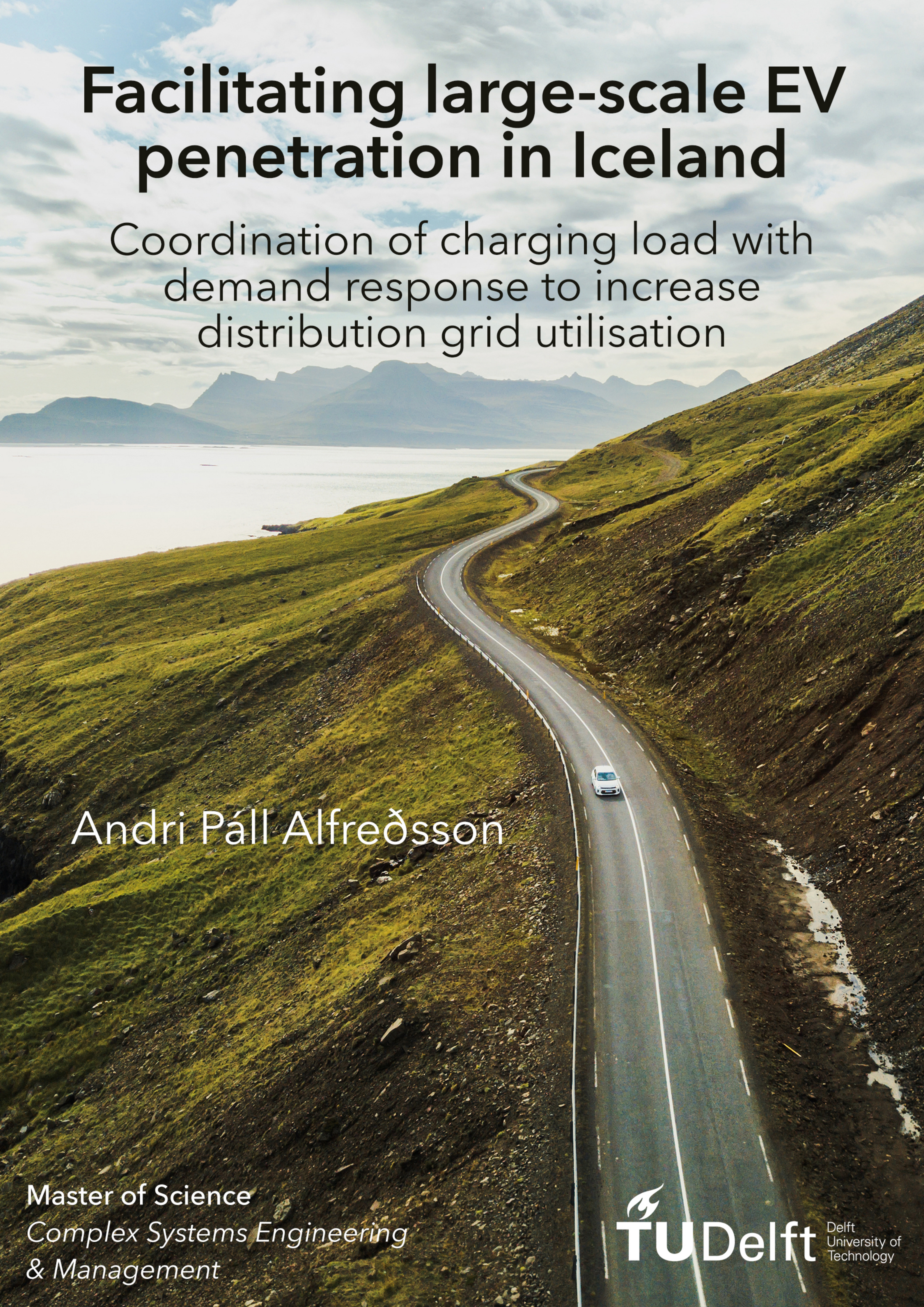
Facilitating large-scale EV penetration in Iceland

Coordination of charging load with demand response to increase distribution grid utilisation



Andri Páll Alfreðsson

Master of Science
Complex Systems Engineering & Management

TU Delft Delft University of Technology

Facilitating large-scale EV penetration in Iceland

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by

Andri Páll Alfreðsson

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	Dr. M.E. Warnier	TU Delft, 2nd supervisor

Preface

This thesis is the result of months of hard but enjoyable work. It is a subject I am deeply interested in and getting the opportunity to focus on Iceland was very rewarding. This thesis would not have been possible without the people who helped me throughout the process. To my first supervisor, Rudi Hakvoort, thank you for your guidance and valuable feedback along the way. I would also like to thank Martijn Warnier, my second supervisor, for structured and clear feedback. Special thanks go to Kári Hreinsson at Veitur, which helped me so much along the way with his great feedback and expert advice. Lastly, Kjartan Rolf Árnason at Rarik was of great help from the very beginning of the process and offered valuable input and helpful advice.

To my family and friends, thank you for your patience and motivation over these last months. To my unexpected thesis partner - due to changed circumstances - my girlfriend Kristín, thank you for your love and support. It means the world to me and without you I could not have completed this thesis. I feel extremely lucky to have been able to work together on our theses everyday for these last six months. To my parents I am forever grateful, you have always supported me and taught me so much about life and especially that hard work pays off, which really helped me finish this challenging thesis project. I also want to thank my grandparents, which have always encouraged me in my studies and inspired me so much.

Originally, this thesis was supposed to be carried out in the Netherlands. The plan was to largely conduct this research alongside my colleagues from CoSEM in the TPM building on the TU Delft campus. Only a month into that process, the covid-19 pandemic hit and the thesis work swiftly moved to Iceland. Therefore almost the entire thesis project has been developed in Iceland. Despite this, it has been a gratifying process and an incredible learning experience.

This thesis topic is one that I largely formulated myself. It took a lot of background research, frustration and effort, but in the end I am extremely proud to have developed this topic and of the resulting thesis that you are about to read. Iceland is an incredible country and one that can truly take the lead in electric vehicles and green transport. I hope this thesis contributes to that journey and that I get to continue to work in this exciting field.

Andri Alfredsson,
Reykjavík, August 2020

Executive summary

With increased awareness of anthropogenic emissions, most sectors are changing rapidly. One of those, is the transport sector which has seen immense change with the increase of electric vehicles in recent years. Although these electric vehicles reduce emissions and are a welcoming sign of change, they greatly increase electrical demand. Furthermore, this demand is often positioned in the lowest levels of the residential distribution grid, which puts increased pressure on power delivery and often causes congestion. Electric vehicles become the biggest appliance of the household and can easily multiply the power demand of a regular household. Conventional city distribution grids were not designed for this high EV penetration and as a result will experience problems with a high penetration of those vehicles. This can lead to overloaded lines, increased system losses and reduction in utilisation of the infrastructure. In the end, it might require reinforcements of the infrastructure on a grand scale in order to maintain grid integrity.

As the supply side of electricity is getting increasingly difficult to optimise, focus has switched to the demand side, in an attempt to affect and reduce demand. One of the ways to do this is by using demand response, which essentially shifts consumption of electricity in time or simply reduces it. This is most often carried out by lowering prices and hoping consumers will respond or by entering bilateral contracts between distribution system operators and consumers. This act of changing consumption of electricity is also something that can be done with EVs, by shifting the time of charging to more favourable times for the grid. With this, grid problems can be reduced and reinforcements avoided or delayed. This increases the utilisation of the grid and allows more EVs to enter the system.

In this master thesis project, Iceland was chosen as a case study, and the effects of EV charging load on the distribution grid in the country's capital region were explored. Additionally, two demand response strategies were implemented and their performance in reducing peaks and minimising the impact on the grid were evaluated. The main methodology was a modelling and simulation approach that considered system properties and findings from a literature review to select applicable demand response strategies. Data and information on the distribution grid was acquired to quantify the performance of those strategies. From this approach, extensive simulation results could be generated and based on that, important insights into the problems of large-scale EV charging in Iceland gathered. More importantly, the model findings could offer solutions on how to solve those problems.

Iceland was chosen as it is one of the fastest growing EV markets in the world. Governmental incentives and regulations have supported this growth and it is only expected to increase. Additionally, Iceland has many unique characteristics which exaggerate the problem of EV load. Car ownership is incredibly high and the vast majority of charging takes place in homes, in residential streets. The current state of the grid is near congestion and delivering power to the lowest levels of the grid, where the EV charging takes place, will be very challenging. From the literature review conducted, certain demand response strategies which are essentially different implementations, were deemed unviable in Iceland. This was mainly based on the need for specialised infrastructure or a more dynamic electricity market. Two strategies were chosen, time of use and direct load control, which were considered to be applicable in the distribution grid in the capital region of Iceland.

The formulation of the model that was used was based on a conceptual model that subsequently guided the implementation of a technical model. A novel charging behaviour dataset was used to represent the charging profile of a large EV fleet. This dataset was based on a study conducted in Iceland and shows specific charging behaviour in the system which was researched. Datasets on primary electricity use, which is all regular consumption in the grid without EV charging, were acquired on two different voltage levels of the grid. This made it possible to analyse the effects of charging load, combined with this primary load from a holistic approach, both from the bottom-up and top-down.

The results of the model showed that with a moderately small EV-fleet and no coordination of the charging of these EVs, the grid's capacity would be exceeded. However, by utilising two different demand response strategies, the load peak could be significantly reduced and a much higher number of EVs could be allowed to enter the system without breaking its limits. However, the results also showed that the bottleneck was in the lower levels of the system and allowed much fewer EVs and became overloaded in all scenarios. The direct load control strategy still offered significant benefits on this level and could thus be a solution to this problem.

