{Arv} \quad \forall\omega, \forall t \tag{A.10}$$

In order to get a system with bidirectional vehicle-to-grid to be successful, the owners of the electric vehicles must be involved and willing to join. As seen in the literature review, range anxiety and user involvement is still an obstacle. With this in mind, this research has introduced a restriction on the departure soc for the different cars. This is done by introducing one maximum soc for the car, equal for both the departure time and for when it is connected to the parking lot. This research has also introduced two different minimum soc for each car — one for when it is connected to the parking lot and one for when it departs. If there was one constant limit for the minimum soc for a given car, it would either be high (to meet the users need in the end) or low (to maximise profit by being more flexible). The expression for the minimum limit on the departure soc is given by equation A.12, while its maximum limit is defined by equation A.13. These expressions will ensure that a car departs with a minimum soc different from the one when it is present in the parking lot.

$$soc_{\omega,t}^{min,dep} = \begin{cases} soc_{\omega,t}^{min,dep} + soc_{n}^{min,dep,car}, & \text{if } t_{\omega,n}^{dep} = t \\ soc_{\omega,t}^{min,dep}, & \text{otherwise} \end{cases} \tag{A.12}$$

$$soc_{\omega,t}^{max,dep} = \begin{cases} soc_{\omega,t}^{max,dep} + soc_{n}^{max,dep,car}, & \text{if } t_{\omega,n}^{dep} = t \\ soc_{\omega,t}^{max,dep}, & \text{otherwise} \end{cases} \tag{A.13}$$

Constraint A.17 ensures that the departure soc is within its limits.

$$soc_{\omega,t}^{min,dep} \leq soc_{\omega,i,t}^{dep} \leq soc_{\omega,t}^{max,dep} \quad \forall \omega, \forall t, \forall i \tag{A.17}$$

In the work by Shafie-Khah et al. (2016), the requirement on the departure soc is not included. They have only one limit for the minimum and maximum soc in equation C.29. This will either, based on input data, benefit the user or the aggregator in their model. With their implementation, there will be a challenge with how they have defined their departure soc. When this thesis was working with strengthening the soc for the departed electric vehicles, the soc departure for the electric vehicles was set to 80%, and the problem ended up being impossible to solve. The model by Shafie-Khah et al. (2016) has limits on the departure soc through the definition of soc^{up} and soc^{down} in equations C.25 and C.26. If there is just a couple of cars left in the parking lot the limits on the departure soc will be put to the initial soc for these specific cars. This means that the cars cannot depart with more energy than they arrived with, because of how $soc_{\omega,t}^{Sc}$ is defined in equation C.27. Due to this, and the increased focus on the inhabitants in the neighbourhood, the mentioned changes to soc departure are introduced. In the original model, a constraint on the soc for each individual car was introduced in equation C.28. This took the soc for every car into account. The variable was never used in their optimisation, hence the constraint was not involved. It was also excluded from the proposed model due to the aggregated soc, as it is harder to have a constraint on each individual car when the soc is aggregated like it is defined.

In addition to these changes, the expressions for soc^{up} and soc^{down} is left out of the proposed model. This is done in order to meet the goal of the research. Since the goal is to maximise profit for the inhabitants, the profit stage in between the parking lot operator and the users is no longer needed. The expressions in equations C.5, C.10 and C.17 in the original model will not be included in this work. The parking fee in equation C.6 is not included in this thesis as the inhabitants are not expected to pay a fee to park at home.

Since a new requirement to the soc departure for the cars is introduced, it is also introduced in the limits for the aggregated soc. In that way, the energy is present in the parking lot that given hour. The lower limit for the parking lot soc is given in equation A.14, while the maximum limit is given in equation A.15.

$$soc^{min,agg}_{\omega,t} = \begin{cases} soc^{min,agg}_{\omega,t} + soc^{min,dep,car}_{n}, & \text{if } t^{dep}_{\omega,n} = t \\ soc^{min,agg}_{\omega,t} + \sum_{n=0}^{N} soc^{min,car}_{n} \times \delta^{Parked}_{\omega,t,n}, & \text{otherwise} \end{cases} \tag{A.14}$$

In equation A.14 and A.15 a binary parameter is introduced. This is to ensure that only the present cars in the parking lot are added to the limits on the soc. In the work by Shafie-Khah et al. (2016) these limits were only dependent on the cars, which will give the same limits on the soc for every hour. It is important that the limits are dependent on whether or not a car is present.

$$soc^{max,agg}_{\omega,t} = \sum_{n=0}^{N} soc^{max,car}_{n} \times \delta^{Parked}_{\omega,t,n} \quad \forall\omega, \forall t \tag{A.15}$$

The total soc for the parking lot is given in equation A.16, with its corresponding limits in equation A.18. The only change here from the original model is the introduction of $P^{ResAct,PL}_{\omega,i,t}$. This is introduced since the activated reserves can come from two different sources in the proposed model, the parking lot and the battery.

$$\begin{aligned} soc_{\omega,i,t} = soc_{\omega,i,t-1} + soc^{arv}_{\omega,t} - soc^{dep}_{\omega,i,t} \\ +P^{En,S2PL}_{\omega,i,t} * \eta^{charge} - \frac{(P^{En,PL2S}_{\omega,i,t} + P^{ResAct,PL}_{\omega,i,t})}{\eta^{discharge}} \quad \forall\omega, \forall i, \forall t \end{aligned} \tag{A.16}$$

$$soc^{min,agg}_{\omega,t} \leq soc_{\omega,i,t} \leq soc^{max,agg}_{\omega,t} \quad \forall\omega, \forall i, \forall t \tag{A.18}$$

Equation A.19 is changed to include the part of the activated reserves that comes from the parking lot. This constraint ensures that the energy provided from the parking lot never exceeds the energy present in the parking lot. The factor μ_t can be adjusted to be stricter in hours where the energy is needed in the system rather than sold or offered back to the external grid.

$$P_{\omega,i,t}^{En,PL2S} + P_{\omega,i,t}^{ResAct,PL} \leq \mu_t \times soc_{\omega,i,t} \quad \forall\omega, \forall i, \forall t \tag{A.19}$$

For the next two constraints, a binary variable is introduced to ensure that within an hour of operation, the energy can only flow to or from the parking lot. Since every parameter within an hour is constant, it will never be economically feasible to buy and sell within the same hour. It is mainly used so, for instance, the flow does not go to the battery from the parking lot, and from the grid to the parking lot within the same hour. The constraints A.20 and A.21 give the charge and discharge limits for the parking lot.

$$P_{\omega,i,t}^{En,S2PL} \leq (N_{\omega,t}^{PEV} \times \gamma^{charge}) \times \delta_{\omega,i,t}^{PL} \quad \forall\omega, \forall i, \forall t \tag{A.20}$$

$$P_{\omega,t}^{En,PL2S} + P_{\omega,t}^{ResAct,PL} \leq (N_{\omega,t}^{PEV} \times \gamma^{discharge}) \times (1 - \delta_{\omega,i,t}^{PL}) \quad \forall\omega, \forall i, \forall t \tag{A.21}$$

The degradation cost for the batteries in the cars is given by equation A.22. This is adjusted so the cost for degrading is equal for charging and discharging the electric vehicles. The reason for this change was not not favour charging nor discharging.

$$Cost_{\omega,t,i}^{Deg,En,PL} = P_{\omega,t,i}^{En,PL2S} \times Cd + P_{\omega,i,t}^{En,S2PL} \times Cd \tag{A.22}$$

For the second step of the optimisation, flexibility on the soc departure is added. This will be used to figure out how flexible the users are and how much they might be willing to pay for this flexibility. This flexibility will be used to cope with the deviation when the reserves are activated in step two. This flexibility could both give a higher and a lower departure soc. The updated constraint on the soc departure is given in equation A.24 with a corresponding expression for the cost in equation A.23. The constraint for $soc^{Min,flex}$ and $soc^{Max,flex}$ is given by equation A.25 and A.26. β^{Flex} gives the percentage on how much reduction the model should allow.

$$soc^{min,dep}_{\omega,t} - soc^{Min,Flex}_{\omega,i,t} \leq soc^{dep}_{\omega,i,t} \leq soc^{max,dep}_{\omega,t} + soc^{Max,Flex}_{\omega,i,t} \quad \forall\omega, \forall t, \forall i \quad \text{(A.24)}$$

$$Cost^{SOC,flex}_{\omega,i,t} = (soc^{Min,Flex}_{\omega,i,t} + soc^{Max,Flex}_{\omega,i,t}) \times soc^{Pen,Fee} \quad \text{(A.23)}$$

$$soc^{Min,Flex}_{\omega,i,t} \leq \beta^{Flex} \times soc^{min,dep}_{\omega,t} \quad \forall\omega, \forall i, \forall t \quad \text{(A.25)}$$

$$soc^{Max,Flex}_{\omega,i,t} \leq \beta^{Flex} \times soc^{max,dep}_{\omega,t} \quad \forall\omega, \forall i, \forall t \quad \text{(A.26)}$$

Since the soc departure requirement is added to the aggregated soc for the parking lot in equation A.14, the flexibility must also be added to the aggregated soc constraint. This is shown in equation A.27.

$$soc^{min,agg}_{\omega,t} - soc^{Min,Flex}_{\omega,i,t} \leq soc_{\omega,i,t} \leq soc^{max,agg}_{\omega,t} + soc^{Max,Flex}_{\omega,i,t} \quad \forall\omega, \forall i, \forall t \quad \text{(A.27)}$$

4.2.6 External battery

With an external battery, the system has a chance to store energy based on the changing prices in the system and the tariffs. With this flexibility, profit maximisation is more suited. As well as this, the battery gives flexibility when it comes to CO_2-emission. The CO_2-footprint for electricity will depend on the energy source, and it has become easier to estimate the sources based on the flows within the transmission grid. Based on this, the system can export energy in the hours where the CO_2-footprint is high, and import in the hours where it is low.

As for the parking lot, the soc for the external battery connected to the system must be within a lower and higher limit. This restriction is given by equation A.29.

$$soc^{min,bat} \leq soc^{Battery}_{\omega,i,t} \leq soc^{max,bat} \quad \forall \omega, \forall i, \forall t \tag{A.29}$$

Soc for the battery is defined in the same way as for the parking lot to be consistent. $P^{ResAct,B}_{\omega,i,t}$ will be the amount of activated reserves from the external battery.

$$\begin{aligned} soc^{Battery}_{\omega,i,t} &= soc^{Battery}_{\omega,i,t-1} + P^{En,S2B}_{\omega,i,t} \times \eta^{converter} \\ &\quad - \frac{P^{En,B2S}_{\omega,i,t} + P^{ResAct,B}_{\omega,i,t}}{\eta^{converter}} \quad \forall \omega, \forall i, \forall t \end{aligned} \tag{A.28}$$

There is also a charge and discharge limit on the battery. This is taken care of by equation A.30 and A.31. Also notice $\delta^{Battery}_{\omega,i,t}$ which is a binary variable. This will make sure, as for the parking lot, that the energy only flows in one direction within an hour.

$$P^{En,B2S}_{\omega,i,t} + P^{ResAct,B}_{\omega,i,t} \leq \gamma^{Charge,B} \times \delta^{Battery}_{\omega,i,t} \quad \forall \omega, \forall i, \forall t \tag{A.30}$$

$$P^{En,S2B}_{\omega,i,t} \leq \gamma^{Discharge,B} \times (1 - \delta^{Battery}_{\omega,i,t}) \quad \forall \omega, \forall i, \forall t \tag{A.31}$$

As for the parking lot there is a limit of how much energy can be provided to the grid for certain hours. This is regulated by the parameter μ_t and equation A.32.

$$P^{En,B2S}_{\omega,i,t} + P^{ResAct,B}_{\omega,i,t} \leq soc^{Battery}_{\omega,i,t} \times \mu_t \quad \forall \omega, \forall i, \forall t \tag{A.32}$$

Equation A.34 gives the degradation cost for the battery. It is designed in the same way as the degradation cost for the parking lot, with the degradation charged both ways.

$$Cost^{Deg,En,B}_{\omega,t,i} = P^{En,B2S}_{\omega,t,i} \times Cd + P^{En,S2B}_{\omega,i,t} \times Cd \tag{A.34}$$

In the end of the analysis it is given that the soc for the battery should be the same as the soc it started with. This is defined in equation A.33. The reason for this is to not give the model any incentives to speculate on the prices in the hours after the end of the optimisation.

$$soc_{\omega,i,t=end}^{Battery} = soc^{start,battery} \quad \forall\omega, \forall i \tag{A.33}$$

4.2.7 Solar power

Solar power gives a unique opportunity to be partly self-sustained with renewable energy. To meet the emission requirement for a Zero Emission Neighbourhood, and to be a prosumer, solar panels are added to the system. The energy produced from the solar panels will be emission-free during operation and can replace non-renewable energy sources in the grid. The proposed model assumes the solar panels to be emission-free as the cost of CO_2 of installing is only considered during installation and not during operation. It is assumed one solar panel for each parking lot. This could be a roof over the parking spot or on houses. As mentioned earlier, it is not necessary to have these components physically beside each other as long as they are connected technically.

Equation A.35 gives the power injected into the system. It is assumed that the lines and converters are able to handle the energy injected by the panels into the system.

$$P_t^{PV2S} = P_t^{Sun,Rad} \times \eta^{Solar} \times \eta^{Converter,solar} \times Areasolar \quad \forall t \tag{A.35}$$

4.2.8 CO_2-emission

As stated earlier a Zero Emission Neighbourhood should strive towards no emission of CO_2. The proposed model considers a zero emission goal over the whole period of the analysis. Equation A.36 makes sure that the system, over the time equal to the set *T*, use equal or more CO_2-neutral energy than CO_2-emitting energy. If the system cannot meet this requirement there will be a penalty, $Pen_{\omega,i}^{\mathrm{CO_2}}$.

$$\sum_{t=0}^{T} m_t^{\mathrm{CO_2}} \times P_{\omega,i,t}^{En,S2G} + Pen_{\omega,i}^{\mathrm{CO_2}} \geq \sum_{t=0}^{T} m_t^{\mathrm{CO_2}} \times P_{\omega,i,t}^{En,G2S} \quad \forall\omega, \forall i \tag{A.36}$$

The income and cost from equation A.36 are defined in equation A.38 and A.37. The last expression, equation A.39, gives the cost of the penalty if the CO_2-emission ends up in imbalance. The cost of CO_2 is given as λ^{CO_2}. As there is no system for smaller consumers for CO_2-penalty the penalty is an internal penalty for the neighbourhood. Another interesting factor with the emission is the term $m_t^{CO_2}$ which gives the mass of CO_2-particles released per produced unit of energy. This will vary based on how the energy is produced, and the location of consumption. This value will define the CO_2-footprint of the energy consumed.

$$Cost_{\omega,i,t}^{CO_2} = \lambda^{CO_2} \times m_t^{CO_2} \times P_{\omega,i,t}^{En,G2S} \tag{A.38}$$

$$Income_{\omega,i,t}^{CO_2} = \lambda^{CO_2} \times m_t^{CO_2} \times P_{\omega,i,t}^{En,S2G} \tag{A.37}$$

$$Cost_{\omega,i}^{Pen,CO_2} = Pen_{\omega,i}^{CO_2} \times \lambda^{Pen,CO_2} \tag{A.39}$$

4.2.9 Connection point

In Shafie-Khah et al. (2016) they had only one component connected to the connection point and the grid, the parking lot. In this analysis, there are three different components connected to the connection point, a parking lot, an external battery and solar panels. Because of this change, there is a need for individual expressions for the power flow to and from the main grid. The flows and the connection point are shown in figure 4.1. An energy balance for the node where all the energy flows meet is needed to have balance within the system. This energy balance is presented in equation A.45. Based on this, the flows to and from the grid can be determined.

$$\begin{aligned} P_{\omega,i,t}^{En,PL2S} + P_{\omega,i,t}^{En,G2S} + P_{\omega,i,t}^{En,B2S} + P_t^{En,PV2S} = \\ P_{\omega,i,t}^{En,S2G} + P_{\omega,i,t}^{En,S2PL} + P_{\omega,i,t}^{En,G2S} \quad \forall\omega, \forall i, \forall t \end{aligned} \tag{A.45}$$

The capacity limits for the grid are shown in equation A.43 and A.44. As for the parking lot and the battery, a binary variable is introduced, $\delta_{\omega,i,t}^{System}$. This is to ensure that the power only flows in one direction in a given hour. It is also especially important for the flow between the grid and the system as $P^{En,G2S}_{\omega,i,t}$ and the direction of the flow will be fixed in step two of the optimisation. The binary variables for the parking lot and the battery do not need to be fixed in step two as the model is free to do whatever it wants within its system as long as the promises made to the grid operator and the power supplier are fulfilled.

$$P^{En,G2S}_{\omega,i,t} \leq \gamma^{Capacity,grid} \times \delta^{System}_{\omega,i,t} \quad \forall\omega, \forall i, \forall t \tag{A.43}$$

$$P^{En,S2G}_{\omega,i,t} \leq \gamma^{Capacity,grid} \times (1 - \delta^{System}_{\omega,i,t}) \quad \forall\omega, \forall i, \forall t \tag{A.44}$$

Equation A.50 will give the income from what is flowing from the system to the main grid. The costs for the case where energy flows from the grid to the system are given by equation A.51.

$$Income^{S2G}_{\omega,t,i} = P^{En,S2G}_{\omega,t,i} \times \lambda^{Energy,loss}_{t} \tag{A.50}$$

$$Cost^{G2S}_{\omega,t,i} = P^{En,G2S}_{\omega,t,i} \times \lambda^{En,tariff}_{t,i} \tag{A.51}$$

To be able to compare the different demand response programs the daily cost for the fixed yearly fee in the tariff is added for all the programs.