The findings of the research demonstrate that large-scale EV charging is an imminent problem, which will affect the distribution grid heavily when the EV fleet increases in size. The grid is most constrained on its lower levels and without any coordination of charging, the desired EV penetration which Iceland hopes for will be hard to realise. Demand response can certainly reduce the load impact and allow for better utilisation of the infrastructure, but in the end reinforcements of the grid seem to be necessary.

Based on the research findings, practical recommendations to the DSO and other energy market players can be offered. The time of use strategy can be seen as the easier choice implementation wise and would be a good starting option. With increased technical level of the infrastructure, direct load control could be implemented. However, two pathways forward are identified, either inactive control, only reinforcing the grid in a reactive manner, or demand response implementation and thus a proactive load control method. The second option is recommended, as it will lower the overall load impact, increase utilisation of the infrastructure and delay reinforcements.

Future research should focus on mapping out the distribution grid better to more accurately measure the load impact on the lower levels. Limited data made this part of the research challenging. This is necessary as this is the part of the system where the bottleneck lies and will improve the approach of the demand response strategies. Different variations of the modelled demand response strategies should also be explored, as that could offer improved performance and lowered peaks.

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List of Abbreviations

BEV	Battery Electric Vehicle
DLC	Direct load control
DR	Demand response
DRP	Demand response programs
DSO	Distribution system operator
EU ETS	European Union Emission Trading System
EU	European Union
EV	Electric Vehicle
GHG	Greenhouse gas emissions
HEMS	Home energy management system
IBP	Incentive-based programs
KPI	Key performance indicator
PBP	Price-based programs
PHEV	Plug-in Hybrid Electric Vehicle
REP	Retail electricity provider
RES	Renewable energy sources
TOU	Time of use
TSO	Transmission system operator

1 Introduction

With rising levels of anthropogenic emissions and their effects on the warming of the planet and subsequent change of climate, sectors are in a transition towards more sustainable use of energy. This is certainly the case in the energy sector, responsible for over 40% of global CO_2 emissions, which is decarbonising rapidly (IEA, n.d.). There is a global push for renewable energy sources (RES), especially for electricity production, with wind and solar being implemented on a large scale. But energy consumed in the form of electricity is only a small share of global energy consumption, around 20% in 2015 (IEA, n.d.). However, this has been changing over the last years, where cooking and heating are increasingly being electrified, replacing gas and other fossil fuels. In recent decades, international agreements have been signed such as the Kyoto protocol, Copenhagen Accord and most recently the Paris agreement. These agreements mainly focus on two things, increasing the share of RES and/or decreasing greenhouse gas emissions (GHG). Worldwide, nations are working hard towards the Paris agreement which was put into place in 2016 and aims to reduce emissions by 40% compared to pre-industrial levels in 1990 (The Council of The European Union, 2016).

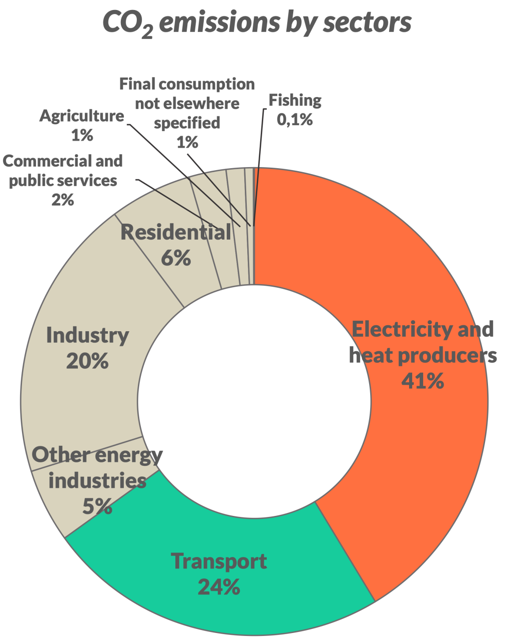


Figure 1.1: Worldwide CO_2 emissions by sectors. Energy and transport sectors are responsible for over 65 % of emissions (IEA, n.d.)

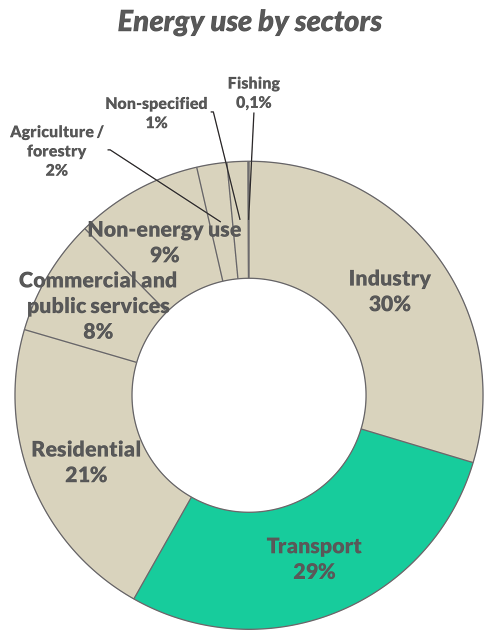


Figure 1.2: Worldwide energy use by sectors. The transport sector consumes almost third of all energy consumed (IEA, n.d.)

Besides the energy sector, another sector which is a big emitter is beginning to change. That is the transport sector, which amounts to roughly 29% of the world's energy consumption and is responsible for almost 24% of global CO_2 emissions (IEA, n.d.). In figure 1.1 and 1.2, an overview of the emissions and energy use of different sectors can be seen. The energy transition in the transport sector is well under way, mainly due to electrification and the use of sustainable fuels that have a much smaller carbon footprint than conventional sources. Freight and train transport are also seeing a big change with increasing numbers of electric trains and vans. Perhaps the most noticeable part of the fuel switching in transport is the electrification of road transport. More and more players in the automotive industry are moving away from the internal combustion engine to electric motors in vehicles. Almost all major car brands now offer battery electric vehicles (BEV) or plug-in hybrid electric vehicles (PHEV). In figure 3 the sales of EVs (both BEVs & PHEVs) in Europe can be seen as well as their market share.

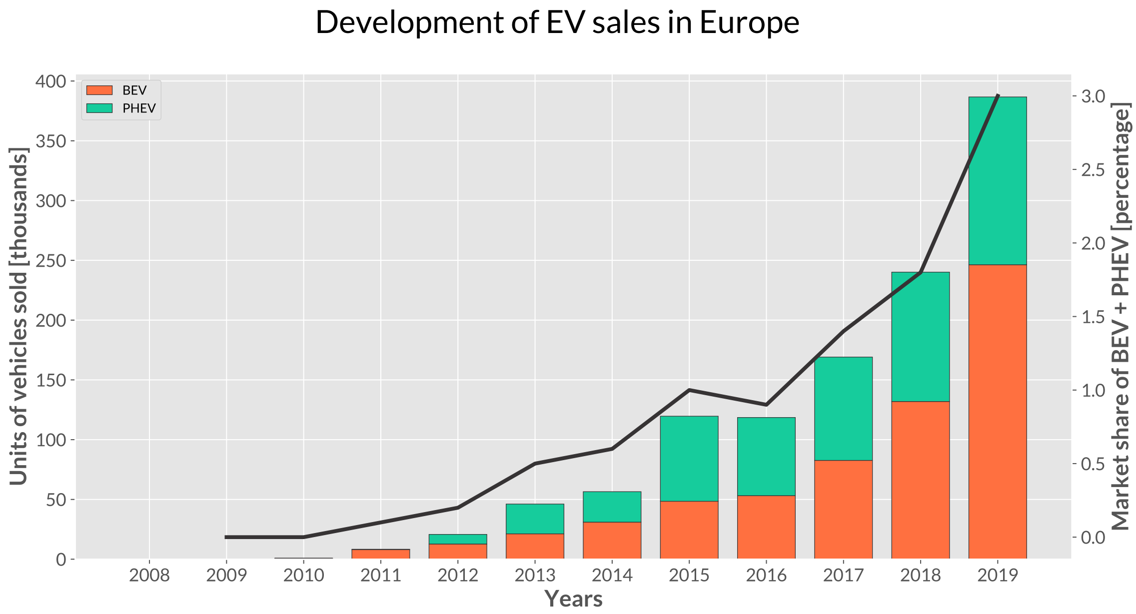


Figure 1.3: The number of new EV registrations and market share of EVs in Europe from 2008-2019 (European Alternative Fuels Observatory, 2019)

1.1. Electric vehicle load

Although the rising numbers of EVs and the move away from fossil fuels in road transport is very positive, this change will still have some major consequences. The biggest impact is the increased electrical demand of that sector. This increases the need for generation capacity and if this electricity is supplied by pollutant power plants, EVs will essentially be contributing to emissions, running on pollutant power. Additionally, this load is mostly positioned in the lower levels of the power system; the residential distribution grid, which can become congested when this increased electricity supply is fed to this part of the system. EVs are mainly adopted by households and businesses which are situated in these lower levels of the distribution grid and the increase in electrical load with a high penetration of EVs can be huge.

To react to this heightened demand, it is either needed to reduce the demand or increase the supply. With the current energy transition, coal and gas are being phased out and replaced with RES and other more sustainable sources, but this conversion is costly and slow. The optimisation of the generation side, that has been going on for the last decades, has thus become much harder as there is a global consensus that these conventional generation sources cannot be sustained and continued to be used. Affecting the demand side of the equation can therefore be very beneficial and has gathered immense interest of researchers and industry players in recent years. This act of affecting the demand is most often referred to as demand-side management (DSM). It can be categorized into two subgroups, energy efficiency (EE) and demand response (DR) (Behrangrad, 2015). Improved energy efficiency essentially makes more out of every unit of produced electricity. With new standards in household appliances and better energy ratings of buildings - largely credited to the EU's directive on energy efficiency instated in 2012 - energy efficiency has gone up tremendously over the last years in Europe (European Comission, 2020). Demand response is a more active method, where consumption of electricity is either shifted in time or reduced to better match the supply. This is precisely something that can be done with EVs. With smart charging and changed behaviour of EV owners, the added demand of EVs can be managed and its impact on the distribution grid minimised. Moreover, research has shown that not only can this EV load impact be minimised with demand response strategies, but it can actually improve the efficiency of the power grid (Lund & Kempton, 2008; Ravi & Jain, 2017). However, uncoordinated charging of EVs can cause distribution grid problems (Clement-Nyns, Haesen, & Driesen, 2011; Blasius, 2017).

1.2. Iceland as a case study

In this thesis project, the load impact of EVs will be explored and how the load can be managed with demand response techniques, based on a case study of Iceland's capital region distribution grid. Iceland is one of the fastest growing EV markets in the world. In 2019, 27.5% of new car sales were EVs (BEVs & PHEVs) (BGS, 2020). Worldwide, only Norway has a higher share of EVs sold (World Economic Forum, 2019). Iceland is a member of the European Union Emissions Trading System (EU ETS), which applies mostly to the aviation and the heavy industry sector (Ministry for the Environment and Natural Resources, 2019). Road transport is responsible for about 20% of the country's total GHG emissions (Ministry for the Environment and Natural Resources, 2019) that fall outside of the ETS system and its energy transition is thus very important for the country's commitments towards climate change. The majority of the generated electricity is transported directly by the transmission system operator (TSO) to industrial end-users, which consume more than 80% of all electricity produced (National Energy Authority, 2019a). Electricity delivered to the country's capital region distribution grid - where roughly 65% of the country's population lives (Statistics Iceland, 2020) - is only possible from certain power plants. The scope of this research project is focused on this capital region which is centered around Iceland's only city, Reykjavik, and its nearby municipalities. In figure 1.4 on page 5 an overview of these municipalities can be seen.

With the rising numbers of EVs, the added electricity demand of a large EV fleet can go up to about half of the current primary electricity use in the capital but more importantly, it can have a multiplier effect on the peak demand in the capital, with a forecasted peak demand increase of up to 100% (National Energy Authority, 2019b). The energy demand of these EVs is not the biggest concern - as households consume only about 5% of the electricity produced (National Energy Authority, 2019a) - but the power demand certainly is, especially for the capital distribution grid. This major increase in demand calls for major reinforcements of the grid, additional power capacity and possibly additional infrastructure to deliver that electricity to the distribution grid. As the distribution grid was designed and implemented before EV development came around, it is not designed to handle a large EV fleet. With steadily increasing numbers of EVs and uncoordinated charging, the distribution grid is at risk and costly reinforcements are needed if grid integrity is to be maintained. However, with demand response techniques, these reinforcements can be rendered unnecessary or at least delayed. By coordinating the charging of EVs, demand can be shifted on small timescales to minimise negative effects on the grid and increase the efficiency of the energy infrastructure. As this is an emerging and recent problem, it is vital to evaluate how electricity demand of a large EV-fleet will affect the distribution grid and how this demand can be controlled to reduce its negative impact.

Demand response with EVs has not been researched before and applied in Iceland and neither has there been conducted an analysis on the effects of large-scale EV charging on the distribution grid in the capital region. This is due to several reasons, but can be viewed as both an academic and a practical knowledge gap. First of all, there is a practical gap from missing data as EV charging data specific to Iceland has never before been available. However, this thesis uses new data from an EV study conducted in Iceland in 2019 and is the first academic project to do so. Additionally, the academic knowledge gap comes from the fact that there is no consensus on what kind of demand response strategies are applicable and viable in Iceland and what is needed to implement them. From this knowledge gap, the main research question derives:

How can demand response strategies be used to coordinate the charging of a large EV-fleet to reduce the load impact on Iceland's capital distribution grid?

This thesis project focuses on understanding how a large EV fleet impacts the distribution grid in Reykjavik, Iceland's capital, what kind of demand response strategies are applicable and how they can reduce this impact. The EVs in question in the project are regular passenger cars, either owned by households or businesses. Freight transport as well as public transport or passenger service cars are not included in this research project. This is due to the fact that these types of vehicles will most likely be electrified later, they do not have the same consumption patterns as passenger EVs (which are situated and driven in the capital most of the time) and they are more unlikely to participate in demand response programs as their flexibility in charging is much less.

1.3. Research approach

Choosing a suitable research approach depends on the nature of the research project. If the main research question is dissected, it becomes clear that is has two main components. First, it is understanding how a large EV-fleet impacts the distribution grid. This can be challenging due to the fact that EVs are a relatively new and emerging technology and currently there are only around 12.000 (ON Power, 2020) EVs (BEV & PHEV) in Iceland or around 4% of all passenger cars (Environment Agency of Iceland, 2019). Moreover, to properly assess the impact of a large EV-fleet, the charging behaviour of EVs must be known or estimated and the capacity and properties of the distribution grid as well. The second component builds on the first one, which is to analyse the effects of different demand response programs based on EV charging and distribution grid properties.

1.3.1. Type of research problem

The problem that the research question aims to solve is a well-grounded one, both popular in literature and present in energy systems around the world. However, Iceland's circumstances are different to most other energy systems, but generally the same theories on demand response and distribution grids will apply. Based on this, a case study approach seems to fit the project in some ways. As (Eisenhardt, 1989, p.534) puts it: (a case study) *"focuses on understanding the dynamics present within single settings"*, which is applicable to certain parts of the project. The settings in Iceland are indeed special, but the behaviour of EVs and their interaction with the grid are very similar to most other studied cases. So to determine the suitable research approach for this project, the problem itself has to be considered. This problem is both focused on understanding the charging behaviour of a large EV fleet in Iceland and exploring different charging strategies. Therefore, the main research approach needs to be one that can solve this problem. This specific research problem is a case study of Iceland, but it is also a more general energy system problem and thus needs a suitable research approach.

1.3.2. Modelling approach

As stated earlier, different types of research projects call for different research approaches. Based on the two components that the research question tries to answer, the answer can be viewed as an exploratory and evaluative type of research question. First it explores the current state of the energy system and uncoordinated charging, but also gathers insights into different charging scenarios and evaluates their effects on the distribution grid. The main research approach thus has to be able to measure the behaviour of this system and explore its performance under these different charging scenarios. For this reason, the main research approach is chosen to be a modelling approach. To be more specific, the chosen approach is a modelling and simulation approach, which can both be considered a method and a tool (TU Delft wiki, 2010). The energy system and distribution grid will be modelled and demand response programs will then be simulated using that model.

There are numerous reasons why this approach is suitable and advantageous for this project. First of all, there are many system uncertainties. This includes uncertainty about EV behaviour, future developments, policies and participation in the different demand response strategies. Different stakeholders can also influence the behaviour of the system, which in this case is the energy market at the distribution grid level. Lastly, the energy market itself is fundamentally a very complex system where many technologies and agents interact. This makes it hard to approach the project with a purely analytical methodology. But modelling and simulation can deal with problems where analytical solutions are hard to find (TU Delft wiki, 2010). For this project and the audience of it; the involved distribution system operator (DSO), energy companies and policy makers, exact numbers and numerical results are not the most important outcome, but rather insights into how different demand response strategies perform and what levels of consumer participation are needed. This kind of problem is also where modelling and simulation is a strong approach (TU Delft wiki, 2010). But in order to effectively model the system of interest, several aspects have to be researched. In order to answer the main research question, several sub-research questions are formulated.

1.3.3. Sub research questions

Although a modelling and simulation approach is the main research approach, the sub-research questions can have their own approaches which together support the solving of the main question. The proposed sub-questions are:

1. *What is the current state of EVs and EV related policies in Iceland?*
2. *What kind of DR strategies are applicable to utilise a large EV-fleet as a DR resource in Iceland?*
3. *How can EV load effects on the distribution grid be measured?*
4. *How can the effect of different demand response strategies be assessed and modelled?*
5. *How does EV charging affect the distribution grid under different DR scenarios?*

In the next section, these sub-research questions are placed in different research phases for the thesis project, where they are described in more detail and their individual methods and approaches are described.

1.4. Project overview

The project will be carried out by creating a model that simulates the load of a large EV fleet based on real EV data from Iceland and then implementing demand response strategies that affect the charging profile of that fleet. This problem involves many technological components but also the behavioural aspect of electricity consumers. This makes it highly complex and is further exaggerated by the number of stakeholders in the energy system, often with different interests and powers. The results of the research will serve mainly two groups, policymakers and energy market players. As will be explained later on in more detail, this problem is primarily the DSO's problem, as the distribution grid is the part of the energy system infrastructure that is most constrained in terms of this increased load. The thesis project is carried out in cooperation with Veitur, a DSO active in the Reykjavik capital area which serves 5 out of 6 municipalities in that area. In figure 1.4 these municipalities can be seen.