$$Cost^{Fixed,tariff}_{i} = YearlyFee_i \tag{A.52}$$

Equation A.40 gives the difference in an hour in the energy drawn from the grid before and after an incentive-based program. As seen from figure 4.1 the energy drawn from the grid is now $P^{En,G2S}_{\omega,i,t}$. The term $P^{Ini}_{omega,t}$ gives the energy drawn for the fixed-rate tariff, when no incentives are used.

$$\Delta P^{En,G2S}_{\omega,i,t} = P^{G2S}_{\omega,i,t} - P^{Ini}_{omega,t} \quad \forall\omega, \forall t, \forall i \tag{A.40}$$

The income and cost for an incentive-based program is given by equations A.53 and A.54. For the penalty the term P^{Cont} is the contracted level for reduction for that given incentive program.

$$Income^{Inc}_{\omega,t,i} = Inc_{t,i} \times \Delta P^{En,G2S}_{\omega,t,i} \tag{A.53}$$

$$Cost^{Pen}_{\omega,t,i} = Pen_{t,i}(P^{Cont}_{t,i} - \Delta P^{En,G2S}_{\omega,t,i}) \tag{A.54}$$

For the second step of the optimisation, some of the equations will change due to the activated reserves from the system operator. The variable $P^{En,S2G}_{\omega,i,t}$ will change in step two as the activated reserves are provided to the grid. However, $P^{En,S2G}_{\omega,i,t}$ still needs to meet the promised energy flows from step one and the day-ahead market. Hence a parameter named $P^{En,S2G,Fixed}_{\omega,i,t}$ is introduced. This parameter is equal to the results from $P^{En,S2G}_{\omega,i,t}$ in step one. The interaction with the grid will also be limited to only be the activated reserves subtracted the reserves the system cannot provide, $P^{Res,Art,Less}_{\omega,i,t}$, seen in equation A.60. In this way, it is not possible to sell or buy more energy in step two. This also changes the calculation of the income from the interaction with the grid. Since no more interaction is allowed, the equation will turn out being a parameter according to equation A.55 in the second step.

$$\begin{gathered} P^{En,S2G,Fixed}_{\omega,i,t} \times (1 - \delta^{System}_{\omega,i,t}) \leq P^{En,S2G}_{\omega,i,t} \leq \\ (P^{En,S2G,Fixed}_{\omega,i,t} + P^{Res,Act}_{\omega,i,t} - P^{Res,Art,Less}_{\omega,i,t}) \times (1 - \delta^{System}_{\omega,i,t}) \quad \forall\omega, \forall i, \forall t \end{gathered} \tag{A.60}$$

$$Income^{S2G}_{\omega,t,i} = P^{En,S2G,Fixed}_{\omega,t,i} \times \lambda^{Energy,loss}_{t} \tag{A.55}$$

Offered and activated reserves

The only flexibility this system can provide to the system operator is exporting energy back into the grid.

The three first constraints, constraints A.46, A.47 and A.48 are added to find how much energy the system can offer to the system operator as reserves. It is important to check for the energy limit, as the system cannot provide more energy in an hour than it has available. It is also important to check for the capacity limit for the system. It should not be possible to offer more capacity to the grid than what it has available within an hour. Hence, $P^{Res}_{\omega,i,t}$ will be less than or equal to the smallest value of these three constraints. This will also increase the probability of offering realistic reserves to the system operator. As seen from the model developed, it does not have any incentives to offer less than maximum, given no assumed activation in step one. The energy constraint is the energy available subtracted the energy that cannot be used, which means the minimum requirement. The two capacity constraints, in equations A.47 and A.48, give the capacity constraint in the chargers for the battery and the parking lot as well as the limit for interacting with the external grid. These kinds of constraints were not present in the work done by Shafie-Khah et al. (2016).

$$P^{Res}_{\omega,i,t} \leq soc_{\omega,i,t} + soc^{Battery}_{\omega,i,t} - soc^{min,agg}_{\omega,t} - soc^{min,bat} \quad \forall \omega, \forall t, \forall i \tag{A.46}$$

$$\begin{aligned} P^{Res}_{\omega,i,t} \leq N^{PEV}_{\omega,t} * \gamma^{Discharge} + \gamma^{Discharge,B} \\ -P^{En,PL2S}_{\omega,i,t} - P^{En,B2S}_{\omega,i,t} \quad \forall \omega, \forall t, \forall i \end{aligned} \tag{A.47}$$

$$P^{Res}_{\omega,i,t} \leq \gamma^{Capacity,grid} \times (1 - \delta^{System}_{\omega,i,t}) \quad \forall \omega, \forall t, \forall i \tag{A.48}$$

The system operator compensates the reserves offered in the system according to equation A.49. Equation A.42 gives the assumed activated reserves from the parking lot and the battery in step one.

$$Income^{Cap,Res}_{\omega,t,i} = P^{Res}_{\omega,t,i} \times \lambda^{Cap}_{t} \tag{A.49}$$

$$P^{Res,Act}_{\omega,i,t} = P^{ResAct,PL}_{\omega,i,t} + P^{ResAct,B}_{\omega,i,t} \quad \forall \omega, \forall t, \forall i \tag{A.42}$$

$P_{\omega,i,t}^{Res,Act}$ is included in several equations in step one in the model. The challenge with an implementation like this is that the model will optimise with the activated reserves equal to zero. Based on how the offered reserves are defined in the model, it will always maximise the offer to the grid, given no assumed activation in the first step. In the second step of the optimisation, there is no capacity for the activated reserves as several variables are changed into parameters in this step, and the room for a changes in the system is limited. The model will, therefore, check for what will happen if some of the offered capacity is assumed to be activated in step one. This assumption is shown in equation A.41.

$$P_{\omega,i,t}^{Res,Act} = P_{\omega,i,t}^{Res} \times \alpha^{First} \quad \forall\omega, \forall t, \forall i \tag{A.41}$$

Out of the offered reserves in the first step, the system operator can activate the offered reserves in the hour of operation or step two of the optimisation. The reserves are once again compensated as the system provides the system operator with actual capacity. This compensation is defined by equation A.56. The term $P_{\omega,t,i}^{Res,Act,Paid}$ gives how much the system has provided to the grid, and is defined according to expression A.65. It is important to distinguish between what is activated and what the system actually provides as the system can take a penalty through the artificial reserves. As a consequence of activated energy, there will be an increase in degradation according to equation A.57.

$$Income_{\omega,t,i}^{Res,Act} = P_{\omega,t,i}^{Res,Act,Paid} \times \lambda_t^{Energy,loss} \tag{A.56}$$

$$P_{\omega,i,t}^{Res,Act,Paid} = P_{\omega,i,t}^{ResAct,B} + P_{\omega,i,t}^{ResAct,PL} \quad \forall\omega, \forall i, \forall t \tag{A.65}$$

$$Cost_{\omega,t,i}^{Deg,Res} = P_{\omega,t,i}^{Res,Act,Paid} \times Cd \tag{A.57}$$

The actual activated energy in step two is given by equation A.61. The percentage,

α^{Second}, gives the amount of activation done by the system operator.

$$P_{\omega,i,t}^{Res,Act} = P_{\omega,i,t}^{Res} \times \alpha^{Second} \quad \forall\omega, \forall i, \forall t \tag{A.61}$$

Equation A.64 defines the energy balance for the activated reserves in step two. To get the balance in the activation correct, the expression contains the actual activated reserves and the artificial reserves. The artificial reserves are the reserves that the system is not able to provide to the system operator in step two. If there is not enough energy in the system in step two, $P_{\omega,i,t}^{Res,Art,Less}$ will be activated. If there is too much assumed activated reserves from step one, $P_{\omega,i,t}^{Res,Art,More}$ will compensate for that energy.

$$\begin{aligned} P_{\omega,i,t}^{Res,Act} &= \\ P_{\omega,i,t}^{ResAct,B} + P_{\omega,i,t}^{ResAct,PL} + P_{\omega,i,t}^{Res,Art,More} + P_{\omega,i,t}^{Res,Art,Less} & \quad \forall\omega, \forall i, \forall t \end{aligned} \tag{A.64}$$

The combined artificial energy for not meeting the activated reserves from both the parking lot and the battery is given in equations A.62 and A.63.

$$P_{\omega,i,t}^{Res,Art,More} = P_{\omega,i,t}^{Res,Art,B,More} + P_{\omega,i,t}^{Res,Art,PL,More} \quad \forall\omega, \forall i, \forall t \tag{A.62}$$

$$P_{\omega,i,t}^{Res,Art,Less} = P_{\omega,i,t}^{Res,Art,B,Less} + P_{\omega,i,t}^{Res,Art,PL,Less} \quad \forall\omega, \forall i, \forall t \tag{A.63}$$

The cost of not meeting the activated capacity is defined in equation A.58 and A.59.

$$Cost_{\omega,i,t}^{Res,Art,More} = P_{\omega,i,t}^{Res,Art,More} \times \lambda_t^{Cap} \tag{A.58}$$

$$Cost_{\omega,i,t}^{Res,Art,Less} = P_{\omega,i,t}^{Res,Art,Less} \times \lambda_t^{Cap} \tag{A.59}$$

The cost of being unavailable from the original model given in equation C.16 is left out of the proposed model. This equation was interpreted as being included in case of a failure. As this is hypothetical and difficult to simulate throughout 24-hours it was taken out. Instead, the cost of not being able to deliver the reserves offered was introduced. This will take care of the inability of the parking lot to meet the system operator's demand due to physical restrictions in the system.

Chapter 5

Case study

The primary goal for this thesis is to come up with a model that minimise the CO_2-emissions from a parking lot within a Zero Emission Neighbourhood consisting of houses and at the same time, maximise profit for its users. In order to fulfil these goals, an external battery and solar panels are introduced in the model. In order to check whether these goals are met, a case study is created. This chapter will give an introduction to the case used in this thesis. The model from chapter 4 will be used for the simulations, while the results will be presented in chapter 6.

Figure 3.3 from chapter 3 shows the different approaches for optimisation of a system with vehicle-to-grid. If this research was to be connected to this figure, the type of vehicle-to-grid would be bidirectional as the model allows the energy to flow both ways. The main services provided would be renewable energy support through the solar panels and grid regulation through balancing markets. As stated earlier, the optimisation objects are revenue maximisation and emission minimisation. As seen in chapter 4, most of the mentioned constraints in the figure are involved in the analysis. These problems are complex, and many different views must be taken into account, and that is also why the different optimisation objects in the figure have several constraints connected to them. This is also the case for the research conducted in this paper.

This neighbourhood will consist of 30 electric vehicles. It is assumed that all the cars arrive in the afternoon and all of them leave in the morning. With this assumption, there will not be cars present between 11:00 and 13:00. In order to get a better understanding of how the proposed system looks, figure 4.1 shows the different components and how they are connected. The simulations will be conducted with ten different scenarios with an equal probability of 10% to happen. This means every car will have ten different initial soc, departure time and arriving time as these are the uncertain parameters in this research.

5.1 Demand response programs

In this case study, three different demand response programs will be tested. Fixed-rate tariff (FR) is included since the FR tariff does not give any economic incentives throughout the period and by that reason easy to compare to other programs. The next program is time-of-use (TOU). This program has been mentioned by several actors in NVEs hearing as the preferred model, as it is easy to understand for the end-user, which means it is easy to react on this model and adjust consumption. Critical-peak-price is a special case of time of use, hence the effect of the program will be somewhat the same as for time of use, and will therefore not be tested in this case study. Out of the two incentive-based programs in this study, the Interruptible/Curtailable program(I/C) will be tested. This program is a better fit for the system than, for instance, the Emergency demand response. Then an emergency response program will force the user to cut its use, while in the I/C program, the user will have the possibility to rather take the penalty. For this reason, the I/C program will be more suited for less flexible systems, like a neighbourhood.

5.2 Input data

In order to reach the overall goal with the research, the correct input data is crucial. The input data used to conduct the analysis are listed in Appendix B. In order to be regarded as a prosumer the limit on the interaction with the grid is set to 100kW. With 30 houses aggregated this limit is quite low, which could be a disadvantage with regarding the houses as one generation unit. The minimum soc for the electric vehicles' when the vehicles are connected to the parking lot is set to 30%, while the maximum limit for the soc is 90% both when it is connected to the parking lot and when it leaves.

5.2.1 Energy prices

The price of energy used is collected from Nordpools system price from the 19th of March 2019. The same date is used for the price in the reserve market, these are gathered from Statnett, the Norwegian system operator and responsible for this market. The prices in table B.3 gives the tariff for each demand response program. They are either gathered from NVE or Shafie-Khah et al. (2016). To compare the different programs and prices, the ratio between the fixed-rate tariff from these sources is found and used to adjust the other programs. The numbers in the table are only the grid tariff; this means without the system price.

5.2.2 Parameters regarding CO_2

CO_2-emissions from the production of energy will vary based on the source used to produce the electricity. This is also why these values deviate a lot within Europe and the rest of the world. In this case study CO_2-footprint from the NO2 market area in Norway and the mean value in Europe will be used. These values are given in table B.8 in Appendix B.

5.2.3 Solar power

Solar radiation for the system is gathered from the 29th of March 2019 from the eastern part of Norway. The reason for the difference between the date for the system prices and the date for the solar radiation is due to good data for solar radiation and prices these days. Since it is just ten days in between it is likely that this could have happened on the same day. The total area of the solar panels was decided by the size of a regular parking lot, and then the area was multiplied by the number of parking lots in the case, ending up at 345 m^2. The panels are assumed to point in the same direction, and has the same efficiency throughout the whole period.

5.3 Python

Python is an open-source programming language founded back in 1991 (Python (2019)). This language is rather easy to use, and through broad communities and forums online, it is easy to get help when needed. There is also a range of packages connected to Python which makes the language versatile. One of the packages used in this thesis is Pyomo. Pyomo is also an open-source code which will allow developing models for optimisation (Pyomo (2019)). It will set up the problem, solve it and analyse it for the user. The solver used to solve the Pyomo-problem is called Gurobi. Gurobi is a licensed solver which can solve different optimisation models (Gurobi (2019)).

5.4 Simulations

The simulations conducted in this thesis will be divided into three steps. First, the original model from Shafie-Khah et al. (2016) will be tested with the changes described in chapter 4. Then the different demand response programs will be simulated with the proposed model, with solar power, external battery and CO_2-minimisation. In the end, a sensitivity analysis will be conducted for certain parameters. The results and discussion from these different simulations will be presented in chapter 6.

5.4.1 Original model

In this simulation, the solar panels and the external battery will be taken out of the model. Also, the minimisation of CO_2-emissions will not be included in the objective function for this part. In this simulation, the time will start at 00:00 and end at 23:59. The assumed activated reserves in step one of the optimisation will be equal to zero, while the actual activated reserves in step two will be equal to 50% of the offered reserves from step one. For this simulation, the departure soc will be fixed at 80%, but it will be flexible. Due to the mentioned change from a two stage model to a two step model, the result and the optimisation will be different from the work done by Shafie-Khah et al. (2016).

5.4.2 Proposed model

When considering the proposed model, solar panels, external battery and CO_2- minimisation are included in the model. In this part, the time will run from 12:00 and end at 11:59. The simulations will have no assumed activation from the first step. In step two, the activated reserves will be equal to 50% of the offered reserves from step one. The results will be divided into the two steps of the simulation in order to get the difference between the decisions at different steps. For this part of the simulation, the departure soc will be fixed at 80%, and the CO_2-footprint will be fixed at NO2-values. The model will be flexible on the soc departure in this analysis.

5.4.3 Sensitivity analysis

In order to understand how the model behaves, and to understand how sensitive the model is to changes, a sensitivity analysis will be conducted. To check this, the TOU demand response program has been chosen.

Reserves and SOC departure

As described in the model description, the optimisation can be conducted with assumed activated reserves and actual activated reserves. In this part, the assumed activated reserves in step one would be tested against actual activation in step two. The assumed reserves will be tested for 0% and 100%. The steps used for the actual reserves activated will be 0%, 50% and 100%. The goal for this analysis is to check if allocating an artificial value in step one will reduce the costs in step two, and how much the assumed reserves will influence the outcome of the analysis.

An important contribution to the model and the work in this field is the introduction of the different soc departures for the electric vehicles. To check how sensitive the departure soc is, and hence how much the parking lot is willing to pay for flexibility on the soc departure, the departure soc is adjusted. The soc will be tested for 90%, 80% and 70%. This test will be conducted together with the reserves in the model. The test will also run for flexible soc departure and non-flexible soc departure. This means with and without equation A.24 from chapter 4. In this case, the soc departure is allowed to be anywhere between $50-100\%$. This means that when soc departure is given to be 90%, it can increase by 10% and decrease with 40%. This is done to see whether the model uses the flexibility or not, and how much it is worth. The cost for the flexibility is put to a negligible penalty price.

CO_2-minimisation

In order to understand how sensitive the system is to signals in terms of CO_2-emissions, the analysis will be tested for the two different emission footprints mentioned, mean EU and NO2. This will be done in order to compare the difference in CO_2-emissions between high and low CO_2-footprints in the electricity-mix.

In addition to changing the CO_2-footprints, the price for emitting CO_2 will be increased from 30 to 100 €/ton. The penalty will be increased by the same amount, to 101 €/ton. The CO_2-footprints used will be the ones from the EU. As the prices and fees for emitting greenhouse gases are likely to increase over the coming years, due to fewer quotas each year, it is essential to see how sensitive the model is to an increase.

These two tests will be conducted with a flexible system for the soc departure, and for soc departure values at 90%, 80% and 70%. The results will be gathered from the first step of the optimisation with an assumed reserves activation of 0%.

Chapter 6

Results

This chapter will present and discuss the main results and graphs from the optimisation of the original and proposed models. The case study used in this analysis is explained in detail in chapter 5 and the model used is described in chapter 4. As stated earlier, the term system refers to the connection point seen in figure 4.1.