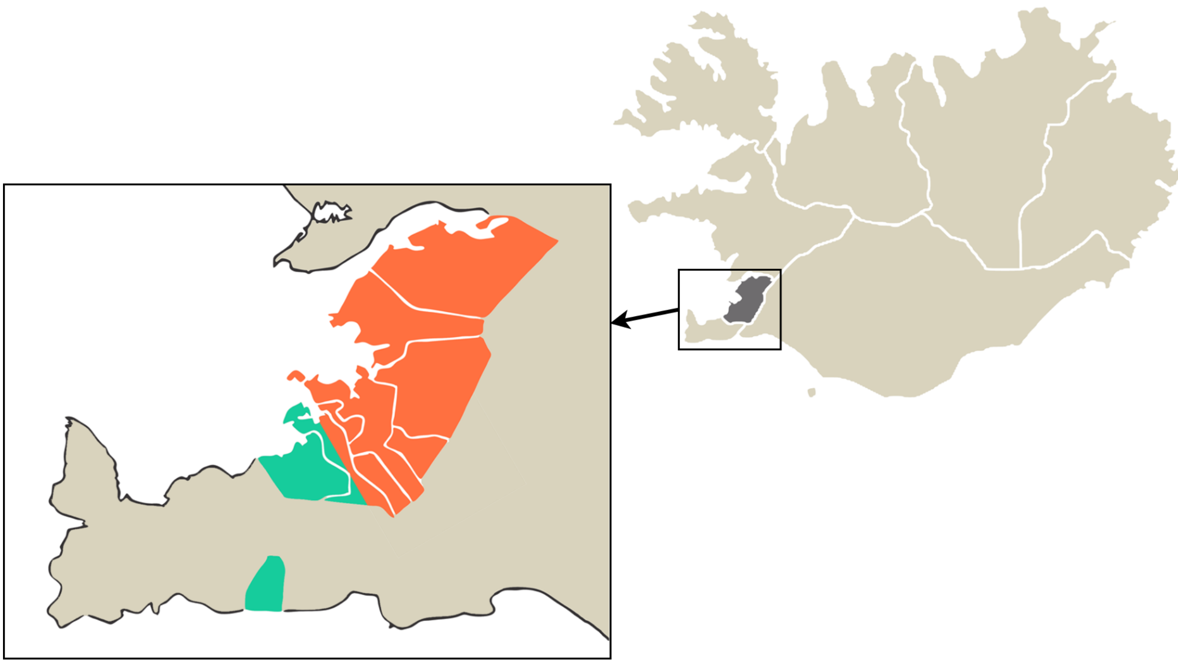


Figure 1.4: The municipalities in the capital region. Orange-marked are municipalities which Veitur is active in. Green-marked are municipalities are where the other DSO in the capital region, HS Veitur, is active. Original pictures from the Icelandic Association of Local Authorities, retrieved from `https://www.samband.is/sveitarfelogin/`

1.4.1. Research phases

The sub research questions (sub-RQs) presented above support the main thesis approach. As the main research approach is modelling and simulation, the sub-RQs can be thought of as a sequence of phases towards a working model that can assess the load impact of a large EV-fleet, which can then simulate different demand response strategies. For this reason, different phases were built around these sub-RQs. These phases create an outline for the creation of the model that will then be used to answer the main research question. Each research phase logically leads to the next one, where it relies on the deliverables of the previous phase. In figure 5, a research flow diagram (RFD) can be seen, which gives a visual overview of the deliverables, theories and methods that are used or produced by each phase. The five sub-RQs can be seen in the RFD, marked with Q and a number. The first four phases are linked to the sub-RQs but the last phase analyses and discusses the results of the created model and simulations and concludes the research project. In this section, the motivation behind these phases and how they contribute towards solving the sub-research questions and ultimately the main research question, will be explained.

Phase 1 - Information & data gathering

The first phase serves as a foundation for the project and an introduction to the state of EVs in Iceland and the energy market. The first sub-RQ in this phase explores the state of EVs in Iceland and current and future policies that affect them. Tax incentives have been deployed over the years to increase the uptake of EVs and in 2030, new registrations vehicles that run solely on diesel and gasoline will be banned (Environment Agency of Iceland, 2019). The current growth of EVs is thus expected to rise substantially in coming years.

The second sub-RQ in this phase explores what kind of DR strategies are available and can be used with EVs. This will be done with a literature review, which is both meant to explore and evaluate DR strategies, as well as provide additional background and theoretical knowledge for the subsequent research phases.

Phase 2 - Model conceptualisation

This phase is the start of the modelling process, where the model is conceptualised. This is done by gathering additional datasets and information and determining how load effects on the distribution grid can be measured. This is done by consulting with industry experts, information gathering and using the theoretical and background knowledge from research phase 1. At the center of this phase is a conceptual model, which is essentially a non-technical representation of what is to be modelled. The process of this model formulation is also carried out in the next phase.

Phase 3 - Model formulation & implementation

This is where the creation of the technical modelling starts. The chosen DR strategies are conceptualised in the conceptual model and after that, the technical model is implemented in a programming language. In this phase, the modelling key performance indicators (KPIs) are also defined, which translate the model outputs into results. The deliverable of this phase is a model that can simulate the load of an uncoordinated EV fleet, then a fleet based on the DR strategies and lastly the impact on the grid, based on the work from phase 2.

Phase 4 - Model use

In this phase the model is used to simulate different scenarios based on the DR strategies and the uncoordinated load. It will also formulate and define the most likely input parameters for the modelling simulations. The simulations are then run for all the intended scenarios. The output of this phase are thus the complete simulation runs for the three different scenarios as explained before as well as outputs for the different KPIs as defined in previous phases.

Phase 5 - Modelling analysis & conclusion

This last phase analyses the results of the model simulations and results of the KPIs. Additionally it will perform a sensitivity analysis on the required parts of the modelling for the discussion part of the thesis. As the model runs will be numerous and extensive, good visualisation of the results is important and will be implemented in this phase.

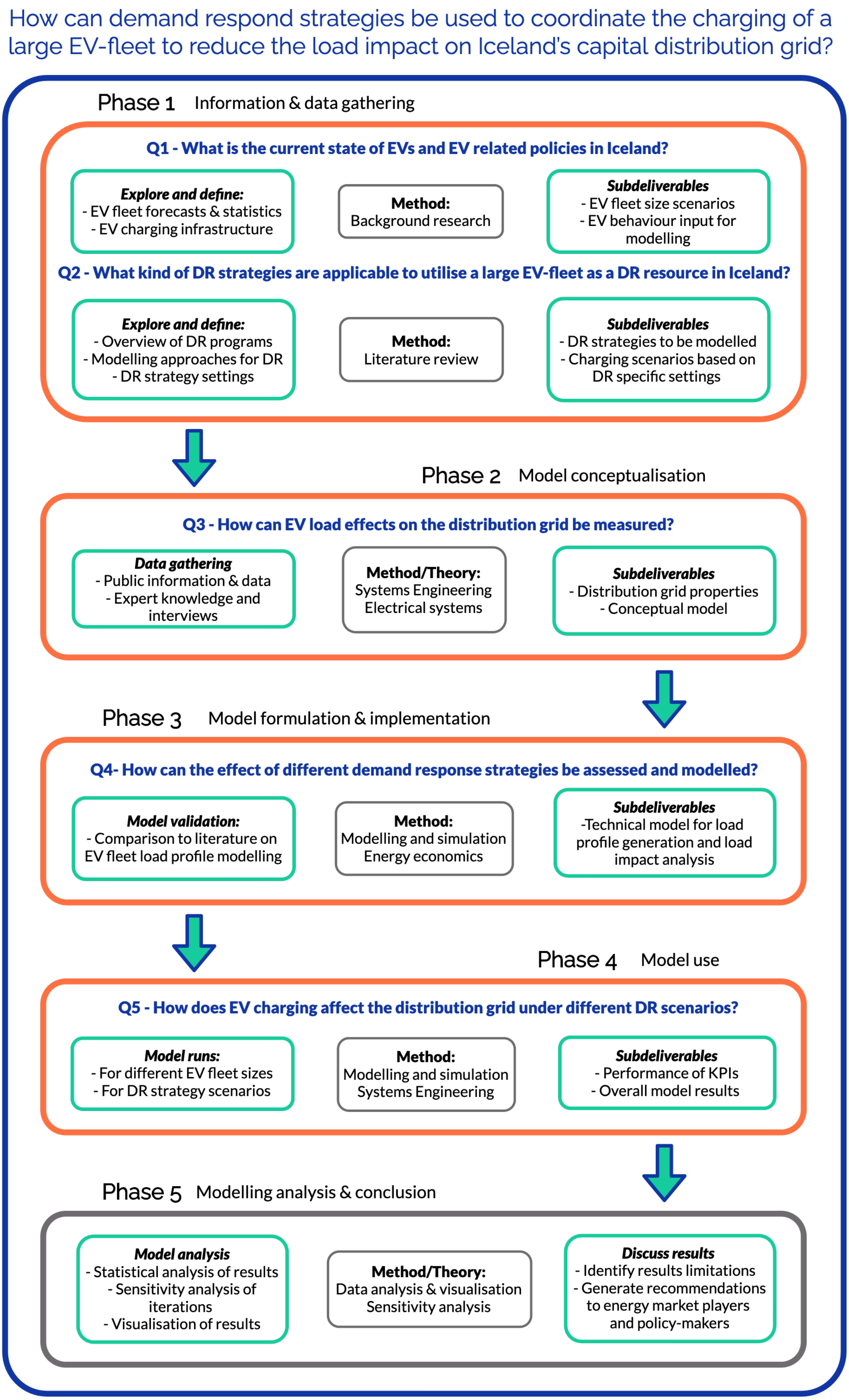


Figure 1.5: The research flow diagram. It provides an overview of the phases of the research and the methods and theories used to produce the deliverables/outputs of the phases.