6.1 Original model

This section presents the results obtained from the optimisation done without solar power, external battery and CO_2-minimisation. It is carried out in the same way as Shafie-Khah et al. (2016), but with the explained changes in the model.

Table 6.1 gives the results for the different demand response programs for the original model. The results from step one are the here-and-now step of the optimisation and in step two the wait-and-see is represented. Step two will be the final result for the users. The system operator penalty (SO penalty) gives the penalty paid to the system operator due to inability to deliver the offered reserves. The soc flex gives the final mean soc departure for the cars due to flexibility. If there is a negative result it means a cost for the end-users, while a positive result means profit.

	FR	TOU	I/C
1.step result[€/day]	-27.08	-32.66	-26.81
2.step result[€/day]	-5.11	-11.64	-5.37
SO penalty [€/day]	0.60	0.56	0.57
soc flex [%]	54.48	56.00	54.34

Table 6.1: Results from the original model with bidirectional charging of EV

6.2 Proposed model

This section presents the results from the proposed model with bidirectional charging of electric vehicles, an external battery, solar panels and CO_2-minimisation. If the flow is negative in the interaction with the grid, it means the energy is flowing into the system, while for the parking lot, it means it is flowing into the parking lot.

In this section, only the first step of the optimisation is presented in figures, which means the here-and-now decisions in the day-ahead market. In this part the assumed activated reserves are equal to zero, while the actual activation in step two is equal to 50%. Table 6.2 gives the result for each demand response program as well as the penalty paid due to CO_2-emissions. As for the original model, the SO penalty is the penalty paid to the system operator if the model is unable to deliver on the offered reserves. The flexible soc is the final value for the departure soc. If there is a negative result it means a cost for the end-users, while a positive result means profit.

	FR	TOU	I/C
1.step result[€/day]	-13.25	-12.04	-13.12
2.step result[€/day]	11.78	12.93	11.82
CO_2-penalty [€/day]	0.23	0.40	0.18
SO penalty [€/day]	0.92	0.87	0.93
soc flex [%]	50.76	50.76	50.76

Table 6.2: Results from the proposed model with bidirectional charging of EV, PV, battery and CO_2-minimisation

Discussion

The first results obtained in the simulation came from the original model based on the work by Shafie-Khah et al. (2016) with the proposed changes. It is not expedient to compare the results obtained in their paper and the results from the original model in this thesis. The reason for this is the number of changes proposed to their model. It is also difficult to compare the results when there are different input parameters. Another factor is that they had a two-stage stochastic model while this paper proposes a two-step stochastic model as explained.

The results obtained from the original model in chapter 6.1 from this thesis is good to compare with the results obtained from the proposed model. By doing this, it is possible to find a value for the solar panels, the battery and CO_2-minimisation. As seen from table 6.1 and 6.2 there is a difference between the tariffs in the original model and the tariffs in the proposed model. It is also worth mentioning again that the reason for a larger profit in step two of the optimisation is due to the flexible soc departure in step two. Both of the models get better results from the second step compared to the first step. All the tariffs in the proposed model make money in the end, while the tariffs in the original lose less in the second step compared to the first. An interesting observation is that the FR tariff is the preferred tariff in the original model, while TOU is the preferred in the proposed. An important factor is that in the original model, the sources of flexibility are limited, and all the energy must be imported from the grid, while for the proposed model there is flexibility through an external battery and ”free” energy through solar panels. Due to less flexibility, high soc departure at 80% and no on-site generation, the original model is forced to import energy in the hours where the price signals gives incentives of no import. Hence, the best solution for the original model would be a FR tariff, where no hours are more expensive than others.

A goal for this master thesis is to make use of different demand response programs in order to maximise profit. From table 6.2, it can be seen that the largest difference in profit is between TOU and the FR. The difference is 1.15€/day, which is quite small when there should be incentives to adjust and shift the import and export based on price signals. This result shows that the incentive the end-user has based on different tariffs is small.

Both of the models and the results show that the flexibility in soc departure is used. For the proposed model, it is almost fully utilised as the limit is 50%. For the original model, it has some left before it is fully utilised. Here, another constraint is most likely binding before it can make full use of that flexibility. Even though the proposed model makes more out of the flexibility on soc departure, it ends up with a higher price paid to the system operator in penalty than the original model. This is due to the offered reserves being higher in the proposed model as the battery is added.

For FR tariff and I/C, the differences are quite small. This is either because it is a small or no import in those hours where there are incentives or the model is not able to adjust the import in these hours. The tariff is equal for the FR tariff and the I/C tariff as there are no price-signals through the I/C tariff.

The proposed model shows that with a TOU tariff the value of having an external battery and solar panels while minimising CO_2-emissions is 24.57€/day. This is a relatively significant difference over a year, but it is crucial to notice that the radiation from the sun will vary over a year. The solar power could explain the difference between these two models as it is ”free” energy where the system neither pays for the energy nor the tariffs.

6.2.1 Net interaction between system and the grid

In this section, the net interaction with the grid and the system is shown for the different demand response programs.

Fixed-rate tariff

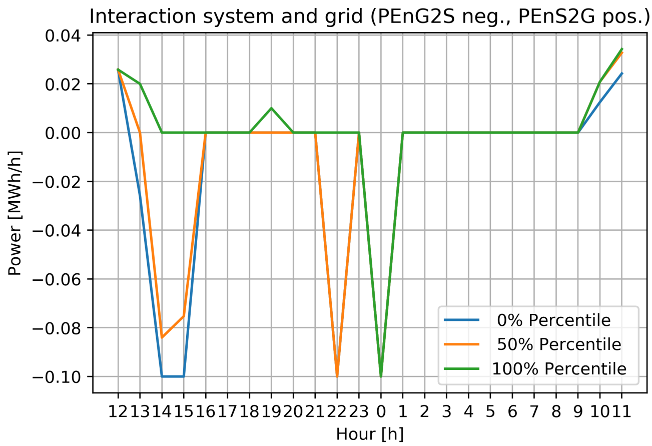

Figure 6.1: Grid interaction with optimisation of FR

Time-of-use tariff

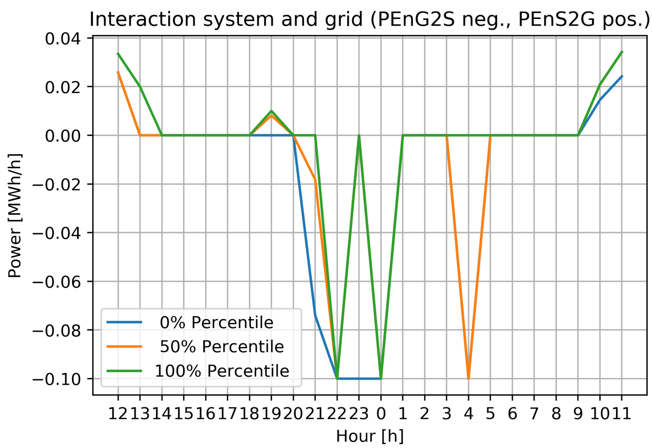

Figure 6.2: Grid interaction with optimisation of TOU

Interruptible/Curtailable tariff

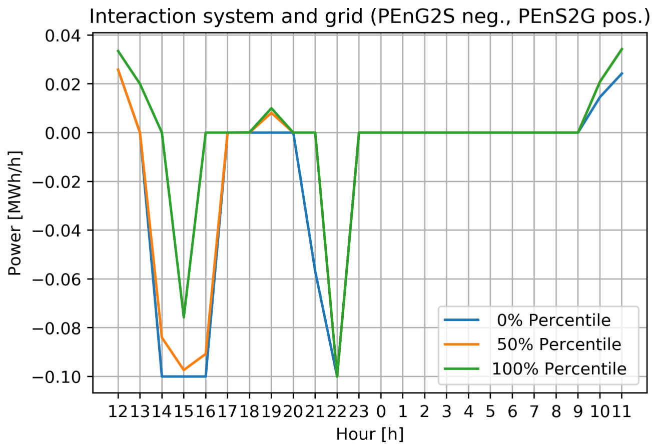

Figure 6.3: Grid interaction with optimisation of I/C

Discussion

To understand the differences in the programs, and understand how they work, it is necessary to dig into the numbers behind the results. Figure 6.1 shows the interaction with the grid for the FR tariff. This shows import of power in hours with low prices and export in hours with higher prices based on the prices from figure B.1. Figure 6.1 also gives information about the different percentiles in the results. Because the proposed model has ten different scenarios with different outcomes percentiles are used to see the gaps between the different scenarios. There are three lines, the 0%, 50% and 100% percentile. These show the minimum, mean and maximum results from the analysis. The results from the I/C incentive-based program in figure 6.3 are somewhat similar to the results from the FR. In this research, the interaction with the grid for the base load (the same as FR tariff from figure 6.1) is low, i.e. there is not much to reduce. Another possibility could be that the incentives are not utilised as they are equal over such a long period. It is an incentive to adjust the base load from 08:00 until 00:00. If the span is too broad, it loses the incentives as the model must interact with the grid within those hours. The interaction with the grid for TOU is presented in figure 6.2. For the TOU, the interaction from the hours between

13:00 until 16:00 is shifted to the night compared to FR and I/C. This is due to the price signal given with a higher tariff in these hours. TOU also exports energy in the same hours as the other programs. Although TOU shifts its usage to the night, the same problem as with the incentive-based program can come up in TOU. The increased tariff lasts for 13 hours, and there is a price signal throughout the whole day to reduce load. The challenge with structuring these programs in this way is that one loses the incentive within an hour or between consecutive hours in order to be flexible. An office building, factory or a storage facility are all examples of consumers that can be flexible within these hours, but not always by shifting 12 hours at a time. Also, regular customers will lose some incentives as charging electric vehicles and cooking is not always possible to move many hours.

Another aspect that is worth discussing is the small interaction with the grid. The difference in price between two hours is small when it comes to the demand response programs. There are some tops in the system price that all the programs make use of. In order to make it beneficial to export and import between hours, the profit must be higher than the internal costs like degradation and loss in converters. The users must also pay a higher price for importing compared to the income with exporting due to the tariffs only being charged one way. When exporting energy, the marginal loss of energy will be paid back and should be included in the cost analysis. The program should be designed so that shifting its consumption from critical periods for the system operator to less critical periods is profitable. There should also be fewer hours with price signals. NVE has also proposed a new tariff called subscribed tariff. This will give a price signal every hour as the customer will have a subscribed limit on the capacity, and has an incentive to keep under this limit. As explained earlier, this program can be hard to understand as it is profitable to use more than the subscribed limit in certain hours. Subscribed capacity will give better incentives throughout the day for reducing consumption. This will also better reflect the actual costs in the grid as the grid is designed to handle the highest maximum peak on capacity. TOU is an energy-based tariff which will charge energy rather than capacity, and hence not take into account equipment that uses much capacity which will force the grid operator to build more grid.

It is also interesting to see how solar power is used internally rather than externally. In the first hours the solar power is exported as there are no cars present, while throughout the day the power is used internally rather than externally. This is because it is not profitable to sell the energy needed and then repurchase it with grid tariffs at a later stage. This is also in line with NVEs definition of a prosumer. They say it is a customer that produces energy and in some hours export the surplus energy to the grid.

6.2.2 Net interaction with the system and the parking lot

Figure 6.4, 6.5 and 6.6 shows the interaction with the system and the parking lot in the analysis.

Fixed-rate tariff

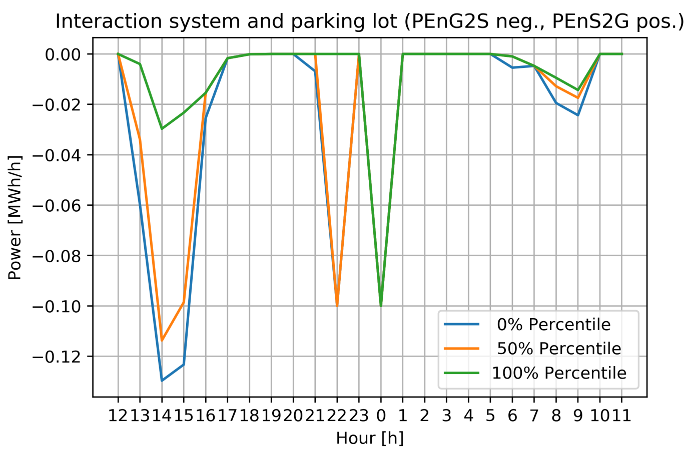

Figure 6.4: Parking lot interaction with optimisation of FR

Time-of-use tariff

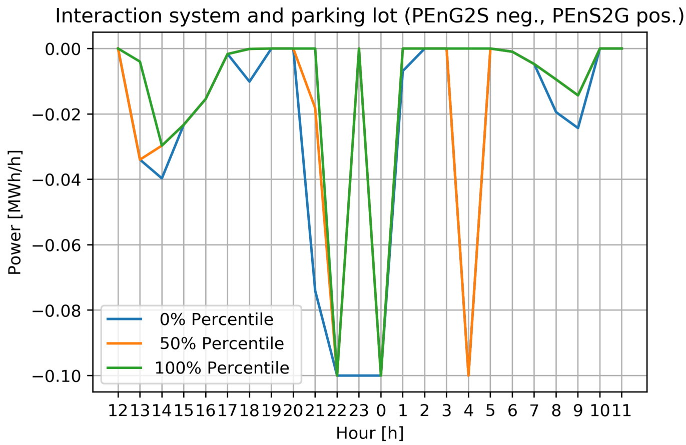

Figure 6.5: Parking lot interaction with optimisation of TOU

Interruptible/Curtailable tariff

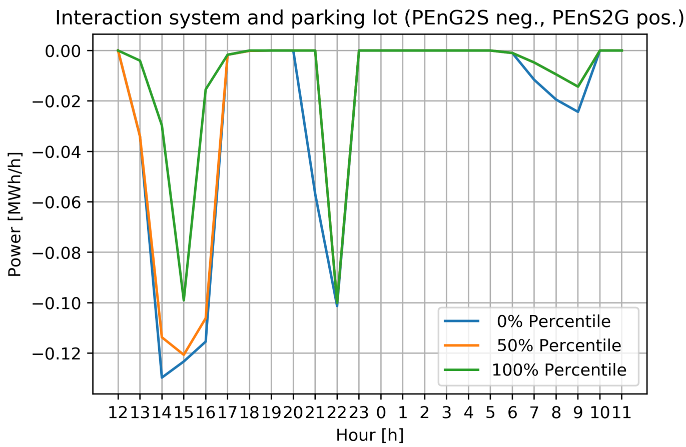

Figure 6.6: Parking lot interaction with optimisation of I/C

Discussion

Figure 6.4 shows the energy flow from the system to the parking lot for FR tariff, and figure 6.6 shows the flow for the I/C tariff. The figures correspond quite accurate with the interaction with the grid. This is expected since a lot of the imported energy arrives in the parking lot. The power flow is higher than the limit for the grid at 100kW. That is allowed since some of the energy also arrives from solar power, and the total charging capacity within the parking lot is higher than grid capacity. This is also why the results from TOU in figure 6.5 shows a power flow for the first hours even though there was no interaction with the grid during the first hours after noon. Even though there are some differences, the patterns between these three programs are somewhat the same for the interaction with the system and the parking lot.

6.2.3 Soc Battery

In the three following figures, the soc for the battery throughout the period is presented for the demand response programs.

Fixed-rate tariff

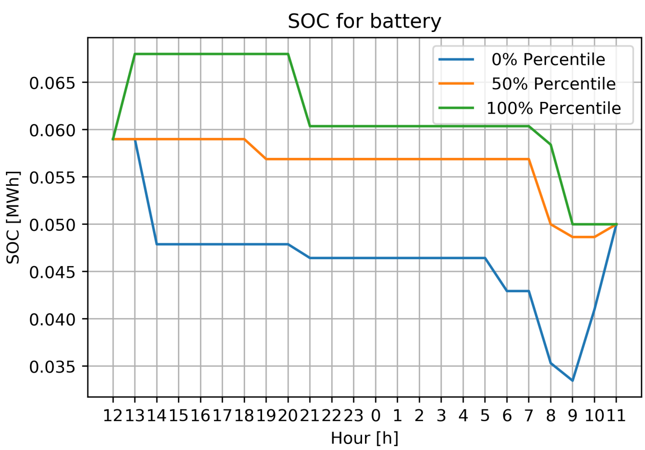

Figure 6.7: Battery soc in optimisation of FR

Time-of-use tariff

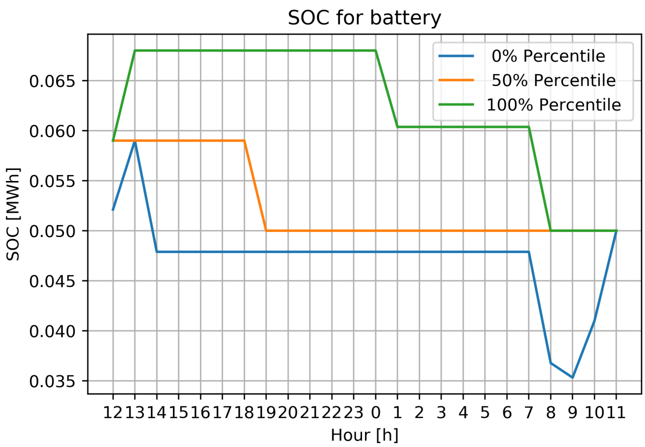

Figure 6.8: Battery soc in optimisation of TOU

Interruptible/Curtailable tariff

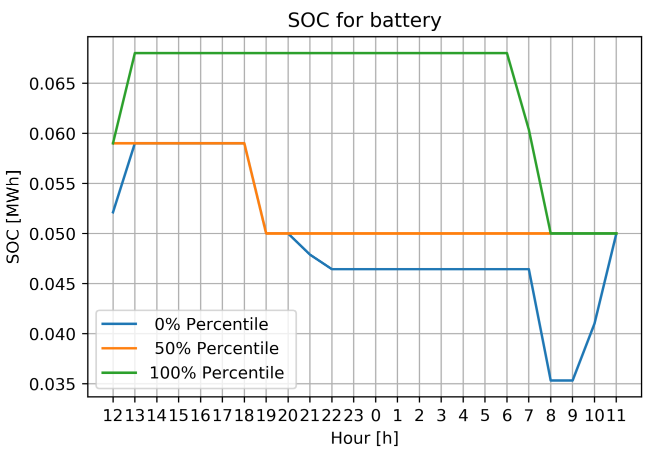

Figure 6.9: Battery soc in optimisation of I/C

Discussion

Figure 6.7 gives the soc for the battery for the FR tariff, TOU is given in figure 6.8 and I/C in 6.9. It should be stated that the soc for the battery at the start will be at 0.050MWh for all programs and percentiles. The reason why it is not shown in these figures is that the soc is calculated at the end of the hour of operation. This means 12:00 is actually at the end of this hour. It is assumed a linear line between the start soc to where the lines in the figures starts. In these results, there is a greater gap between the percentiles than in the others, which shows that the battery is more exposed to changes in the stochastic parameters. An observation is that the battery is unused for most of the hours for all the programs. The battery was implemented, so the system had flexibility to adjust for prices and CO_2-footprint in imported energy. In all programs, the battery is used at around 20:00 to export power. This export is also shown in the figures presenting the system's interaction with the grid. This is also the hour where the system price is at its top. The battery is also used in the morning for export to the grid and departed electric vehicles; this is equal for all the demand response programs. This is simultaneous with the second highest peak in the system price. Even though the interaction with the system and the battery is quite small, the interaction happens at strategic places with either high system price, excess solar power within the system or many departed electric vehicles. The importance of making use of these events like the battery does can be forgotten when just looking at the interaction for the different demand response programs.