1.4.2. Thesis outline

This thesis report is divided into multiple chapters. In the same way as the research phases, these chapters guide the reader through a sequential process from problem definition in the beginning to results and concluding remarks in the end. Below a short explanation of these chapters is provided.

2. Background
This chapter provides background information on the energy system in Iceland and the state of EVs in Iceland.

3. Literature review
In this chapter the existing literature on DR strategies for EVS is reviewed. Theoretical knowledge and core concepts for the research are also laid out and lastly the knowledge gap motivating the research is identified.

4. Conceptual model
In chapter four, the main methodology of the thesis project, the conceptual model is formulated. It goes through all of the elements needed to create this model, as well as the assumptions and simplifications of that process.

5. Data
This chapter explains and analyses the data that is used in this thesis project. These datasets are largely based on the inputs of the conceptual model, formulated in the previous chapter.

6. Technical model implementation
Chapter six explains the implementation of the technical model, which is based on the conceptual model. These implementation steps will be explained in detail.

7. Results
The results of the use of the technical model are presented in this chapter. First the input parameters and setup of the simulations will be explained and then the results will be displayed in separate subsections.

8. Discussion
In this chapter the findings of the thesis are discussed, first based on the general research and then on the model results. The limitations of the methodology will also be discussed.

9. Conclusion
This chapter concludes this thesis. The answer to the research questions are provided, first to the main one and then to the sub-research questions. Lastly, the thesis project will be reflected upon, both from an academic and a practical viewpoint.

2
Background

This chapter is dedicated to providing background knowledge on the Icelandic energy system and the state of EVs in Iceland. Together with chapter 3, the literature review, these two chapters create a knowledge foundation for this thesis project to make the decision-making, methodology and analyses more understandable.

2.1. Energy system overview

The Icelandic energy system is truly unique. Almost all of the electricity (99.97% (National Energy Authority, 2019b)) produced in Iceland is renewable. Installed electricity capacity is roughly 2850 MW, with the majority made up of hydropower (2095 MW) and geothermal energy (753 MW) (IRENA, 2020). Additional to that there are roughly 2 MW (Landsvirkjun, n.d.) of installed wind capacity and a very small aggregate capacity of fuel engines. In figure 2.1, the electricity production in 2018 can be seen.

This extraordinary energy system did not evolve by chance. Iceland's unique geology and landscape shaped the development of this energy system. Situated on the divergent boundary between the Eurasian plate and the North American plate, Iceland was shaped by tectonic activity and subsequently has a number of volcanoes, glaciers and mountains and regularly experiences massive seismic activity. But what makes it even more special from an energy standpoint is the vast amounts of heat in Iceland's subsurface. The temperature gradient is quite high, meaning that at a quite shallow depth, very hot water can be found. In the capital region, roughly half of houses are heated directly with source hot water coming from low temperature geothermal wells in the capital area itself and the other half is heated with hot water that has been warmed up from source hot water from high temperature geothermal power plants outside of the capital area (Veitur / OR, 2020). This means that geothermal energy does not only provide a quarter of the annual electric supply, but also roughly 90% of the heating supply (Samorka, n.d.-c). What this means is essentially that the energy consumption of the average household in Iceland is vastly different than other European countries, as only around 9% of houses in the country are heated with electricity (Samorka, n.d.-c). The capital region utilises district heating so there are no electrical components needed for the heating. This has an effect on the household electricity consumption, as it is only then used to power appliances, lighting and regular tasks in the home.

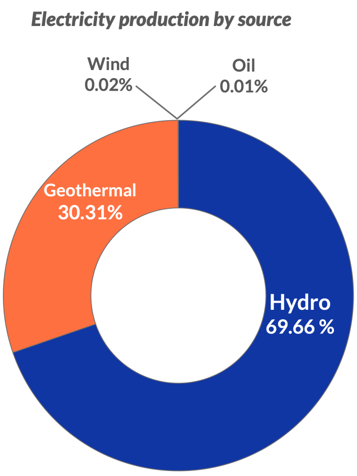


Figure 2.1: Overview of electricity production by energy carriers in Iceland in 2018 (National Energy Authority, 2019b)

Additionally, due to the climate in Iceland, there is almost no cooling or air conditioning required, which is mostly generated with electricity in Europe (European Commission, 2016). As this chapter is dedicated to providing context on the Icelandic energy system, it is important to identify what these circumstances mean. These settings for EV growth are somewhat different to other European countries. In the next decades, with the energy transition hopefully gaining more traction, fossil fuels will be phased out and cooking and heating will more be electrified, as reported on in chapter 1. With this, electricity consumption of households will inevitably rise. As this is already starting to happen, grids might have a better chance of catching up with this gradual increase. In Iceland however, the biggest increase in residential electricity use is predicted to be EV charging. And as mentioned before, this increase could be quite substantial. If it happens quickly, the grid might not handle it. Apart from the energy sources and renewable share of the energy system, the electricity consumption between sectors is also quite different to most European countries. As said before, households consume only about 5% of generated electricity. Heavy industry, mostly aluminum smelters, consume roughly 80% of total electricity produced. As can be seen on figure 2.2, the trend in the EU is vastly different.

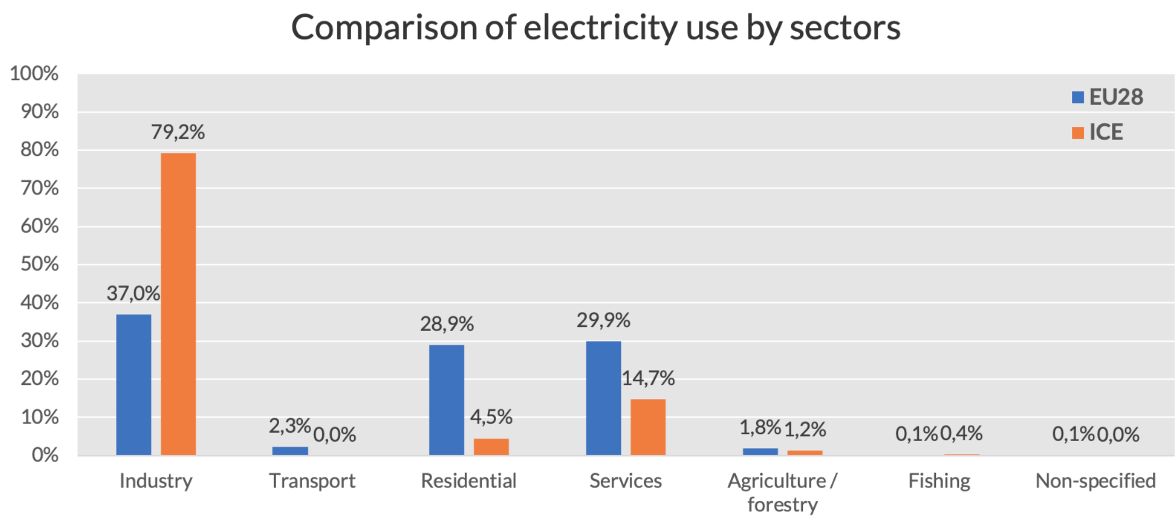


Figure 2.2: Overview of electricity consumption by sectors of the European Union member states and Iceland (IEA, n.d.)

This heavy industry is characterised by a few big companies that process and manufacture commodities such as silica and aluminum along with a few data centers. These big consumers are connected directly to the transmission grid and their cumulative power use in 2020 is expected to be just shy of 1900 MW (National Energy Authority, 2019b). As stated in Chapter 1, power delivery to the capital region is only possible from certain power plants. This can best be explained on figure 2.3 on the next page, taken from a report from Landsnet, the national TSO. In this report, their long-term development plan for 2019-2028 is laid out. In the figure, the remaining power delivery capacity at their delivery points can be seen, based on the peak power of the system in 2019. As can be seen, there is no remaining power delivery available, or slack in the system, in almost all places. This means that transmission system is highly congested as it is today and delivering more power to the capital region requires additional infrastructure.

To understand this power delivery problem better, a visualisation of the part of the power system that is inside the scope of this project can be seen in figure 4.1 on the next page. In the visualisation, the different levels of the power system, focusing on the capital region system, can be seen. Following the schematic from top to bottom, goes through the different voltage levels of the grid and on the right hand side of the graph is the regional grid of the DSO Veitur, with whose cooperation this project is carried out. The delivery congestion that is so apparent in figure 2.3 is at the top level of this visualisation. This figure explains the different voltage levels all the way down to the end consumer with the EV load positioned at the very bottom of the system. This visualisation will be used extensively in future chapters to explain how charging load affects the distribution grid.

Summarising this energy system overview; even though households and regular consumers amount to only a small percentage of the total usage, the energy consumption is not the problem when it comes to increased EV penetration. Even if the energy consumption from charging a large EV fleet becomes the same as households, which would mean a 5% increase in total energy consumption, the power increase would be a much bigger problem. As is so visually apparent in the graph from the TSO's report, it will be really hard to increase power delivery to the capital region. This is the real challenge of a large EV fleet.