The other argument for storage capacity was reduced CO_2- footprint. The CO_2- footprints used come from the NO2 area in Norway, and the differences between hours are quite small. This is also supported by the results in table 6.2, which show a low penalty. The CO_2- footprint is higher in the night compared to the day, but the emissions are still small. From the interaction with the grid, it is shown for all the programs that the export happens when the CO_2- footprint is at its lowest, and import happens both in high and low footprint periods. Then a small penalty indicates small incentives for adjusting based on CO_2- footprint. This will be further discussed in the sensitivity analysis.

6.2.4 Soc Parking lot

The aggregated soc for the parking lot is presented in the three graphs in this section.

Fixed-rate tariff

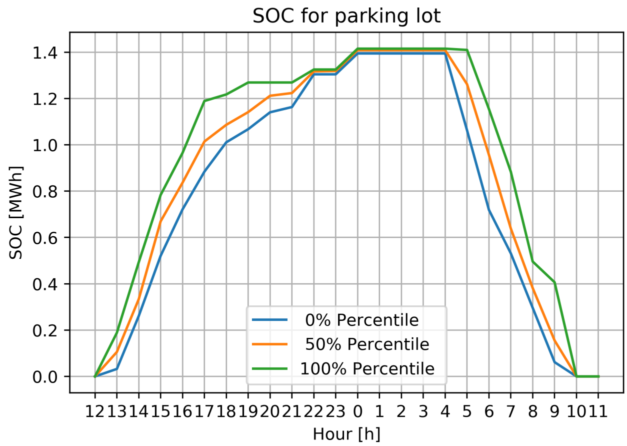

Figure 6.10: Soc parking lot in optimisation of FR

Time-of-use tariff

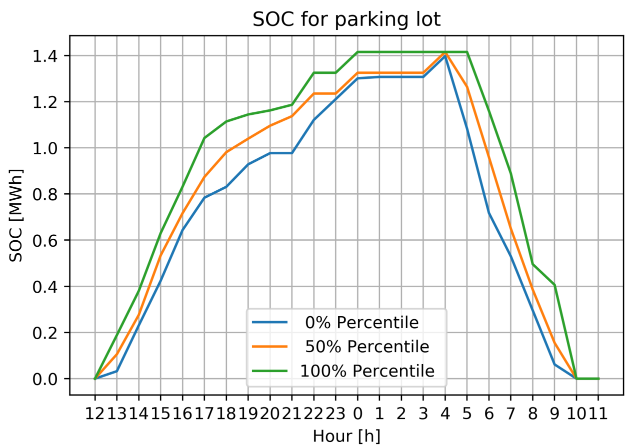

Figure 6.11: Soc parking lot in optimisation of TOU

Interruptible/Curtailable tariff

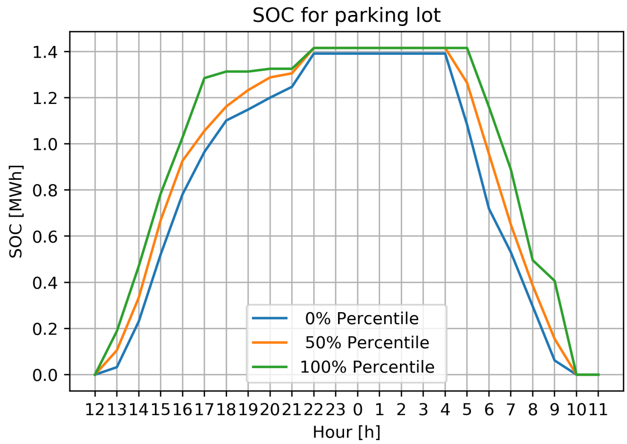

Figure 6.12: Soc parking lot in optimisation of I/C

Discussion

The soc for the parking lot for the FR, TOU and I/C tariff is given in figure 6.10, 6.11 and 6.12, respectively. These figures show that the soc pattern for the three different programs is quite similar. It is worth mentioning that these numbers are aggregated. Although the figures are quite similar, some differences should be mentioned. All of them reaches a constant level without interaction throughout the night. This means that the system does not make use of the electric vehicles during the night. The I/C programs slope towards the constant soc, that every tariff has, is steeper compared to the others. They all decrease their soc as the cars depart in the morning.

As seen from the results in this section, the patterns and the results from TOU tariff and I/C tariff are quite similar to the FR tariff. This means that there are other factors than price-signals in TOU and incentives in I/C that is the driving force behind how the system behaves. First, solar radiation and ”free” energy is equal for all the cases. The system makes use of this resource internally with some export at the beginning of the period and at the end where no electric vehicles are present. The driving force is still the system price.

This price is on the top of the tariff and paid to the power supplier and is always higher than the tariff paid to the system operator. In some hours it is almost four times as high. This price is equal for all of the programs, and if the programs should be more important, the price difference between hours should be more significant, and the incentive should be more specific on certain hours where the system has its critical peaks.

6.3 Sensitivity analysis

This section presents the sensitivity analysis in this research. The details for this analysis are presented in chapter 5.

In this section, there are several notations used to make the readability of the figures easier. If the letter ”A” is used in the figures, it stands for alpha and represents either the assumed activated energy in the first step or the actual activated energy in step two. If a figure denotes something as flexible, it means that the model has allowed the soc departure to be flexible according to the case.

6.3.1 Soc departure

The first analysis to be shown is the comparison of a flexible system and a non-flexible system. The simulation is carried out for 90%, 80% and 70% soc departure. Figure 6.13 gives the final result from step two for a flexible system while figure 6.14 shows the same just for a non-flexible system. Figure 6.15 presents the average soc departure for the cars for a flexible system. The number before ”A1” in these figures denotes the initial soc departure requirement for the electric vehicles.

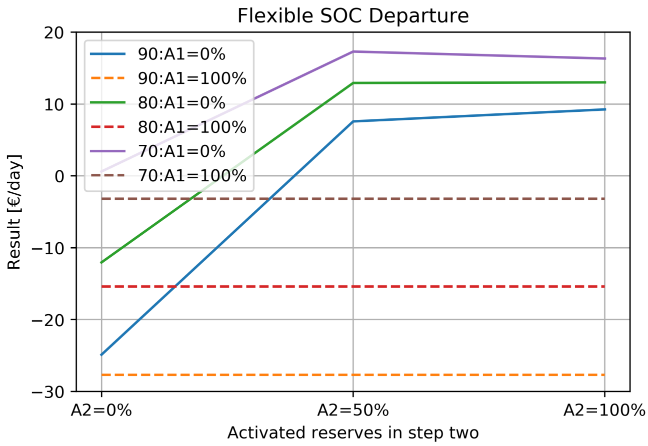

Figure 6.13: Results with flexible soc departure

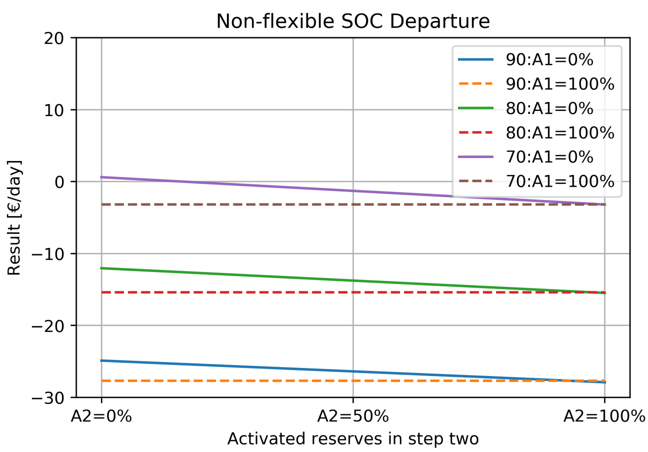

Figure 6.14: Results with non-flexible soc departure

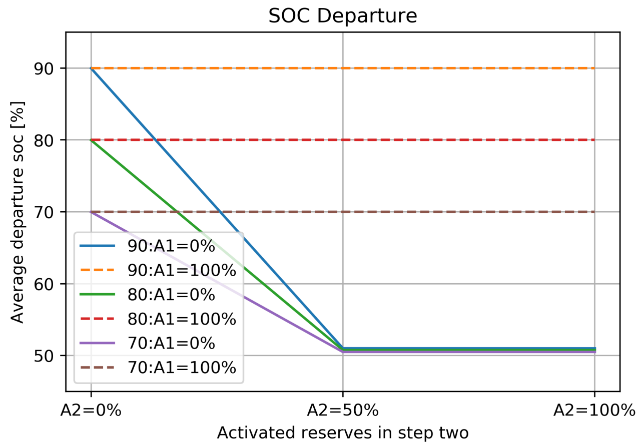

Figure 6.15: Average soc departure

Table 6.3 shows the total offered reserves for the analysis from the first step and the penalty paid to the system operator in the second step for different initial soc departures requirement. The results are gathered from a flexible system with an assumed activation from the first step at 0% and an actual activation at 100% in step two.

	soc dep = 90%	soc dep = 80%	soc dep = 70%
$P^{Res}_{\omega,i,t}$ [MWh/h]	1.50	1.70	1.89
Penalty [€/day]	2.09	2.75	3.34

Table 6.3: The offered reserves and penalty paid for different departure soc

Discussion

The first analysis was conducted with flexible soc departure. This means the soc departure can deviate down to 50% and up to 100% from its initial goal on either 90%, 80% or 70%. Figure 6.13 shows the different soc goals with either no assumed activation or 100% assumed activation in the first step, against 0%, 50% or 100% actual activation by the system operator in step two.

If there is 100% assumed activation in the first step the model does not allocate reserves in the first step, and hence the results are equal for the second step as there is nothing to activate. This can also be seen in figure 6.15 where the percentage is constant at the soc departure requirement, hence no flexibility is used. The reason for this is because of the flexibility the model has in step two is not present in step one. This flexibility will be on the soc departure, but also on the chance to pay a penalty to the system operator. Hence it is not possible to allocate reserves and at the same time maintain the constraints in the model. In other words, this would be the solution if no flexibility on the soc departure was allowed, and if it was not allowed to pay a penalty to the system operator. In section 7.5, it will be discussed that assuming no allowed penalty from the system operator is a reasonable assumption.

For the case in figure 6.13 where the assumed activation is 0% in step one, the graph is quite different. In this scenario, the model offers as much reserves as it can to the system operator as there are no costs or constraints on the actual activation present in step one. As one can see, the profit increases from 0% actual activated to 50% actual activated. While between the two next steps, 50% and 100% actual activated reserves, the profit decreases for the 70% and slightly increases for 80% and 90%. The decrease for 70% happens as the flexibility in the soc departure is used, and everything over that point will be paid to the system operator as a penalty. This is also reflected in figure 6.15 where the flexibility is used between 50% and 100%. The situation is different for the requirement of 80%. Here, the profit slightly increases, but this is hard to see in figure 6.13. This means there is some flexibility left when going from 50% to 100% activation, but most of the flexibility is already used as the flexibility is free to use in this analysis. This can also be seen in figure 6.15, where the average departure soc is almost constant between the two last steps of activation. When considering 90% soc departure there is a slight visible increase in profit for the two last steps of activation, hence the average soc departure also decrease in the same area. This shows that there is still flexibility to use for this scenario.

The trends for the three levels of soc departure when using flexibility are quite similar, and it shows that there is a clear value in the flexibility the owners offer. As the flexibility is free and the income from the activated reserves is so large the model will always make use of the flexibility. This is also why the model ends up at 50% regardless of whether it started at 90% or 70%. In this study the electric vehicles arrived with a mean soc at 50%

with some over and some under. With the usage of flexibility all the cars leave with 50%. This could end up in a problem for the next day or period as they might arrive with a lower mean, and the flexibility is no longer there. This is a balance the operator must take into consideration as the users cannot be flexible like this every day.

Even though the profit decreases for the 70% soc departure, it will always be more profitable. The reason for this is in the first step, the model can offer more reserves in the first step, and hence there are more to activate and earn money on in the second step. This is also reflected in table 6.3. This table shows that the lower requirement on soc departure the more offered reserves. With more offered reserves, the penalty will increase as well; this can also be seen as the different levels of soc departure uses all the flexibility available. Since the degradation cost and the penalty are so much lower than the price paid for the energy by the system operator in this model, it would always be profitable to take the penalty. This will be further discussed.

Figure 6.14 gives the values for the different soc departure for a non-flexible system. This means that the limit on the departure soc for the different cars is strict and not flexible. In other words, the difference between the flexible results in figure 6.13 and the non-flexible results in figure 6.14 is the value of the flexibility provided by the users. The results from the non-flexible soc departure are equal in the case where 100% is assumed activated in step one. This is because the model is not offering reserves in step one. Hence, there is nothing to activate in step two. As for the flexible case, the system does not know about the possibility to pay a penalty in step two.

For the 0% assumed activation in step one, the results for nothing activated by the system operator is equal to the flexible case. This is obvious as these steps are equal, and no flexibility and penalty in step two are needed. The interesting part is when activation happens for this case. As there is no chance to be flexible in the soc for the parking lot (equation A.16) and the battery (equation A.28) all of the activated energy must be paid as a penalty, and there is no income as nothing of the activated reserves are provided to the system operator. This is also why the graph is decreasing for all the different levels on soc departure, ending up paying everything back when 100% is activated. The reason why the graphs meet in the end is that the penalty is the same as the price paid for offering reserves.

For the results in both figure 6.13 and in figure 6.14 the difference between 0% and 100% assumed activation with 0% actual activated is the value of providing this flexibility to the system operator through the balancing market.

The value of flexibility for TOU with zero assumed activation and 100% activated in step two given a soc departure at 70% is 19.52€/day. This is the difference between a positive result and a negative result. However, maybe more important, it means less penalty to the system operator and the ability to deliver more of the activated reserves. As mentioned the difference between the results for the flexible and non-flexible soc departure cases is the value of the flexibility provided by the users. If there is no activation by the system operator, this flexibility is worth nothing as it is not needed in step two of the optimisation.

6.3.2 CO_2-footprint

This sensitivity analysis checks how sensitive the system is for changes in the CO_2-footprint from the energy in the external grid. The CO_2-footprints used in the analysis is from the price area in Norway called NO2 and from a mean value in the EU. Figure 6.16 shows the emissions from the system with the two different CO_2-footprints. The graph shows both the emission through the import of energy and the CO_2-penalty compensation from equation A.39 from chapter 4. The test is carried out for soc departure at 90%, 80% and 70%. The results are from the first step of the optimisation with zero assumed activation of reserves.

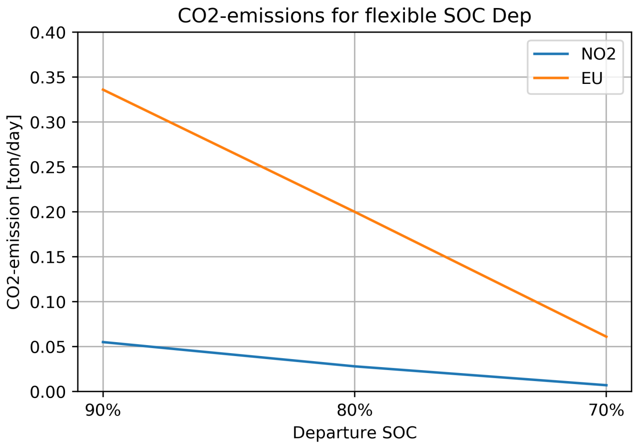

Figure 6.16: Emissions for different CO_2-footprints

Discussion

As discussed earlier, reducing greenhouse gases is the main goal for a Zero Emission Neighbourhood. In order to understand CO_2-emission and the differences in the CO_2-footprint, it is essential to test this model for different footprints. The results are given in figure 6.16, and are given with the CO_2 emitted from the import of energy and the penalty paid. The reduction in emissions from solar power is not included. The model is tested with low CO_2-footprint from the NO2-area in Norway and high footprint from a mean value in Europe with more coal and gas in the electricity mix. The figure shows that the emissions decreases as the requirement of soc departure decreases. This is because the interaction with the grid decreases as the requirement on the soc departure decreases. Meaning that less non-renewable energy must be compensated by on-site generation to fulfil the requirement on zero emission. The system developed in this thesis is almost emission-free at 70% departure soc. The emissions for the NO2 area is stable low for all the soc departures, while for the EU, it decreases rather much between 90% and 70% soc departure. This is a quite interesting observation for a Zero Emission Neighbourhood. The definition for a Zero Emission Neighbourhood states that there should be on-site generation. For a neighbourhood with an EU mean CO_2-footprint, the on-site generation will be essential to compensate for the energy bought from the grid as the CO_2-footprint is quite high. For the NO2 case, it is not equally important as the emission is stable, low and less dependent on the interaction with the grid. For a system within an area with low CO_2-footprint, it is not the same yield in terms of compensating emissions by having on-site generation. It could be an alternative to be more aware of the differences between hours in this case and make use of flexibility. Regardless of where the Zero Emission Neighbourhood is located, CO_2-balance will be decisive if a project is a success or a failure. On-site generation will be vital as it is clean emission-free energy independent on the CO_2-footprint in the grid.

The question is what role these values and the difference between them will have in the future of electricity markets, or for energy consumption. An idea could be to mark the energy within defined areas as green, or if the power supplier guarantees emission-free energy. This could be similar to the Guarantee of origin (Statnett (2018)) where the energy is labelled with the share of renewable sources. The CO_2-footprint of manufactured goods can be more important in the future, and then systems like the proposed system in this thesis could play an important role. Another possible use of these numbers could be sending CO_2-signals to the end-users. In the same way tariffs send price-signals it could also be implemented CO_2-signals.

6.3.3 CO_2-price

This section presents the sensitivity analysis carried out on the prices of CO_2-emission. The two different prices can be divided into high and low according to the values defined in the case. Both prices have CO_2-footprint according to the EU-values. Figure 6.17 presents the different penalties paid for the CO_2-imbalance for both high and low CO_2-price. The test is carried out for soc departure at 90%, 80% and 70% with assumed activated reserves equal to 0%. The results are gathered from the first step of the optimisation.

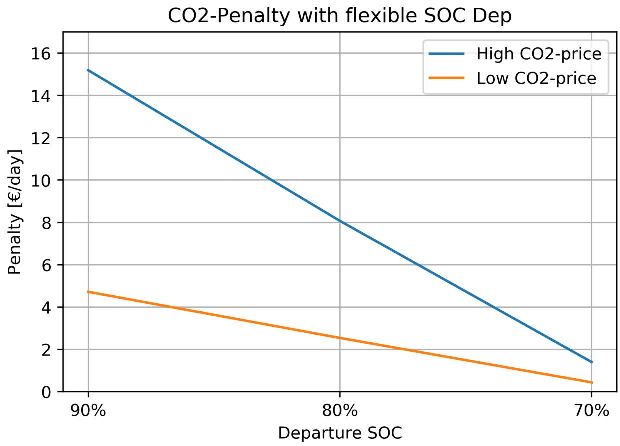

Figure 6.17: Cost of CO_2-imbalance for different CO_2-penalties

Discussion

Another part of CO_2-emission that will be interesting to follow in the future is the development in price on emitting CO_2. The low price in figure 6.17 is the highest price over the summer of 2019 from the market of CO_2, while the high price is a fictitious value higher than the prices of today. Both lines in figure 6.17 have the same CO_2-footprint in power consumed from the mean EU. The same trend from the sensitivity analysis on CO_2-footprints is present here as the emission from the system is at is highest at high requirement on the departure soc. If the price went up to 100€/ton like in the high price instance in figure 6.17, then the value of renewable energy would be high as more companies and industries regulated by the EU Emission Trading System would pay a high price for CO_2-quotas. In the future, there could be more sectors involved in the quota system, and that can allow regular households to intervene in this market. Then a Zero Emission Neighbourhood could be profitable as it has systems to react on CO_2-signals and equipment to reduce the overall CO_2-emissions. After all, the price set on the CO_2-penalty is an internal cost for the system, and the neighbourhood is free to put that value to whatever it wants. As it is right now, where the households within Norway and Europe are allowed to release CO_2, the rational economic solution would be to not care about CO_2 as it is no incentives in this. In other words, it is not profitable for a Zero Emission Neighbourhood to care about this specific area. This is a challenge for Zero Emission Neighbourhoods and other CO_2-minimising ideas. There are some indirect incentives for reducing CO_2-emissions by installing solar panels and buying an electric vehicle.

Chapter 7

Discussion

This chapter will discuss the models from chapter 4 and the results obtained through the optimisation presented in chapter 6. There will also be discussions about the system developed in this thesis with regards to the rules today and the future.

7.1 Uncertain parameters

In order to get the most realistic results as possible in a stochastic system, it is essential to choose the uncertain parameters with care. One way to represent these parameters is to make distributions out of it. This is what Shafie-Khah et al. (2016) have done in their research. They have chosen the arrival time, departure time and the initial soc for the electric vehicles as their uncertain parameters. They have used a truncated Gaussian distribution to reflect the probability of the different outcomes. This method was also used in this thesis, with the same uncertain parameters and the same distribution. When looking at the results from the different demand response program with the proposed model, it can be seen that the difference between the 0%, 50% and 100% percentile are quite similar for the grid interaction, parking lot interaction and soc parking lot. Based on this, it is reasonable to question the choice on the uncertain parameters connected to the electric vehicles. It might be that the behaviour of electric vehicle users is more predictable than expected. In other words, if one guesses the arrival and departure time for a car connected to a house, it is less uncertain than what the user might say. It should also be mentioned that the user might characterise themselves as uncertain because they want to be better safe than sorry. It is also worth questioning the number of scenarios when the percentiles are close to one another. In an aggregated model like this, the uncertainty within the cars can be evened out as one might leave earlier than expected, and in the same time, a car arrives earlier than expected leaving it at the same expected case.

Discrete values could be used to represent the uncertainty in the capacity of the cars used in the model, and for the number of cars analysed. The reason why that was not used in this research is due to its boundaries. The model assumes a parking lot within a Zero Emission Neighbourhood. It is assumed that the cars belonging to the neighbourhood return every night and that the number of electric vehicles is fixed. The number and the capacity of electric vehicles could be more relevant to look at if there was a commercial parking lot where the selection of possible cars is larger.

As the system price and the price in the balancing market is volatile, it could be an idea to represent these parameters as uncertain in the model. Then it would be possible to see how this impact the final results and the ability for the system to minimise CO_2-emission. The need for flexible soc departure will also vary with the prices in the market because if there are large differences in price the need for flexibility will increase. The price for CO_2 and the CO_2-footprint will also have an impact on the system as seen in the sensitivity analysis. As seen in the results, the solar power is vital for the system, and changes in this could cause variation in results and CO_2-emission, as this is also an uncertain parameter.

7.2 Model

There are some limitations to the proposed model and the original model by Shafie-Khah et al. (2016). By aggregating the soc for the parking lot, it is harder to take each users interest into account. For this research an aggregated soc departure is used, and if more than one car leave there are no guarantees that one particular car left with enough power. Another challenge with aggregating soc in the parking lot is that the degradation between cars is not included. This means that a car can be charged by the other cars if one car arrives with more energy than the requirement, this will not be taken into account by the degradation of the cars, as this is only charged for the net interaction between the system and the parking lot.

Another challenge generally with optimisation models, tariffs and prices is that energy is assumed to flow at a constant rate for an hour. In the physical world, this will not be the case. The power and its direction can and will change several times within one hour. The value used in tariffs and optimisation is then a mean net flow of power within that hour. In the financial world, this could be sufficient, but in the physical world, everything must be in balance every second. Hence, the results in the model and the real physical world will deviate. For instance, the binary variables on the flow in this research would change several times within an hour of operation, but it would never be the same, neither in the model nor in the physical world.

7.3 Investment or connection charges

From a rational economic view, an investment must pay off over time and have more income than expenses over the analysed period. This means that for the system developed in this research, the investment in bidirectional charging, a battery and solar panels, the profit or reduction in costs must be higher than the alternative. An alternative cost for this project will be to pay the local grid operator for a higher capacity. If the aggregated capacity installed in the neighbourhood is high enough, the grid operator is responsible for the capacity being good enough, and then the cost is only the additional cost of energy. An investment analysis has not been conducted in this research.

If the proposed system gives a higher cost than not investing in the system, it would be more challenging to go through with the proposed system as it will cost money to have this solution. As discussed earlier, a system where incentives are given to minimise CO_2-emission can be necessary in order to realise a Zero Emission Neighbourhood. The question from this discussion is whether a Zero Emission Neighbourhood or even just a system with smart bidirectional charging is profitable. From the results presented in table 6.1 and 6.2 the difference in profit for the second step TOU is 24.57€/day which is 0.819€/day per household in the neighbourhood assuming one electric vehicle per parking lot. This is the added value of solar power, external battery and minimisation of emission.

The case is during a sunny day in March; hence, this situation will not be the case for every day throughout the analysis. In order to conclude what the rational decision should be, the result must be compared to an investment analysis. However, assumed equal input over a year, this system will only save 299€ for each household which is quite low compared to the prices of solar panels and external batteries, even when taking the lifetime of those components into account. These numbers can change when looking at the proposed system with the rest of the Zero Emission Neighbourhood. It is necessary to include the value of adding the proposed system to buildings and other loads to understand the real savings over a year.

This Zero Emission Neighbourhood with its given boundaries has one connection point to the grid, meaning that the neighbourhood will only be charged the tariff through this metering point. As mentioned earlier, the need for the grid will be the same for this system regardless of solar power and smart systems reacting on today's price signals. Hence, the tariff that from before was paid by 30 houses are now paid by one metering point, and the fixed yearly fee for a tariff will be divided on thirty instead of one. The neighbourhood will forward the bill and the reduction in cost over to the rest of the customers. The capacity in the grid is not dependent on how many hours the users use it, but the highest peak over a period for that user. One of the motivations for the change towards a capacity-based tariff is to better deal with these loopholes where the prosumers do not pay the right amount of tariff due to on-site production. An argument against is that the government and the system operator should value the injection of renewable energy into the grid. NVE has stated that there will be a hearing during the winter of 2020 regarding how on-site production and metering should be when there are several housing units working together (Norwegian Energy Regulatory Authority (2019b)).

7.4 Social factors

In order to make the system developed in this research successful, the owners of the electric vehicles must be willing to join. To make them join, it has to be something in it for them as they risk their battery through degradation and their flexibility through bidirectional charging. The question is whether a profit of 299€ excluding cost for the investment is a good enough profit for the user. It should also be mentioned that this profit is including a flexible soc departure which means the users are leaving with 50% soc no matter what they wanted in the first place. It can be challenging to get people to be flexible at home since the security on charging at home can be crucial. There are no guarantees that the user will be in a place with a charging station throughout a day. A parking lot or public charging spot can also charge more than home through a profit on the power bought or parking fees, which makes it even more important for the users to charge at home.

If the value of the flexibility is divided on all the electric vehicles, it will be 0.651 €/day. If an electric vehicle with a capacity of 100kW get 50% instead of 90% and it is compensated with a maximum of 0.651 € that would be 0.0163 €/kWh. The lowest price for electricity in this analysis was 0.04033 €/kWh. The price for flexibility is not enough to cover the cost for the user. However, this research has not connected the proposed system to a full Zero Emission Neighbourhood with its buildings, then the value of this flexibility might increase to a profitable level. The value of the flexibility can also increase in the future if it provides ancillary functions to the grid where the system operator can get around investments.

Another question that is relevant to ask in a discussion like this is who will operate the system developed? In the research conducted by Shafie-Khah et al. (2016), there was a parking lot operator who had profit as a goal. The research in this paper changed this into profit maximisation for the users. If an external actor is in the parking lot, it would be important for that actor to make a profit, while for the users itself it would be to reach the goal of zero emission, charged cars and then make a profit. The users will most likely accept an external actor if the interests coincide. However, as seen from the results, the lower the soc departure, the more money is made in profit. Hence, an external operator could risk the departure soc more than an internal operator. This discussion is also the basis for a change done in the proposed model in this research compared to the work done by Shafie-Khah et al. (2016). In the work by Shafie-Khah et al. (2016) they had a step in between the user and the grid where the parking lot operator could benefit from the user. It also had a parking fee for the parked electric vehicles. This step was taken away due to the changed focus on the user. For a system like this to work, the users must trust the operator as many variables will work together, and it will be hard for unskilled people to verify the choices made.

The goal for this research was to use demand response programs to maximise profit and minimise CO_2-emission. As seen from the results, the difference between the demand response programs was quite small, and the driving force for the choices made was the system price. The selection of the demand response program is essential in order to stimulate the desired behaviour. As discussed earlier, the incentives in the tested programs are equal in so many consecutive hours that the model loses incentive. It will also be hard for the users to react when they are not home or awake in those hours where the consumption should be moved to. The incentive-based programs can also be hard to react on as many people do not have a relationship with the consumption in their home. It can be hard to know how much a contracted level of reduction would be, as a 10% reduction in consumption says nothing on what needs to be reduced. It can also be hard to see the benefits and penalty up against each other as the end-user has a choice to take a penalty. TOU would be a more straightforward model to understand for the end-users. It would be a model that most consumers are known to through road toll payments during rush hour. The problem here is also that the price-signals is not pointed good enough on the hours with the critical grid operations. The capacity-based programs give the price-signals every hour. Although, as stated earlier, it would be harder for the customer to understand how to chose a subscribed limit where it exceeds some hours. It is also hard to know when it exceeds. If subscribed capacity is made easier to understand, it would be the preferred model as it better reflects the costs in the grid and gives the right incentives every hour. The end-users have to understand how to use and react to signals from the tariffs. It should be easy for an end-user to know when to charge the electric vehicle, cook, and what to not do at the same time. If they do not understand that it will be hard to make use of it, and the operation of the grid will be difficult. The choice of tariff is important to get full utilisation of the possibilities present in the proposed system. Both the system operator and the end-user can profit from it.

If people in the future are more aware of their CO_2-footprint, a Zero Emission Neighbourhood can be important for people even though it may not be profitable yet. Status can be important for people, and also the effect on the neighbours doing the same. The government is also giving incentives and tries to influence people. In Norway, there are tax cuts on electric vehicles, and Enova, governmental financial support for green energy solutions, is giving up to 28750NOK in support when installing solar panels (Enova (2019)). These are all social factors that have not been looked into in this research, but that can determine the future for the proposed system.

7.5 Balancing market and offering of reserves

As the balancing markets in Norway is designed today, the proposed system is not able to join as it cannot place a minimum bid. This research has assumed that the system can join, but there are challenges with the proposed system in the balancing markets. As seen from the analysis, the model want to offer as much reserves as possible if it does not see the consequences in step one. Even though there is flexibility in the departure soc, it ends up paying a penalty as seen in table 6.3. If an actor in the market is not able to provide balance to the system operator according to the offered reserves, it is looked upon as breaking the Norwegian law on energy. Hence, the system must be able to provide the flexibility promised to the system operator. Another consequence and the most likely consequence is to be thrown out of the market if the activation is not delivered. For a stochastic system like a parking lot within a Zero Emission Neighbourhood, it would be hard to know what flexibility one has the day head of an hour. This would be easier for a generator, which is also the regular customers in the market today. To stimulate a higher delivery rate, an internal fee reflecting the value of being in the market can be introduced. This fee can be put on top of the penalty for the system operator, making it less beneficial to take the penalty. This could give the system the right incentives to avoid the situation where it is not able to deliver the reserves to the system operator.

If a system like the proposed system in this thesis should be involved in this market today, it should probably be through an aggregator who has other sources of flexibility besides. In that way, it is possible not to deliver what it is supposed to do as there is an aggregator in between. If the system alone should be in the balancing market, there should be a new balancing market designed for smaller flexible sources where the uncertainty of human behaviour is taken into account.

The background for this research was partly based on the increased need for flexibility in a changing energy system. As more unregulated renewable energy is injected into the system at distribution grid levels, the need for flexibility increases. There could be bottlenecks or congestion where systems like the proposed system in this thesis will be of good use. The system analysed in this research has shown the ability to be flexible; this means there is a potential for the system operator to use it. A future market for flexibility should reflect the strengths of these systems.

Chapter 8

Conclusion

In this master thesis, the goal was to utilise demand response programs to maximise profit for the electric vehicle users within a Zero Emission Neighbourhood. To do so, a bidirectional charging system, an external battery and solar panels were implemented. The model also had an aim to minimise CO_2-emissions, and examine the flexibility in the system. A two-step stochastic model was implemented and solved to reach the goals. The proposed model was based on the work done by Shafie-Khah et al. (2016). In the proposed model, a requirement on the soc departure was introduced to take care of the interests for the inhabitants concerning the desired departure soc. The research in this work looked at fixed-rate-, time-of-use- and interruptible/curtailable tariff as the different demand response programs.

This research found that the profit increases at the most by 24.67€/day with the implementation of solar panels, an external battery and CO_2-minimisation. The solar power is mainly used internally in the system, while the use of the battery is limited but present at critical points. The difference within the different demand response programs is quite small, with 1.15€/day at its largest. The behaviour of the system was found to be more dependent on the system price rather than the demand response program. The behaviour in the system for the different demand response programs was rather similar, as there are small incentives to move or adjust load within the proposed programs. Time-of-use was the desired program for the proposed system.