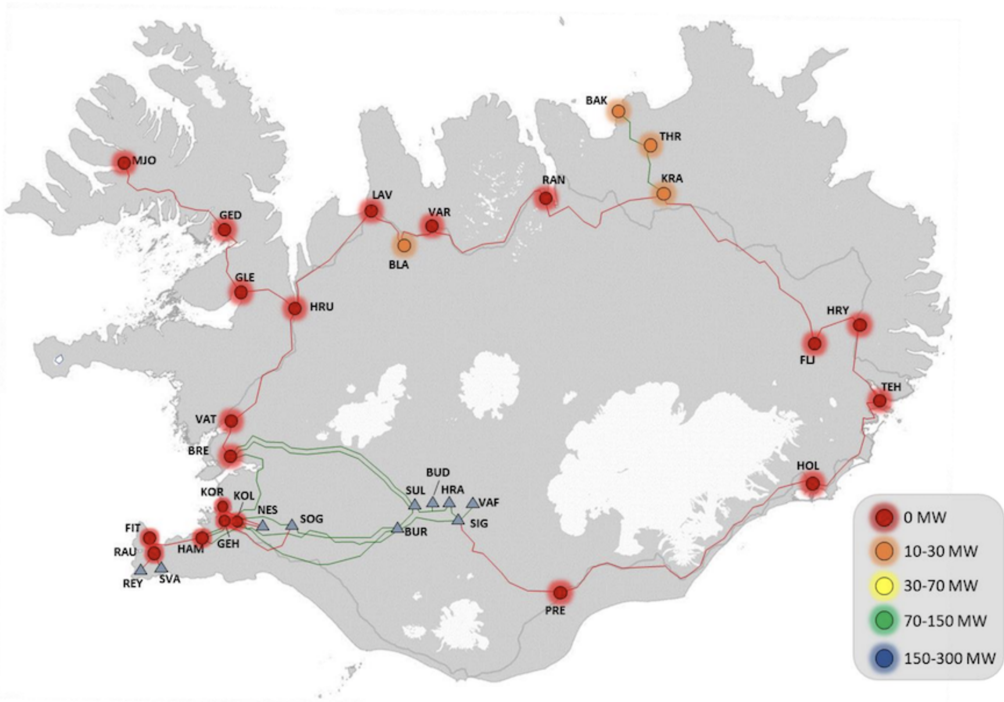


Figure 2.3: Overview of the remaining power delivery capacity at delivery points of the TSO (Landsnet, 2019, p.18)

2.2. State of EVs in Iceland

But is this really an imminent challenge? Is there a serious problem in the making? To figure that out the EV market in Iceland must be understood. As said in chapter 1, Iceland is the second biggest EV market in the world by market share. EVs are penetrating the market more than ever before and in April this year, out of all new passenger cars registered, 53% were EVs (Icelandic Transport Authority, 2020a). That is a massive market share and it is clear that EVs are on the rise in Iceland. In figure 2.4, the cumulative historic numbers of new registrations of passenger BEVs and PHEVs can be seen. In recent years, the registrations have grown massively. By doing a simple time-series forecast with an ARIMA (auto regressive integrated moving average) model, the next few years can be forecasted based on the historic data.

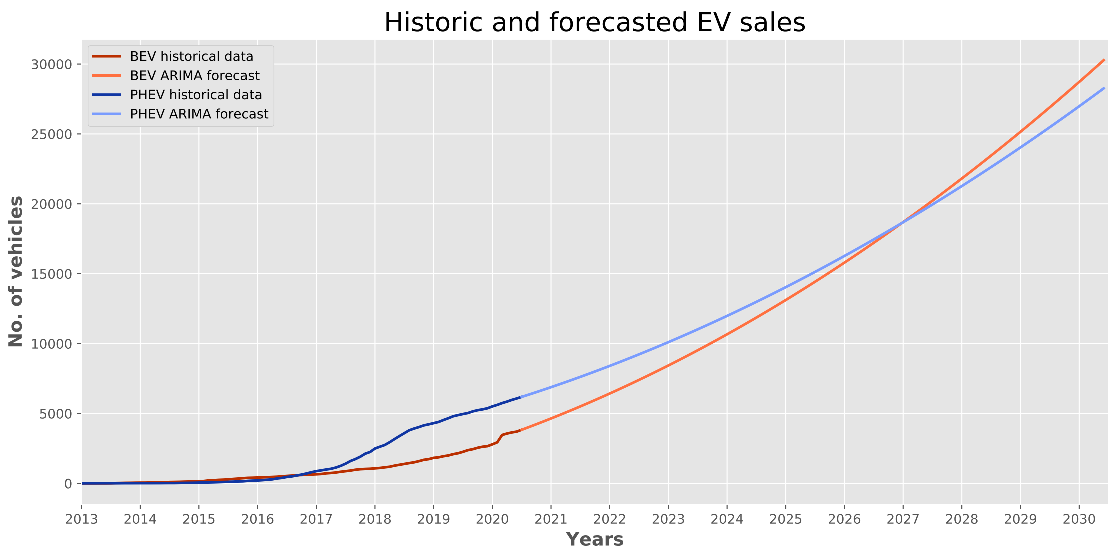


Figure 2.4: Overview of historic and forecast EV registration of new passenger BEVs and PHEV. Based on historical data from (Icelandic Transport Authority, 2020a) and the time-series forecast.

With this forecasting technique, it can be seen that the dominant EVs currently, PHEV or plug-in hybrids, will be surpassed by battery vehicles in a few years. The total number of cars based on this simple forecast are roughly 60.000 passenger cars mid-year 2030. However, the official predictions are much higher, as the growth is expected to be much faster. According to a power-industry working group on the energy transition in transport, which is working on translating the environmental goals of Iceland for 2030 into EV numbers, the forecasted number of BEVs in Iceland will be 145,440 in 2030. But what is behind this anticipated growth and why have EVs become so popular in Iceland? As said before, road transport is a sector that is very important to decarbonise if Iceland is to achieve their environmental goals for future years and withhold international agreements. In late 2018, the Icelandic government released the Climate Action Plan for 2018-2030. This plan is intended to guide the process towards reaching the Paris Agreement targets for 2030 and ultimately Iceland's ambitious goals of becoming carbon neutral before 2040 (Ministry for the Environment and Natural Resources, 2019). In this action plan, and the updated version that came out in June 2020, there is a big focus on EVs. In the past few years major incentives have been provided to potential EV owners and other measures put into place that make EVs desirable.

These measures can be classified into two groups essentially, direct incentives for EVs and EV infrastructure growth and then carbon taxation. Starting with the latter, Iceland is a part of the EU ETS and the directive was incorporated into Icelandic law in 2012 (Environment Agency of Iceland, 2019, p. 13). Additional to the EU ETS installment, the government has increased carbon tax. Carbon taxes were raised by 50% in early 2018 and raised again in 2019 and 2020 (Environment Agency of Iceland, 2019, p. 58). Incentive schemes have also played a very important role in the growth of EVs. Many of those have been law and taxation concessions in order to make EVs more appealing to the public.

One of the biggest acts was the revokement of a 24% VAT (value-added tax) on new and used (up to three years old) imported EVs. With this, EVs became significantly cheaper and more price competitive. For BEVs or hydrogen based fuel cell electric vehicles (FCEV) this tax reduction can go up to 1.53 millions Icelandic kronas (ISK) (approx. 10,000 €) but for PHEVs it is 1.02 millions ISK (approx. 6,700 €). This law, which was first instated in 2012, has been reviewed a few times and always been extended. In December of 2019, this law was again reviewed and changed. This change puts an end date on this incentive but reduces the incentive in steps for PHEVs, i.e. the tax deductible amount, but keeps the amount the same for BEVs (Icelandic Parliament, n.d.). This is done to further increase battery electric vehicles and reduce vehicles that are not solely electric.

The immense growth of EVs over the past years can largely be attributed to these actions that were mentioned earlier. But going forward, the Icelandic government have even more ambitious plans. To reach its desired carbon neutrality, many things have to be done. Besides the focus on the transition in the transport sector, efforts in afforestation and carbon capture, utilisation and storage (CCUS) have been amped up in recent years and are expected to play a big role to offset emissions (Environment Agency of Iceland, 2019). Additional to the EV measures in place already, future efforts have been announced and will undoubtedly increase the growth even further. Perhaps the biggest is a ban on new registrations of all vehicles that are solely run on diesel and gasoline cars after 2030. This forces new car owners to choose either EVs or other cars using sustainable fuels. With this regulation in place, the phase-out of conventional diesel or petrol cars will be accelerated. Along with this regulation, there are a number of other measure that will specifically support EV growth. Building regulations have been updated to take into account vehicle charging. Grants and tax rebates for charging infrastructure are being handed out to strengthen the public charging grid.

3

Literature review

In order to position this thesis in the the relevant literature, explore the core concepts and to identify a possible knowledge gap, a literature review was conducted. The research field of interest is primarily demand response with EVs, as well as load caused by EV charging. The purpose of this review is first to introduce available demand response strategies, give an overview of their strengths and differences and then to select which ones to model and simulate for the case study of this thesis. This chapter is divided into three subsections. First, the methodology of the literature review is explained and what role it plays in this thesis project. Second, the core concepts and background knowledge regarding the research field will be explained. Lastly, the review and overview of relevant literature is given in subsection 3, where selected papers are discussed, findings laid out and properties and features of past studies are compared. This subsection is concluded with the description of the knowledge gap motivating this research.