The results also showed that flexible soc departure is crucial in order to meet the offered reserves if they are activated by the grid operator. If no flexibility or penalty is possible, the system will not participate in the balancing market. The flexibility within the battery was not crucial for the CO_2-emissions, as the internal penalty and CO_2-footprint was low. The main contributor to low CO_2-penalty was on-site generation through solar power. The power from the solar panels was mainly consumed internally in the proposed system. CO_2-emissions from the system is dependent on the interaction with the grid, the internal penalty and the CO_2-footprint for the imported energy.

The proposed uncertain parameters on the arrival time, departure time and initial soc were less determining than anticipated. To understand the profit and the possibilities the proposed system must be included in a complete Zero Emission Neighbourhood as there are other loads in the system as well as the electric vehicles. Systems like this still have a challenge with getting the end-user to join in. That is why this research has made several adjustments to the operator role with the results of lower profit, but higher end-user consideration. There is a need for better designed demand response programs where it is easier to react and adjust to the given signals. Based on the results, a new balancing market should be developed for smaller, more stochastic customers as today's market is not flexible enough. The research showed that the proposed system is able to provide flexibility, and hence it can be important in the future with more unregulated renewable energy.

Chapter 9

Future work

Based on the results and discussion presented in this research, there are several areas which need more research in the future. This will be important for the future of the proposed system in this research, and especially with regards to a Zero Emission Neighbourhood.

As seen from the results in this research, the balancing market must be adjusted to better fit with the services a system like the proposed system can offer. Future work should look into whether a market like this can be of any use for the system operator, and how to structure it. With bottlenecks further down in the system and more fluctuating energy production, the flexibility from smaller consumers can be vital. Future research should also see how the system will react to reserves being offered the other way, imported energy on signals from the system operator.

The results in these models show that using bidirectional charging, solar power, an external battery and CO_2-minimisation will increase the profit compared to only using bidirectional charging. However, an analysis of the investment in terms of the alternative cost of not investing should be conducted to see whether it is profitable or not to invest in such a system, if it is not, new economic incentives should be explored and discussed.

As discussed, this system has a lot of uncertain parameters and variables. Future work should look into the possibility of regarding the system prices as uncertain. The system price is volatile over the year, and it would be helpful for future work on the proposed system and Zero Emission Neighbourhood to see how it reacts to changes in price over a year.

Here future prospects for the system price can be used as the energy system within Norway will go through, according to Statnett, a transition with a more significant difference between the top and bottom on prices.

Social factors are vital in a system where humans and their behaviour are an important influence in the system. Future research should look into human behaviour and how people in a system like this interact. It would also be interesting to know how the effect on peoples status intervenes with the investment decision. If future research could quantify the users flexibility and their willingness to join, it would be a breakthrough on research on flexibility and future energy system with a more active user. More work is also needed to get a demand response program which is easy to understand, easy to react on, and that reflects the costs in the grid.

This research did not look into how the proposed system could have intervened with the rest of the Zero Emission Neighbourhood. Can the proposed system give more functions to the neighbourhood in order to reach the goal on zero emission? Hence, future works should try to implement the proposed model into a complete neighbourhood with the other components like heat, hot water, users behaviour et cetera.

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Appendix A

Proposed model

This chapter presents the proposed model developed in the master thesis. The different sections are divided into subsections based on what kind of equation it is. If it is under the term expression it is simply an expression used in the model. The term constraint will show the different constraints used in the optimisation. In the end of each section the constraints, expressions and objective functions that either is changed or introduced in the second step of the optimisation is presented. When the system is mentioned it is the connection point where the solar panels, external battery, parking lot and the external gird meets. This point can be found in figure 4.1.

A.1 Nomenclature

This section presents the sets, parameters, variables and binary variables used to develop the proposed model. Some variables from the first step are changed to parameters in the second step. This is written behind the variable. The notation used in this overview is the state the parameter or variable has in the first step.

Sets

$\Omega \in \omega$	Scenarios
$DRP \in i$	Demand response programs
$T \in t$	Time
$N \in n$	Electric vehicles

Parameters

ϵ	Probability of each outcome
α_i	The share of each DRP involved
$N_{\omega,t}^{PEV}$	Number of EVs present at PL
$N_{\omega,t}^{PEV,arv}$	Number of EVs arriving at PL
$N_{\omega,t}^{PEV,dep}$	Number of EVs departing from PL
$t_{\omega,n}^{dep}$	Departure time for an EV
$t^{dep,min}$	Minimum departure time for EV
$t^{dep,max}$	Maximum departure time for EV
$t_{\omega,n}^{arv}$	Arrival time for an EV
$t^{arv,min}$	Minimum arrival time for EV
$t^{arv,max}$	Maximum arrival time for EV
μ_{dep}	Mean departure time
σ_{dep}^2	Variance for departure time
μ_{arv}	Mean arrival time
σ_{arv}^2	Variance for arrival time
$soc_{\omega,t}^{arv}$	Aggregated initial soc for arriving EVs
Cap_n^{PEV}	Capacity for an EV
$soc_{\omega,n}^{PEV,ini}$	Arrival soc for an EV
$\delta_{\omega,t,n}^{Arv}$	1 if an EV arrives and 0 otherwise
μ_{soc}	Mean initial soc
σ_{soc}^2	Variance of initial soc
$soc^{PEV,min}$	Minimum initial soc

$soc^{PEV,max}$	Maximum initial soc
$soc_{\omega,t}^{min,dep}$	Minimum aggregated soc departure
$soc_{n}^{min,dep,car}$	Minimum departure soc for an EV
$soc_{\omega,t}^{min,agg}$	Minimum aggregated soc for the PL
$soc_{n}^{min,car}$	Minimum soc for a EV connected to PL
$\delta_{\omega,t,n}^{Parked}$	1 if EV is parked 0 otherwise
$soc_{\omega,t}^{max,dep}$	Maximum aggregated soc departure
$soc_{n}^{max,car}$	The maximum soc for a parked EV
$soc_{\omega,t}^{max,agg}$	The maximum aggregated soc for the PL
η^{charge}	Efficiency charging PL
$\eta^{discharge}$	Efficiency discharging PL
μ_t	Aggregated percentage of soc in PL
γ^{charge}	Rate of charge PL
$\gamma^{discharge}$	Rate of discharge PL
Cd	Degradation costs
$soc^{Pen,Fee}$	Penalty for flexible soc departure
β^{Flex}	Allowed percentage flexibility on soc dep
$\eta^{converter}$	Efficiency of battery charger
$soc^{min,bat}$	Minimum soc for the battery
$soc^{max,bat}$	Maximum soc for the battery
$\gamma^{Charge,B}$	Rate of charge battery
$\gamma^{Discharge,B}$	Rate of discharge battery
$soc^{start,battery}$	Start soc for the battery
P_t^{PV2S}	Power flow from PV to Sys
$P_t^{Sun,Rad}$	Solar radiation
η^{Solar}	Efficiency for the solar panel
$\eta^{Converter,solar}$	Efficiency for the PV-converter
$Areasolar$	Area of solar panels

λ^{CO_2}	CO_2-price
$m_t^{\mathrm{CO}_2}$	CO_2-footprint
$\lambda^{Pen,\mathrm{CO}_2}$	Penalty price for net emitting CO_2
$P_{omega,t}^{Ini}$	The initial interaction with grid without incentives
α^{First}	Assumed activated energy in first step
$\gamma^{Capacity,grid}$	Capacity on the interaction with grid
λ_t^{Cap}	Price for capacity
$\lambda_t^{Energy,loss}$	System price for energy plus marginal loss
$\lambda_{t,i}^{En,tariff}$	System price for energy plus tariff
$YearlyFee_i$	Yearly fee for a DRP
$Cost_i^{Fixed,tariff}$	Cost of the yearly fee
$Inc_{t,i}$	Price for incentives for the incentive-based DRP
$Pen_{t,i}$	Price for penalty for incentive-based DRP
$P_{t,i}^{Cont}$	The contracted level of reduction in power for DRP
$P_{\omega,i,t}^{En,S2G,Fixed}$	Sys to grid interaction from first step. Used in step two
α^{Second}	The activated reserves in step two

Variables

$Income_{\omega,i,t}^{HereAndNow}$	Income from the first step
$Cost_{\omega,i,t}^{HereAndNow}$	Cost for the first step
$Income_{\omega,i,t}^{WaitAndSee}$	Income from the second step
$Cost_{\omega,i,t}^{WaitAndSee}$	Cost from the second step
$Income_{\omega,i,t}^{En,S2G}$	Income from the interaction with the grid
$Income_{\omega,i,t}^{Cap,Res}$	Income from its offered reserves
$Income_{\omega,i,t}^{Inc}$	Income from the incentive-based programs
$Income_{\omega,i,t}^{\mathrm{CO}_2}$	Income from CO_2-compensation
$Cost_{\omega,i,t}^{En,G2S}$	Cost of interaction with the grid
$Cost_{\omega,i,t}^{Deg,PL}$	Cost of degradation of the parking lot
$Cost_{\omega,i,t}^{Deg,B}$	Cost of degradation of battery

$Cost^{Pen}_{\omega,i,t}$	Cost from penalty in incentive-based DRP
$Cost^{CO_2}_{\omega,i,t}$	Cost of emitting CO_2
$Cost^{Pen,CO_2}_{\omega,i}$	Cost of imbalance of CO_2-emission
$Income^{Res,Act}_{\omega,i,t}$	Income from the activated reserves
$Cost^{Deg,Res}_{\omega,i,t}$	Cost of degradation due to activated reserves
$Cost^{Art,More}_{\omega,i,t}$	Cost of having too much energy in the system in second step
$Cost^{Art,Less}_{\omega,i,t}$	Cost of having less energy than the activated available
$Cost^{SOC,flex}_{\omega,i,t}$	Cost of being flexible with soc departure
$soc_{\omega,i,t}$	Aggregated soc for the parking lot
$soc^{dep}_{\omega,i,t}$	Aggregated departure soc for the EVs
$P^{En,S2PL}_{\omega,i,t}$	Energy flowing from the system to the PL
$P^{En,PL2S}_{\omega,i,t}$	Energy flowing from the PL to the system
$P^{ResAct,PL}_{\omega,i,t}$	Offered reserves from the sys to the SO (Parameter in step two)
$soc^{Min,Flex}_{\omega,i,t}$	Lower flexibility for the soc departure. Introduced in step two
$soc^{Max,Flex}_{\omega,i,t}$	Higher flexibility for the soc departure. Introduced in step two
$soc^{Battery}_{\omega,i,t}$	Soc for the battery
$P^{En,S2B}_{\omega,i,t}$	Energy flow from the system to the battery
$P^{En,B2S}_{\omega,i,t}$	Energy flow from the battery to the system
$P^{ResAct,B}_{\omega,i,t}$	Activated reserves from battery (Parameter in step two)
$P^{En,S2G}_{\omega,i,t}$	Energy flow from system to grid
$P^{En,G2S}_{\omega,i,t}$	Energy flow from grid to system (Parameter in step two)
$Pen^{CO_2}_{\omega,i}$	Penalty of being in CO_2-imbalance
$\Delta P^{En,G2S}_{\omega,i,t}$	Net energy difference for the incentive-based DRP.
$P^{Res,Act}_{\omega,i,t}$	Total activated reserves(Parameter in step two)
$P^{Res}_{\omega,i,t}$	Offered reserves from the sys to the SO (Parameter in step two)
$P^{Res,Act,Paid}_{\omega,t,i}$	Actual energy provided to the SO in step two.
$P^{Res,Art,More}_{\omega,i,t}$	The artificial value of too much energy in the system in step two
$P^{Res,Art,Less}_{\omega,i,t}$	The artificial value of too little energy in the system in step two.
$P^{Res,Art,B,More}_{\omega,i,t}$	Artificial value from the battery. Too much energy in sys
$P^{Res,Art,PL,More}_{\omega,i,t}$	Artificial value from the PL. Too much energy in sys.

$P_{\omega,i,t}^{Res,Art,B,Less}$	Artificial value of too little energy from the PL in step two
$P_{\omega,i,t}^{Res,Art,PL,Less}$	Artificial value of too little energy from the battery in step two

Binary variables

$\delta_{\omega,i,t}^{PL}$	1 if energy is flowing into the PL and 0 if energy is flowing out
$\delta_{\omega,i,t}^{Battery}$	1 if energy is flowing from battery and 0 if energy is flowing in
$\delta_{\omega,i,t}^{System}$	1 if energy is flowing into the sys and 0 if out(Parameter in step two)

A.2 Objective function

The objective function for this problem is given by equation A.1.

$$\begin{aligned} \max profit^{Sys} = \\ [\,\epsilon_{\omega_1} \sum_{t \in T} \sum_{i \in DRPs} \alpha_i \{Income_{\omega,i,t}^{HereAndNow} - Cost_{\omega,i,t}^{HereAndNow}\} \\ +\epsilon_{\omega_2|\omega_1} [\,\alpha_i \{Income_{\omega,i,t}^{WaitAndSee} - Cost_{\omega,i,t}^{WaitAndSee}\}]\,] \end{aligned} \tag{A.1}$$

Equation A.2 through A.5 gives the different components of the objective function.

$$\begin{aligned} Income_{\omega,i,t}^{HereAndNow} = \\ Income_{\omega,i,t}^{En,S2G} + Income_{\omega,i,t}^{Cap,Res} + Income_{\omega,i,t}^{Inc} + Income_{\omega,i,t}^{\mathrm{CO_2}} \end{aligned} \tag{A.2}$$

$$\begin{aligned} Cost_{\omega,i,t}^{HereAndNow} = \\ Cost_{\omega,i,t}^{En,G2S} + Cost_{\omega,i,t}^{Deg,PL} + Cost_{\omega,i,t}^{Deg,B} + Cost_{i}^{Fixed} \\ +Cost_{\omega,i,t}^{Pen} + Cost_{\omega,i,t}^{\mathrm{CO_2}} + Cost_{\omega,i}^{Pen,\mathrm{CO_2}} \end{aligned} \tag{A.3}$$

$$Income_{\omega,i,t}^{WaitAndSee} = Income_{\omega,i,t}^{Res,Act} \tag{A.4}$$

$$Cost^{WaitAndSee}_{\omega,i,t} = Cost^{Deg,Res}_{\omega,i,t} + Cost^{Art,More}_{\omega,i,t} + Cost^{Art,Less}_{\omega,i,t} + Cost^{SOC,flex}_{\omega,i,t} \tag{A.5}$$

A.3 Parking lot

In the following section the equations concerning the parking lot is presented.

Expressions

Expression A.6 is the number of cars present in the parking lot.

$$N^{PEV}_{\omega,t} = N^{PEV,arv}_{\omega,t} - N^{PEV,dep}_{\omega,t} + N^{PEV}_{\omega,t-1} \quad \forall\omega, \forall t \tag{A.6}$$

The following two expressions gives the formula for the departure and arrival times for the cars.

$$t^{dep}_{\omega,n} = f(x) = f_{TG}(x; \mu_{dep}, \sigma^2_{dep}, (t^{dep,min}, t^{dep,max})) \quad \forall\omega, \forall n \tag{A.7}$$

$$t^{arv}_{\omega,n} = f(x) = f_{TG}(x; \mu_{arv}, \sigma^2_{arv}, (Max\{t^{arv,min}, t^{dep}_n\}, t^{arv,max}) \quad \forall\omega, \forall n \tag{A.8}$$

Equation A.9 ensures that a car never arrives before it has departed.

$$t^{dep}_{\omega,n} < t^{arv}_{\omega,n} \quad \forall\omega, \forall n \tag{A.9}$$

The next expression gives the aggregated soc for the arrived cars.

$$soc^{arv}_{\omega,t} = \sum_{n=1}^{N_{\omega,t}} Cap^{PEV}_n \times soc^{PEV,ini}_{\omega,n} \times \delta^{Arv}_{\omega,t,n} \quad \forall\omega, \forall t \tag{A.10}$$

The following equation is used to determine the different initial soc for the cars for each scenario.

$$soc_{\omega,n}^{PEV,ini} = f(x) = f_{TG}(x; \mu_{soc}, \sigma_{soc}^2, (soc^{PEV,min}, soc^{PEV,max})) \quad \forall\omega, \forall n \tag{A.11}$$

Equation A.12 and A.13 gives the minimum and maximum departure soc respectively for the parking lot for a given hour in each scenario.

$$soc_{\omega,t}^{min,dep} = \begin{cases} soc_{\omega,t}^{min,dep} + soc_{n}^{min,dep,car}, & \text{if } t_{\omega,n}^{dep} = t \\ soc_{\omega,t}^{min,dep}, & \text{otherwise} \end{cases} \tag{A.12}$$

$$soc_{\omega,t}^{max,dep} = \begin{cases} soc_{\omega,t}^{max,dep} + soc_{n}^{max,dep,car}, & \text{if } t_{\omega,n}^{dep} = t \\ soc_{\omega,t}^{max,dep}, & \text{otherwise} \end{cases} \tag{A.13}$$

The next equation gives the minimum aggregated soc for the parking lot at time t for scenario ω.

$$soc_{\omega,t}^{min,agg} = \begin{cases} soc_{\omega,t}^{min,agg} + soc_{n}^{min,dep,car}, & \text{if } t_{\omega,n}^{dep} = t \\ soc_{\omega,t}^{min,agg} + \sum_{n=0}^{N} soc_{n}^{min,car} \times \delta_{\omega,t,n}^{Parked}, & \text{otherwise} \end{cases} \tag{A.14}$$

The maximum aggregated soc for the parking lot at time t for scenario ω is given by:

$$soc_{\omega,t}^{max,agg} = \sum_{n=0}^{N} soc_{n}^{max,car} \times \delta_{\omega,t,n}^{Parked} \quad \forall\omega, \forall t \tag{A.15}$$

Expression A.16 gives the soc for the parking lot.

$$\begin{aligned} soc_{\omega,i,t} &= soc_{\omega,i,t-1} + soc_{\omega,t}^{arv} - soc_{\omega,i,t}^{dep} \\ +P_{\omega,i,t}^{En,S2PL} * \eta^{charge} &- \frac{(P_{\omega,i,t}^{En,PL2S} + P_{\omega,i,t}^{ResAct,PL})}{\eta^{discharge}} \quad \forall\omega, \forall i, \forall t \end{aligned} \tag{A.16}$$

Constraints

The first constraint for the parking lot gives the limit on the aggregated departure soc.

$$soc_{\omega,t}^{min,dep} \leq soc_{\omega,i,t}^{dep} \leq soc_{\omega,t}^{max,dep} \quad \forall\omega, \forall t, \forall i \tag{A.17}$$

Constraint A.18 gives the limit on the soc for the parking lot.

$$soc_{\omega,t}^{min,agg} \leq soc_{\omega,i,t} \leq soc_{\omega,t}^{max,agg} \quad \forall\omega, \forall i, \forall t \tag{A.18}$$

The next constraint set a limit on the power offered from the parking lot to the grid, based on the soc for the parking lot.

$$P_{\omega,i,t}^{En,PL2S} + P_{\omega,i,t}^{ResAct,PL} \leq \mu_t \times soc_{\omega,i,t} \quad \forall\omega, \forall i, \forall t \tag{A.19}$$

Constraint A.20 and A.21 ensures that power limits from the parking lot to the system are maintained.

$$P_{\omega,i,t}^{En,S2PL} \leq (N_{\omega,t}^{PEV} \times \gamma^{charge}) \times \delta_{\omega,i,t}^{PL} \quad \forall\omega, \forall i, \forall t \tag{A.20}$$

$$P_{\omega,i,t}^{En,PL2S} + P_{\omega,i,t}^{ResAct,PL} \leq (N_{\omega,t}^{PEV} \times \gamma^{discharge}) \times (1 - \delta_{\omega,i,t}^{PL}) \quad \forall\omega, \forall i, \forall t \tag{A.21}$$

Objective definitions

The following term is the degradation cost for the parking lot.

$$Cost_{\omega,t,i}^{Deg,En,PL} = P_{\omega,t,i}^{En,PL2S} \times Cd + P_{\omega,i,t}^{En,S2PL} \times Cd \tag{A.22}$$

Objective definitions wait-and-see

Equation A.23 gives the cost of being flexible with the departure soc for the electric vehicles.

$$Cost^{SOC,flex}_{\omega,i,t} = (soc^{Min,Flex}_{\omega,i,t} + soc^{Max,Flex}_{\omega,i,t}) \times soc^{Pen,Fee} \tag{A.23}$$

Constraints/Expressions wait-and-see

Equation A.24 shows the limits on the departure soc with the flexibility added in step two in the model. The limits on this flexibility is defined by equation A.25 and A.26.

$$soc^{min,dep}_{\omega,t} - soc^{Min,Flex}_{\omega,i,t} \leq soc^{dep}_{\omega,i,t} \leq soc^{max,dep}_{\omega,t} + soc^{Max,Flex}_{\omega,i,t} \quad \forall\omega, \forall t, \forall i \tag{A.24}$$

$$soc^{Min,Flex}_{\omega,i,t} \leq \beta^{Flex} \times soc^{min,dep}_{\omega,t} \quad \forall\omega, \forall i, \forall t \tag{A.25}$$

$$soc^{Max,Flex}_{\omega,i,t} \leq \beta^{Flex} \times soc^{max,dep}_{\omega,t} \quad \forall\omega, \forall i, \forall t \tag{A.26}$$

Equation A.27 shows the limit for aggregated soc in the parking lot for the second step of the optimisation if flexibility is added to the system.

$$soc^{min,agg}_{\omega,t} - soc^{Min,Flex}_{\omega,i,t} \leq soc_{\omega,i,t} \leq soc^{max,agg}_{\omega,t} + soc^{Max,Flex}_{\omega,i,t} \quad \forall\omega, \forall i, \forall t \tag{A.27}$$

A.4 External battery

This section contains the expressions added due to the external battery in the system.

Constraints

Soc for the battery is given by expression A.28

$$
\begin{aligned}
soc^{Battery}_{\omega,i,t} = soc^{Battery}_{\omega,i,t-1} + P^{En,S2B}_{\omega,i,t} \times \eta^{converter} \\
- \frac{P^{En,B2S}_{\omega,i,t} + P^{ResAct,B}_{\omega,i,t}}{\eta^{converter}} \quad \forall\omega, \forall i, \forall t
\end{aligned}
\tag{A.28}
$$

The lower and higher limits for the soc in the battery are defined in the following constraint.

$$
soc^{min,bat} \leq soc^{Battery}_{\omega,i,t} \leq soc^{max,bat} \quad \forall\omega, \forall i, \forall t \tag{A.29}
$$

Equation A.30 and A.31 states the charge- and discharge rate for the external battery. Constraint on the available energy in the system is given by A.32.

$$
P^{En,B2S}_{\omega,i,t} + P^{ResAct,B}_{\omega,i,t} \leq \gamma^{Charge,B} \times \delta^{Battery}_{\omega,i,t} \quad \forall\omega, \forall i, \forall t \tag{A.30}
$$

$$
P^{En,S2B}_{\omega,i,t} \leq \gamma^{Discharge,B} \times (1 - \delta^{Battery}_{\omega,i,t}) \quad \forall\omega, \forall i, \forall t \tag{A.31}
$$

$$
P^{En,B2S}_{\omega,i,t} + P^{ResAct,B}_{\omega,i,t} \leq soc^{Battery}_{\omega,i,t} \times \mu_t \quad \forall\omega, \forall i, \forall t \tag{A.32}
$$

The next definition states that the initial soc for the battery must be equal to the soc in the end of the analysis.

$$
soc^{Battery}_{\omega,i,t=end} = soc^{start,battery} \quad \forall\omega, \forall i \tag{A.33}
$$

Objective definitions

The degradation of the external battery is shown in equation A.34.

$$Cost_{\omega,t,i}^{Deg,En,B} = P_{\omega,t,i}^{En,B2S} \times Cd + P_{\omega,i,t}^{En,S2B} \times Cd \tag{A.34}$$

A.5 Solar power

Expressions

Equation A.35 gives the power produced by the panels and injected into the system.

$$P_t^{PV2S} = P_t^{Sun,Rad} \times \eta^{Solar} \times \eta^{Converter,solar} \times Areasolar \quad \forall t \tag{A.35}$$

A.6 Emission

Constraints

Expression A.36 gives the CO_2-balance in the system.

$$\sum_{t=0}^{T} m_t^{\mathrm{CO_2}} \times P_{\omega,i,t}^{En,S2G} + Pen_{\omega,i}^{\mathrm{CO_2}} \geq \sum_{t=0}^{T} m_t^{\mathrm{CO_2}} \times P_{\omega,i,t}^{En,G2S} \quad \forall \omega, \forall i \tag{A.36}$$

Objective definitions

Equation A.37 and A.38 gives the income and cost for CO_2 in the system, while equation A.39 defines the penalty connected to the CO_2.

$$Income_{\omega,i,t}^{\mathrm{CO_2}} = \lambda^{\mathrm{CO_2}} \times m_t^{\mathrm{CO_2}} \times P_{\omega,i,t}^{En,S2G} \tag{A.37}$$

$$Cost_{\omega,i,t}^{\mathrm{CO_2}} = \lambda^{\mathrm{CO_2}} \times m_t^{\mathrm{CO_2}} \times P_{\omega,i,t}^{En,G2S} \tag{A.38}$$

$$Cost_{\omega,i}^{Pen,\mathrm{CO_2}} = Pen_{\omega,i}^{\mathrm{CO_2}} \times \lambda^{Pen,\mathrm{CO_2}} \tag{A.39}$$

A.7 Connection point

Expressions

The first expression gives the reduction in power consumed for the incentive-based programs.

$$\Delta P^{En,G2S}_{\omega,i,t} = P^{En,G2S}_{\omega,i,t} - P^{Ini}_{omega,t} \quad \forall\omega, \forall t, \forall i \tag{A.40}$$

Equation A.41 define how much reserves that are assumed activated in the first step.

$$P^{Res,Act}_{\omega,i,t} = P^{Res}_{\omega,i,t} \times \alpha^{First} \quad \forall\omega, \forall t, \forall i \tag{A.41}$$

Expression A.42 gives the total activated reserves from step one.

$$P^{Res,Act}_{\omega,i,t} = P^{ResAct,PL}_{\omega,i,t} + P^{ResAct,B}_{\omega,i,t} \quad \forall\omega, \forall t, \forall i \tag{A.42}$$

Constraints

Constraints A.43 and A.44 gives the limit on the interaction with the grid.

$$P^{En,G2S}_{\omega,i,t} \leq \gamma^{Capacity,grid} \times \delta^{System}_{\omega,i,t} \quad \forall\omega, \forall i, \forall t \tag{A.43}$$

$$P^{En,S2G}_{\omega,i,t} \leq \gamma^{Capacity,grid} \times (1 - \delta^{System}_{\omega,i,t}) \quad \forall\omega, \forall i, \forall t \tag{A.44}$$

Energy balance for the system is given by equation A.45.

$$\begin{aligned} P^{En,PL2S}_{\omega,i,t} + P^{En,G2S}_{\omega,i,t} + P^{En,B2S}_{\omega,i,t} + P^{En,PV2S}_{t} = \\ P^{En,S2G}_{\omega,i,t} + P^{En,S2PL}_{\omega,i,t} + P^{En,G2S}_{\omega,i,t} \quad \forall\omega, \forall i, \forall t \end{aligned} \tag{A.45}$$

Equation A.46 denotes the energy constraint for the reserves offered to the grid from the system. While equation A.47 shows the limit with regards to capacity from the parking lot and the external battery. Equation A.48 makes sure that the offered reserves never exceeds the capacity in the grid.

$$P^{Res}_{\omega,i,t} \leq soc_{\omega,i,t} + soc^{Battery}_{\omega,i,t} - soc^{min,agg}_{\omega,t} - soc^{min,bat} \quad \forall\omega, \forall t, \forall i \tag{A.46}$$

$$\begin{aligned} P^{Res}_{\omega,i,t} \leq N^{PEV}_{\omega,t} * \gamma^{Discharge} + \gamma^{Discharge,B} \\ -P^{En,PL2S}_{\omega,i,t} - P^{En,B2S}_{\omega,i,t} \quad \forall\omega, \forall t, \forall i \end{aligned} \tag{A.47}$$

$$P^{Res}_{\omega,i,t} \leq \gamma^{Capacity,grid} \times (1 - \delta^{System}_{\omega,i,t}) \quad \forall\omega, \forall t, \forall i \tag{A.48}$$

Objective definitions

The following term gives the income for the system from the offered reserve capacity.

$$Income^{Cap,Res}_{\omega,t,i} = P^{Res}_{\omega,t,i} \times \lambda^{Cap}_{t} \tag{A.49}$$

Equation A.50 defines the income from the sold energy to the grid, while A.51 defines the cost from buying energy from the grid.

$$Income^{S2G}_{\omega,t,i} = P^{En,S2G}_{\omega,t,i} \times \lambda^{Energy,loss}_{t} \tag{A.50}$$

$$Cost^{G2S}_{\omega,t,i} = P^{En,G2S}_{\omega,t,i} \times \lambda^{En,tariff}_{t,i} \tag{A.51}$$

The next term, equation A.52 gives the daily cost of the annual fixed tariff.

$$Cost^{Fixed,tariff}_{i} = YearlyFee_{i} \tag{A.52}$$

Expression A.53 gives the income from the incentive-based programs. While equation

A.54 gives the costs within these programs.

$$Income_{\omega,t,i}^{Inc} = Inc_{t,i} \times \Delta P_{\omega,t,i}^{En,G2S} \tag{A.53}$$

$$Cost_{\omega,t,i}^{Pen} = Pen_{t,i}(P_{t,i}^{Cont} - \Delta P_{\omega,t,i}^{En,G2S}) \tag{A.54}$$

Objective definitions wait-and-see

Equation A.55 gives the income from the energy sold in the grid from step two.

$$Income_{\omega,t,i}^{S2G} = P_{\omega,t,i}^{En,S2G,Fixed} \times \lambda_t^{Energy,loss} \tag{A.55}$$

The income from the activated reserves are defined by equation A.56 and the equation gives the degradation cost for this activated energy under.

$$Income_{\omega,t,i}^{Res,Act} = P_{\omega,t,i}^{Res,Act,Paid} \times \lambda_t^{Energy,loss} \tag{A.56}$$

$$Cost_{\omega,t,i}^{Deg,Res} = P_{\omega,t,i}^{Res,Act,Paid} \times Cd \tag{A.57}$$

The cost for the artificial activated reserves from step two in the optimisation is given in equation A.58 and A.59.

$$Cost_{\omega,i,t}^{Res,Art,More} = P_{\omega,i,t}^{Res,Art,More} \times \lambda_t^{Cap} \tag{A.58}$$

$$Cost_{\omega,i,t}^{Res,Art,Less} = P_{\omega,i,t}^{Res,Art,Less} \times \lambda_t^{Cap} \tag{A.59}$$

Constraints/Expressions wait-and-see

The first constraint gives the limits for the energy provided to the grid in step two.

$$\begin{aligned} P^{En,S2G,Fixed}_{\omega,i,t} \times (1-\delta^{System}_{\omega,i,t}) \le P^{En,S2G}_{\omega,i,t} \le \\ (P^{En,S2G,Fixed}_{\omega,i,t} + P^{Res,Act}_{\omega,i,t} - P^{Res,Art,Less}_{\omega,i,t}) \times (1-\delta^{System}_{\omega,i,t}) \quad \forall\omega, \forall i, \forall t \end{aligned} \tag{A.60}$$

Equation A.61 states the amount of activated reserves from the system operator.

$$P^{Res,Act}_{\omega,i,t} = P^{Res}_{\omega,i,t} \times \alpha^{Second} \quad \forall\omega, \forall i, \forall t \tag{A.61}$$

The total artificial activated reserves from step two in the optimisation model is defined in equation A.62 and A.63.

$$P^{Res,Art,More}_{\omega,i,t} = P^{Res,Art,B,More}_{\omega,i,t} + P^{Res,Art,PL,More}_{\omega,i,t} \quad \forall\omega, \forall i, \forall t \tag{A.62}$$

$$P^{Res,Art,Less}_{\omega,i,t} = P^{Res,Art,B,Less}_{\omega,i,t} + P^{Res,Art,PL,Less}_{\omega,i,t} \quad \forall\omega, \forall i, \forall t \tag{A.63}$$

Equation A.64 gives the expression for the activated reserves in step two. Equation A.65 defines the actual energy provided to the grid.

$$\begin{aligned} P^{Res,Act}_{\omega,i,t} = \\ P^{ResAct,B}_{\omega,i,t} + P^{ResAct,PL}_{\omega,i,t} + P^{Res,Art,More}_{\omega,i,t} + P^{Res,Art,Less}_{\omega,i,t} \quad \forall\omega, \forall i, \forall t \end{aligned} \tag{A.64}$$

$$P^{Res,Act,Paid}_{\omega,i,t} = P^{ResAct,B}_{\omega,i,t} + P^{ResAct,PL}_{\omega,i,t} \quad \forall\omega, \forall i, \forall t \tag{A.65}$$

Appendix B

Parameters

In this section, the input data and the different scenarios are listed. This data is used in the model to get the results presented in the thesis.

Sets

The different sets used in the analysis are listed below.

Ω = [0,1,2,3,4,5,6,7,8,9]

DRP = [0,1,2]

T = [12,13,14,15,16,17,18,19,20,21,22,23,0,1,2,3,4,5,6,7,8,9,10,11]

N = [0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,24,25,26,27,28,29]

The different constant parameters used in the analysis are shown in table B.1.

Parameter	Value
$\eta^{Charge,car}$	90%
$\eta^{Discharge,car}$	90%
$N^{PEV,Max}$	30 cars
$\lambda^{Degradation}$	0.0580 €
$\lambda^{Marginalloss}$	5.135€ /MWh
$\gamma^{Charge,car}$	22kW
$\gamma^{Discharge,car}$	22kW
Capacity, battery	100kW
$\gamma^{Charge,battery}$	10kW
$\gamma^{Discharge,battery}$	10kW
$soc^{min,battery}$	5%
$soc^{max,battery}$	95%
$\eta^{Converter,battery}$	90%
$soc^{t=0,battery}$	50%
Area solar	$11.5m^2$
η^{Solar}	20%
$\eta^{Converter,solar}$	90%
$\gamma^{Capacity,grid}$	100kW
$soc^{Pen,Fee}$	0.001€
λ^{CO_2}	30€ /ton
$\lambda^{Pen,\mathrm{CO}_2}$	31€ /ton
μ_t	100% const

Table B.1: Constant parameters

The different electric vehicles have the same capacity for the whole simulation. The capacity for the cars is shown in table B.2.

Car	Capacity [kWh]	Car	Capacity [kWh]
1	100	16	35
2	100	17	40
3	75	18	28
4	75	19	36
5	67	20	95
6	60	21	86
7	75	22	75
8	90	23	44
9	67	24	42
10	67	25	35
11	95	26	40
12	86	27	28
13	75	28	36
14	44	29	28
15	42	30	36

Table B.2: Capacity for the 30 cars in the analysis (Norsk Elbilforening (2019)).