3.1. Methodology

The literature search was carried out in a semi-structured way. The main literature base that was included in this review was found through a structured search on the online database Scopus with a single specific search string. Additional articles and papers that are important to this research were either found by snowballing from this literature base or by selecting highly cited articles in this field. To compose the search string used on Scopus, keywords relevant to the field of interest were used. Demand response in itself is a very broad topic. As stated in the introduction, different demand response strategies will be explored, so the structured part of the literature search acts as an exploration of the different strategies that are applicable to EVs. It was therefore desirable to explore literature that was specifically focused on demand response with EVs.

Through the development of the search string, it became clear that a large part of the literature on demand response with EVs also focused on an emerging topic in the field of EVs, which is bidirectional energy transfer to and from EVs, most often called vehicle-to-grid (V2G). However, such V2G systems - which utilise EVs as a storage medium - have a fundamentally different approach to demand response with EVs. Therefore literature focusing on that was excluded from the search. Similarly another topic that frequently came up was microgrids which often use distributed or decentralised generation sources and can also be self-sufficient and non grid-connected. Since demand response strategies in such systems are also of a different nature compared to a conventional distribution grid, this was also excluded. In Appendix A.1, the full search string can be found. In figure 3.1 an overview of the literature search can be seen where the process of the selected reviewed papers is explained.

3.2. Core concepts

To identify the main topics of the chosen academic field and guide the discovery towards a possible academic knowledge gap, the fundamental concepts of the field have to be defined and explained. Demand response and EV loads are both broad topics, but their connected field has some key elements.

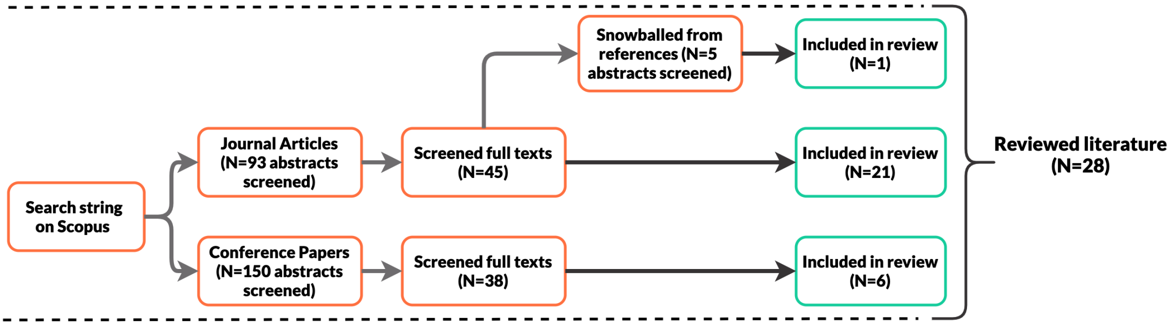


Figure 3.1: Flow chart showing the included studies and their source

3.2.1. EV charging

As already explained in earlier sections, EVs are on the rise and are steadily increasing in numbers. With this development, they become the biggest appliance of the household with a much higher electrical load. While large home appliances like a washer or a dryer can go all the way up to 3 kW in power demand, EV charging at home typically goes up to 7.2 kW in power in Iceland and for much longer periods. EVs will thus not only increase the energy demand of regular households (Ghazvini et al., 2019; Shinde & Swarup, 2018) but also increase the system peak substantially (Sharma & Jain, 2019; Lu et al., 2017). EVs have various properties that affect how their users charge them.

Notable properties from the literature are State of Charge (SOC), charging power, battery capacity and travelling distance (Sharma & Jain, 2019; L. Chen, Zhang, & Figueiredo, 2019). These properties will affect how users behave and charge their cars. The SOC and the available charging power will largely determine the required duration of charging. Another parameter which is very important is the simultaneous charging factor (Chen et al., 2019), which depicts how many EVs are being charged at the same time in a given system. The higher the factor value, the higher the overall peak will become. Uncoordinated charging of EVs - where users behave as they want - leads to high simultaneous loads (Ghazvini et al., 2019). As explained before, individual charging energy needs of a large EV fleet is most often not a problem in terms of energy, but simultaneous charging from a large EV fleet becomes a capacity problem (Saele & Petersen, 2018)

Apart from household-level charging, public charging infrastructures are also growing rapidly in Europe, often offering very high charging speeds at so-called fast-charging or super-charging stations. These fast-charging stations have a much higher power demand, from 22kW all the way up to 150 kW superchargers, which means even higher peak demand. However, according to a study in Norway, which is very similar to Iceland, the vast majority of EV users charge at home most of the time and rarely use fast-charging or regular public stations, only monthly or so (Saele & Petersen, 2018).

Another important aspect to EV charging is the kind of load it is. In the energy system, there exist many types of loads, many of whom are uninterruptible base loads (Y. Wang, Lin, Liu, Sun, & Wennersten, 2018). Those are loads that cannot be altered or moved and most always run continuously. An example of this is a fridge in a household or a constant manufacturing process in a factory. Residential EV charging is however considered a shiftable load (Rassaei, Soh, & Chua, 2015; Ghazvini, Soares, Abrishambaf, Castro, & Vale, 2017). This means that moving these loads intra-day and changing the time of consumption can be done without breaking the needs of the consumer. This is essentially what makes DR possible with EVs. However, there are certain properties, as described before, which influence how much the load of EV charging can be delayed or altered. This must be kept in mind and can have an effect on the effectiveness of different DR strategies.

3.2.2. Load impact on distribution grids

But what are the effects of the charging of a large EV fleet? This increased load can indeed have a bad impact on the distribution grid and create grid congestion. Most notably, these negative impacts are overloading of lines and transformers (Ghazvini et al., 2019; Sarker et al., 2016; Shao et al., 2011), increased system losses (Sharma & Jain, 2019; Lu et al., 2017) and decreased power quality (Muratori & Rizzoni, 2016), often resulting in the need for costly reinforcements of the network (Sharma & Jain, 2019; Sarker et al., 2016). As explained in the subsection before, EV charging load is proportionally very large compared to regular household loads and therefore puts major stress on the distribution grid in various places and levels. High levels of EV penetration will increase the system peak substantially if there is no coordination of this load. However, scheduled charging through DR strategies, can reduce these peaks drastically (Dupont, Dietrich, Jonghe, Ramos, & Belmans, 2014) and in some scenarios be reduced to a level where it has no contribution to the peak demand (Z. Wang & Paranjape, 2015).

In recent years, many electric loads in the household have become more flexible as smart home appliances can schedule their consumption based on price or convenience of the user. This is often done with a home energy management system (HEMS), which is often used by households to schedule the use of home appliances and charging of EVs (Ghazvini et al., 2019, 2017; Y. Wang et al., 2018). Still, if all households adopt such technologies and delay their charging, there could still be a problem with this as it can create new peaks (Sharma & Jain, 2019; Ghazvini et al., 2019). Therefore, there is a need to actively coordinate the charging of EVs on a higher system level. The charging from individual consumers utilising their HEMS systems can still be uncoordinated from the view of the DSO, as it is based on the needs of the individual consumers, and thus can be unable to reduce grid congestion (Ghazvini et al., 2019). This is where demand response strategies come into play.

3.2.3. Demand response

As stated before in chapter 1.1, demand response is considered one of the two subgroups of demand-side management, along with energy efficiency (Behrangrad, 2015). In the highly cited paper of (Albadi & El-Saadany, 2008), two types of demand response programs are identified: incentive based programs (IBP) and price based programs (PBP). These two distinct programs have been steadily used as a standard when discussing demand response. In figure 3.2, an overview of these two programs and the different strategies within them can be seen. In this paper, a good definition of demand response can also be found: *"Demand response can be defined 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. Further, DR can be also defined as the incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized"* (Albadi & El-Saadany, 2008, p.1990). It can clearly be seen that price is included in the definition of demand response, as both demand response programs are based on price changes or payments in some way.

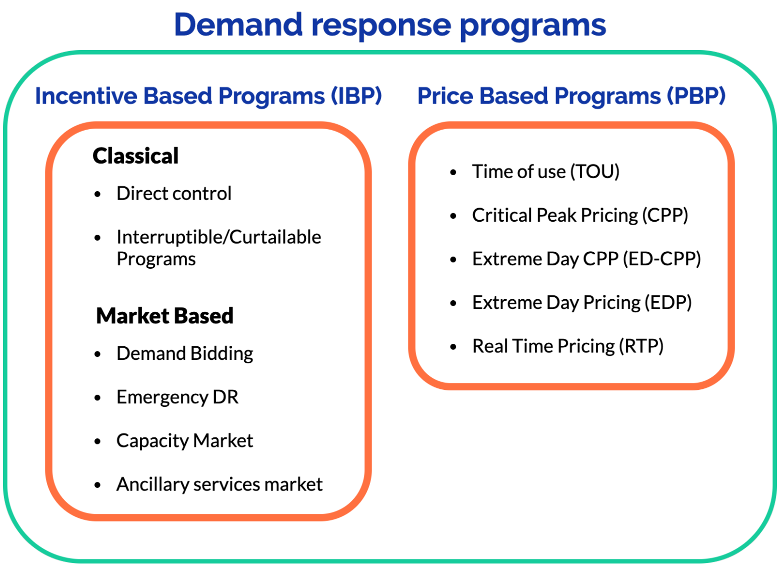


Figure 3.2: The two demand response programs and their classifications. Original diagram from (Albadi & El-Saadany, 2008) p.1990.