The uncertainty in this stochastic model is connected to the initial soc of the cars, when the cars arrive and when they leaves. To model this uncertainty the $soc_{\omega,n}^{PEV,ini}$, $t_{\omega,n}^{arv}$ and $t_{\omega,n}^{dep}$ is given by a truncated Gaussian distribution. The data used in order to produce the scenarios is given by table B.3

	Mean	Standard deviation	Min	Max
Initial PEV SOC (%)	50	25	30	90
Departure time (h)	8	3	5	11
Arrival time (h)	16	3	13	23

Table B.3: Input for the scenarios (Shafie-Khah et al. (2016))

The system price in the Nordic area is used as the market price in the analysis. The prices are shown in figure B.1. The prices from the balancing market in the NO2-area in Norway are given in figure B.2.

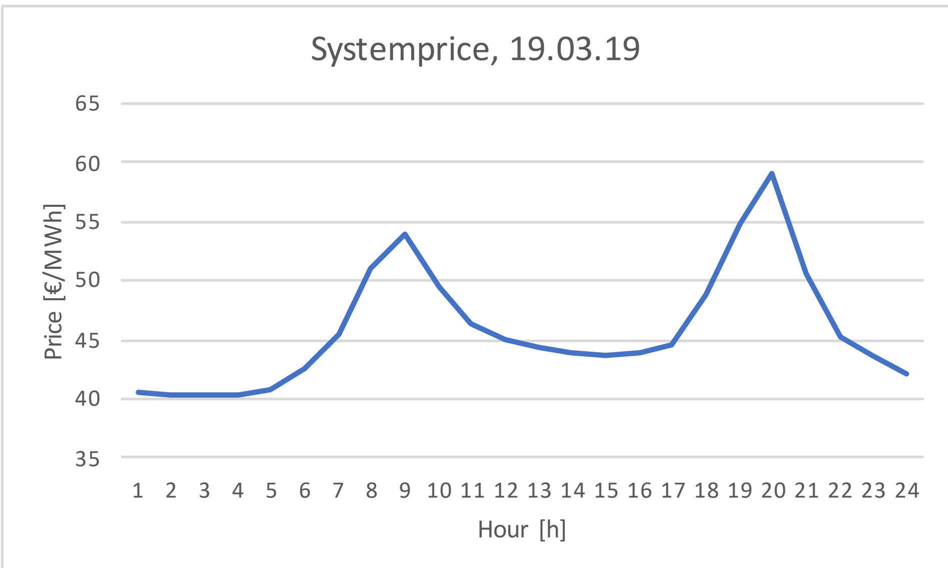

Figure B.1: Systemprice 19.03.2019 (Nord Pool Spot (2019)).

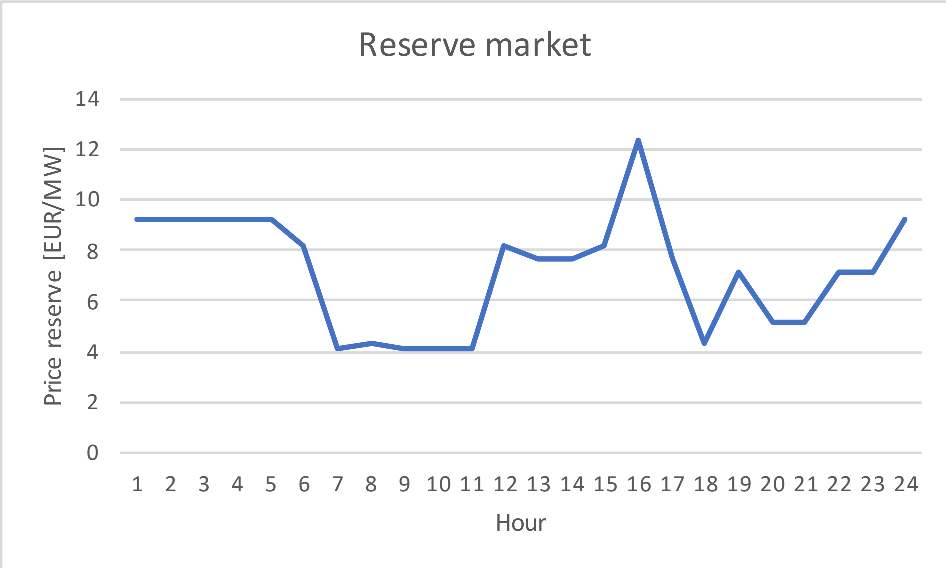

Figure B.2: Reserve market in NO2 from 29.03.19 (Statnett (2019a)).

The price for the tariffs for the different demand response programs and in the different hours are shown in table B.4.

The incentives for the I/C DRP is given in table B.5, while the penalty is given in B.6. The contracted level of reduction is given in table B.7

Hour	I/C tariff
0-7	0
8-23	1.992

Table B.5: Incentives for the I/C DRP in €/MWh (Shafie-Khah et al. (2016))

Hour	I/C tariff
0-7	0
8-23	1.992

Table B.6: Penalties for the I/C DRP in €/MWh (Shafie-Khah et al. (2016))

Hour	FR	TOU	I/C
0	19,92	15,61	19,92
1	19,92	15,61	19,92
2	19,92	15,61	19,92
3	19,92	15,61	19,92
4	19,92	15,61	19,92
5	19,92	15,61	19,92
6	19,92	39,03	19,92
7	19,92	39,03	19,92
8	19,92	39,03	19,92
9	19,92	39,03	19,92
10	19,92	39,03	19,92
11	19,92	39,03	19,92
12	19,92	39,03	19,92
13	19,92	39,03	19,92
14	19,92	39,03	19,92
15	19,92	39,03	19,92
16	19,92	39,03	19,92
17	19,92	39,03	19,92
18	19,92	39,03	19,92
19	19,92	39,03	19,92
20	19,92	15,61	19,92
21	19,92	15,61	19,92
22	19,92	15,61	19,92
23	19,92	15,61	19,92

Table B.4: The different demand response programs in €/MWh (Shafie-Khah et al. (2016) and Hansen et al. (2017))

Hour	$P_{i,t}^{Cont}$
0-7	0%
8-15	5%
16-23	10%

Table B.7: The contracted reduction for the I/C DRP (Shafie-Khah et al. (2016))

Table B.8 shows the CO_2-emission per produced unit of energy in both the NO2-area in Norway, and as mean value in the EU.

The fixed cost of the different demand response programs per day is given in table B.9.

Hour	CO_2-emission, NO2	Hour	CO_2-emission, EU
0	41	0	358
1	85	1	357
2	87	2	356
3	86	3	351
4	85	4	349
5	68	5	348
6	24	6	346
7	24	7	342
8	24	8	330
9	24	9	324
10	24	10	325
11	24	11	329
12	24	12	329
13	24	13	334
14	24	14	329
15	24	15	323
16	24	16	321
17	24	17	323
18	24	18	327
19	24	19	334
20	24	20	337
21	24	21	339
22	24	22	337
23	73	23	327

Table B.8: CO2-emissions [g/kWh] (Tomorrow (2019))

	FR	TOU	I/C
Yearly fee/day	0,49	0,49	0,49

Table B.9: Daily cost of DRP in €/day (Hansen et al. (2017))

The solar radiation used in the optimisation is shown in figure B.3.

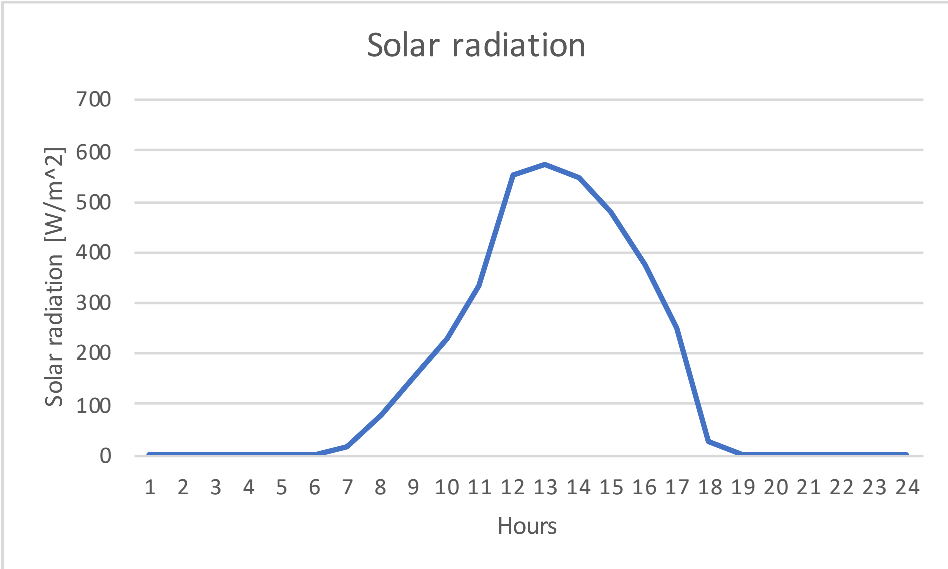

Figure B.3: Solar radiation from 29.03.19 (LanbruksMeteorologisk Tjeneste (2019))

Appendix C

Original model

This chapter presents the mathematical model developed by Shafie-Khah et al. (2016).

C.1 Objective function

The objective function in this model has a goal to maximise profit for the system according to the equation C.1 below.

$$\begin{aligned} \max profit^{PL} = \\ [\,\epsilon_{\omega_1} \sum_{t \in T} \sum_{i \in DRPs} \alpha_i \{Income^{HereAndNow}_{\omega,i,t} - Cost^{HereAndNow}_{\omega,i,t}\} \\ + \epsilon_{\omega_2|\omega_1} [\,\alpha_i \{Income^{WaitAndSee}_{\omega,i,t} - Cost^{WaitAndSee}_{\omega,i,t}\}]\,] \end{aligned} \tag{C.1}$$

Income here-and-now

$$\begin{aligned} Income^{HereAndNow}_{\omega,i,t} = \\ Income^{En,S2G}_{\omega,t,i} + Income^{Cap,Res}_{\omega,t,i} + Income^{En,Tariff}_{\omega,i,t} \\ + Income^{Stay}_{\omega,t,i} + Income^{Inc}_{\omega,t,i} \end{aligned} \tag{C.2}$$

$$Income^{En,S2G}_{\omega,t,i} = P^{En,PL2S}_{\omega,i,t} \times \lambda^{En}_{i,t} \tag{C.3}$$

$$Income^{Cap,Res}_{\omega,t,i} = P^{Res}_{\omega,i,t} \times \lambda^{Cap,Res}_{t} \tag{C.4}$$

$$Income^{En,Tariff}_{\omega,i,t} = soc^{up}_{\omega,i,t} \times \lambda^{Tariff,PL2V}_{t} \tag{C.5}$$

$$Income^{Stay}_{\omega,t,i} = N^{PEV}_{\omega,i,t} \times \lambda^{Tariff,stay} \tag{C.6}$$

$$Income^{Inc}_{\omega,t,i} = Inc_{t,i} \times \Delta P^{En,G2PL}_{\omega,i,t} \tag{C.7}$$

Cost here-and-now

$$\begin{aligned} Cost^{HereAndNow}_{\omega,i,t} = \\ Cost^{En,G2S}_{\omega,t,i} + Cost^{En,Tariff}_{\omega,t,i} + Cost^{Deg,En,PL}_{\omega,t,i} + Cost^{Pen}_{\omega,t,i} \end{aligned} \tag{C.8}$$

$$Cost^{En,G2S}_{\omega,t,i} = P^{En,G2S}_{\omega,i,t} \times \lambda^{En}_{t,i} \tag{C.9}$$

$$Cost^{En,Tariff}_{\omega,t,i} = soc^{down}_{\omega,i,t} \times \lambda^{Tariff,V2PL}_{t} \tag{C.10}$$

$$Cost^{Deg,En,PL}_{\omega,t,i} = P^{En,PL2S}_{\omega,i,t} \times Cd \tag{C.11}$$

$$Cost^{Pen}_{\omega,t,i} = Pen_{i,t} \times (P^{Cont}_{t,i} - \Delta P^{En,G2PL}_{\omega,i,t}) \tag{C.12}$$

Income wait-and-see

$$Income^{WaitAndSee}_{\omega,i,t} = Income^{Res,Act}_{\omega,t,i} = P^{Res,Act}_{\omega,i,t} \times \lambda^{Res}_{t} \tag{C.13}$$

Cost wait-and-see

$$Cost^{WaitAndSee}_{\omega,i,t} = Cost^{Deg,Res}_{\omega,t,i} + Cost^{Unavailable}_{\omega,t,i} + Cost^{Res,Tariff}_{\omega,t,i} \tag{C.14}$$

$$Cost^{Deg,Res}_{\omega,t,i} = P^{Res,Act}_{\omega,i,t} \times Cd \tag{C.15}$$

$$Cost^{Unavailable}_{\omega,t,i} = P^{Res,Act}_{\omega,i,t} \times \lambda^{Res}_{t} \times \Gamma^{Res} \times FOR^{PL}_{t} \tag{C.16}$$

$$Cost^{Res,Tariff}_{\omega,t,i} = P^{Res,Tariff}_{\omega,i,t} \times \lambda^{Tariff,V2PL}_{t} \tag{C.17}$$

C.2 Constraints and expressions

$$0 \leq \alpha_i \leq 1 \quad \forall i \in DRPs \tag{C.18}$$

$$\sum_{i \in DRP} \alpha_i = 1 \tag{C.19}$$

$$Cd = \frac{C^{Battery}}{L_{ET}} \tag{C.20}$$

$$P_{\omega,t}^{En,S2PL} \leq N_{\omega,t}^{PEV} \times \gamma^{charge} \quad \forall\omega, \forall t \tag{C.21}$$

$$P_{\omega,t}^{En,PL2S} + P_{\omega,t}^{Res,Act} \leq N_{\omega,t}^{PEV} \times \gamma^{discharge} \quad \forall\omega, \forall t \tag{C.22}$$

$$\begin{aligned} soc_{\omega,t} = soc_{\omega,t-1} + soc_{\omega,t}^{arv} - soc_{\omega,t}^{dep} + P_{\omega,t}^{En,S2PL} \times \eta^{charge} \\ -(P_{\omega,t}^{En,PL2S} + P_{\omega,t}^{Res,Act})/\eta^{discharge} \quad \forall\omega, \forall t \end{aligned} \tag{C.23}$$

$$soc_{\omega,t}^{arv} = \sum_{n=1}^{N_{\omega,t}} Cap_{\omega,t,n}^{PEV} \times soc_{\omega,t,n}^{PEV,ini} \quad \forall\omega, \forall t \tag{C.24}$$

$$soc_{\omega,t}^{up} = \begin{cases} 0, & \text{if } soc_{\omega,t}^{dep} \leq (soc_{\omega,t-1}^{Sc} - soc_{\omega,t}^{Sc}) \\ soc_{\omega,t}^{dep} - (soc_{\omega,t-1}^{Sc} - soc_{\omega,t}^{Sc}), & \text{otherwise} \end{cases} \tag{C.25}$$

$$soc_{\omega,t}^{down} = \begin{cases} 0, & \text{if } (soc_{\omega,t-1}^{Sc} - soc_{\omega,t}^{Sc}) \leq soc_{\omega,t}^{dep} \\ (soc_{\omega,t-1}^{Sc} - soc_{\omega,t}^{Sc}) - soc_{\omega,t}^{dep}, & \text{otherwise} \end{cases} \tag{C.26}$$

$$soc_{\omega,t}^{Sc} = \sum_{n=1}^{N_{\omega,t}} Cap_{\omega,t,n}^{PEV} \times soc_{\omega,t,n}^{PEV,Sc} \quad \forall\omega, \forall t \tag{C.27}$$

$$soc_{n}^{PEV,min} \leq soc_{\omega,t,n}^{PEV} \leq soc_{n}^{PEV,max} \quad \forall \omega, \forall t, \forall n \tag{C.28}$$

$$\sum_{n=1}^{N_{\omega,t}} soc_{n}^{PEV,min} \leq soc_{\omega,t} \leq \sum_{n=1}^{N_{\omega,t}} soc_{n}^{PEV,max} \quad \forall \omega, \forall t \tag{C.29}$$

$$P_{\omega,t}^{En,PL2S} + P_{\omega,t}^{Res,Act} \leq \mu_{t} \times soc_{\omega,t} \quad \forall \omega, \forall t \tag{C.30}$$

C.3 Uncertainty expressions

$$soc_{n}^{PEV,ini} = f(x) = f_{TG}(x; \mu_{soc}, \sigma_{soc}^{2}, (soc_{n}^{PEV,min}, soc_{n}^{PEV,max})) \quad \forall n \tag{C.31}$$

$$t_{n}^{arv} = f(x) = f_{TG}(x; \mu_{arv}, \sigma_{arv}^{2}, (t_{n}^{arv,min}, t_{n}^{arv,max})) \quad \forall n \tag{C.32}$$

$$t_{n}^{arv} < t_{n}^{dep} \quad \forall n \tag{C.33}$$

$$t_{n}^{dep} = f(x) = f_{TG}(x; \mu_{dep}, \sigma_{dep}^{2}, (Max\{t_{n}^{dep,min}, t_{n}^{arv}\}, t_{n}^{dep,max})) \quad \forall n \tag{C.34}$$

$$soc_{t,n}^{PEV,Sc} = \begin{cases} soc_{n}^{PEV,ini}, & \text{if } t_{n}^{arv} \leq t < t_{n}^{dep} \\ 0, & \text{otherwise} \end{cases} \tag{C.35}$$

$$N_t^{PEV} = N_t^{PEV,arv} - N_t^{PEV,dep} + N_{t-1}^{PEV} \quad \forall t \tag{C.36}$$

$$N_n^{PEV} \leq N^{PEV,max} \quad \forall t \tag{C.37}$$

$$f(x) = \begin{cases} 1/P_{\omega,t}^{Res}, & \text{if } 0 \leq x \leq P_{\omega,t}^{Res} \\ 0, & \text{otherwise} \end{cases} \tag{C.38}$$

Thomas Kallevik

NTNU
Norwegian University of
Science and Technology