The main difference between the two programs is that price based programs use price changes to motivate electricity consumers to alter their consumption on their own, whereas incentive based programs is where consumers are recruited for participation with financial incentives. IBPs can therefore be considered to be more active and perhaps secure, as PBPs put trust in that the electricity pricing will be enough motivation for the user to alter or reduce their consumption. For the studied case in this project, there are doubts whether PBPs will work as the electricity price in Iceland is really low and there is one static price for household consumers throughout the year.

3.2.4. Energy market players

When considering demand response, it is not only the type of program or their different strategies that matter but also where in the market it will be done. Different market players can participate or facilitate demand response. The HEMS as mentioned before, can in some scenarios alleviate or coordinate the impact load on the distribution grid when retail electricity providers (REP) can have control over the HEMS of households (Ghazvini et al., 2019). Both IBP or PBP can be introduced with such a system.

With the liberalisation and undbundling of European energy markets in recent years, household consumers are free to choose their REPs and switch between providers when they want. The distribution system operators (DSO) distribute the energy to households, but the REPs sell it. This is also the case in Iceland. This way, it could well be that a large street or building that the DSO is delivering to has many different REPs, making it hard to coordinate demand response as this house or street will most likely use the same main power line. The question is therefore, which market player will coordinate the DR programs?

As stated earlier, individual households with HEMS and thus participating in DR do not necessarily decrease the overall system load. A new market player, so-called EV aggregator (EVA), is prominent in the literature as a mediator between households and the grid (Sharma & Jain, 2019). These aggregators are essentially providers of shiftable load and demand response resources of their consumers to the DSO or the electricity market (Falvo, Graditi, & Siano, 2014, p.549). These aggregators can thus act as some kind of retailer, selling electricity to EV charging consumers, but (Yoon et al., 2016) makes an important distinction between them: *"A retailer aims to make a profit by selling electricity, whereas an aggregator is an agent for EV customers"* (Yoon et al., 2016, p.4173).

3.3. Literature findings

In this section, the major findings of the reviewed literature are discussed. The type of literature that was reviewed can be classified into two main categories. First, it is articles or papers that focus on a specific case or implementation of DR. These are case studies, modelling projects or designs of specific DR strategies and their implementation. These papers give a good insight into the differences of the DR strategies and what works in what kind of circumstances. The other type of literature is an overview or review of many DR strategies. This category also often focuses on other properties of DR, such as customers and consumers involved, type of energy or electricity resources. Others explore the barriers to or benefits of implementation. An overview of all of the reviewed literature can be found in table 3.1. The majority of the reviewed literature is of the first category. For those articles and papers, the two demand response program (DRP) types; price based (PB) and incentive based (IB), and the different strategies within these two programs can be seen in the overview table. For each of the papers, the main distinguishing features are also listed in the table.

3.3.1. Literature themes

The results of the reviewed literature have many things in common. Many of these things can be explained from the perspective of the core concepts that were defined. The results can be categorised into three main themes.

DR strategies

As can be seen in table 3.1, a large share of the articles focus on the price based DR of RTP. This strategy evolves around changing prices hourly or more frequently, based on the wholesale price of electricity (Z. Wang & Paranjape, 2014). This strategy is found to incentivise consumers to more efficient electricity consumption (Lu et al., 2017) and make demand and supply more connected (Y. Wang et al., 2018). However, (Sharma & Jain, 2019) find that RTP is too dynamic for EVs and (Ghazvini et al., 2019) finds that RTP can contribute to the creation of a second peak as explained in the core concepts. The bottom line is however that for RTP to work efficiently, there has to be specialised infrastructure; a smart metering communication system (Lu et al., 2017).

Based on the shortcomings of RTP, a number of articles suggested TOU as a feasible alternative. (Shinde & Swarup, 2018) and (Yoon et al., 2016) implemented that in a game-theoretical based way. The latter article

Paper	DRP	DR strategy	Main features
(Yoon et al., 2016)	PB, IB	Time of use (TOU) Direct control	Stackelberg game-model Maximisation of both REP and consumer
(Albadi & El-Saadany, 2008)	-	-	DR overview paper
(Dupont et al., 2014)	IB	Curtailment	Residential decentralised DR EVs considered as shiftable load
(Gouin, Herault, & Raison, 2018)	IB	Curtailment	Modelling under network uncertainties Whether to perform DR or expand the grid
(Kumar & Tseng, 2016)	IB	Direct control	Effects of DR programs on chargeability of EVs based on SOC EVs modelled as interruptible load
(Shao et al., 2011)	IB	Direct control Curtailable load	Consumers set load priority or convenience preference
(Afzalan & Jazizadeh, 2019)	IB	Direct control Curtailable load	User identification for DR
(Ghazvini et al., 2019)	PB	Dynamic tariffs (DT) Daily power-based tariffs (DPT)	Consumption and EVs based on a HEMS DR coordinated by REP
(Rassaei et al., 2015)	IB	Demand bidding	REP as an EV aggregator Both a centralised and a decentralised approach
(Ni et al., 2016)	IB	Multiple	Congestion management optimisation Aggregator's behaviour based on price signals
(Shinde & Swarup, 2018)	PB	Multiple	Stackelberg game-model Both multiple and a single utility company Consumer behaviour implemented
(Y. Wang et al., 2018)	PB	Multiple	Multi agent system modelling with HEMS as an agent Loads organised based on shiftability
(Ghazvini et al., 2017)	PB, IB	Multiple	HEMS which reacts to DR programs, both PBDR and IBDR
(L. Chen et al., 2019)	PB, IB	Multiple	EV travel behaviour Both single EV and an EVA Multiple DR strategies modelled
(Saele & Petersen, 2018)	-	Multiple	Assesses charging behaviour and the potential for DR
(Falvo et al., 2014)	-	Multiple	Focus on DR customers and integrating EV into DR
(Lu et al., 2017)	PB	Real time pricing (RTP)	Willingness to charge and participation in DR researched
(Sadeghian et al., 2019)	PB	Real time pricing (RTP)	Particle swarm optimisation algorithm
(Zhao, Yan, & Ren, 2019)	PB	Real time pricing (RTP)	Loading algorithm used to determine EV load
(L. Chen et al., 2019)	PB	Real time pricing (RTP)	Peak load shaving and valley filling with RTP SOC used as demand level indication
(Muratori & Rizzoni, 2016)	PB	Real time pricing (RTP)	Automated decentralised DR
(Sarker et al., 2016)	PB, IB	Real time pricing (RTP)	Decentralised EVA approach to DR Combination of RTP and in IBP
(Z. Wang & Paranjape, 2015)	PB	Real time pricing (RTP)	Scheduled charging can reduce peak contribution
(Sharma & Jain, 2019)	PB	Time of use (TOU)	EV aggregator facilitating DR
(Mallette & Venkataramanan, 2010)	PB	Time of use (TOU)	Explores necessary financial incentives for DR participation
(Zhang et al., 2012)	PB	Time of use (TOU)	Multiple TOU tariffs for different customer groups
(Z. Wang & Paranjape, 2014)	PB	Time of use (TOU)	Different levels of EV penetration are considered
(Rastegar et al., 2014)	PB	Time of use (TOU) Real time pricing (RTP) Inclining block rate (IBR)	Decentralised DR based on HEMS system

Table 3.1: Overview of the reviewed literature

found that the game is solved when both the retailer's profits and the customer's utility function is maximised (Yoon et al., 2016), whereas (Shinde & Swarup, 2018) find that increased competition with multiple utility companies can accompany higher penetration of EVs. From this it seems that with more REPs in the market, where the EV aggregators maximise their profits, in this case the REP, can indeed be beneficial. TOU as a DR strategy is also beneficial for its simplicity, as opposed to RTP. It essentially divides up the day into different blocks based on prices, most often based on peak or off-peak hours. This structure easily allows residential EV owners to optimize energy use (Mallette & Venkataramanan, 2010). Similar to RTP, TOU can also create a second peak and even in a more drastic way, when charging load of EVs shifts to the off-peak hours (Sharma & Jain, 2019).

However, TOU can also be made more complicated and its weaknesses possibly mitigated. (Zhang et al., 2012) propose a TOU strategy with multiple tariffs, where customers are grouped and each group gets a different tariff. Their results show that this method achieves lower energy prices for consumers than a single TOU tariff, as well as a better distribution of the load. Lastly, the three others PBPs, mostly evolve around the same principle. Critical peak pricing (CPP) is a combination of TOU and RTP, where hours where demand is abnormally high have much higher tariffs (Z. Wang & Paranjape, 2014). Extreme day CPP and extreme day pricing both use time-dependant pricing schemes, but seem to be less popular than CPP, which is still quite absent from the literature.

Going over to the other DRP, it is evident that incentive-based DR (IB DR) is often carried out with an autonomous system. As explained in the core concepts, HEMS are systems that can do such things. According to (Z. Wang & Paranjape, 2014), a HEMS can control EV charging to minimise the electricity cost. In (Ghazvini et al., 2017), a load priority method is used to determine how the consumption changes under a DR event. (Kumar & Tseng, 2016) examine similar things and find that EVs can be interrupted as they are considered a quite flexible load. Similar to RTP, these strategies still need smart infrastructure to minimise disruption to consumers and let them best choose their own priority preferences. The control of the different demand response strategies can also be implemented differently, both centralised and decentralised (Sarker et al., 2016). IB DR is quite different to the price-based DR (PB DR). In PB DR, the DSO or system operator changes the price hoping that the consumers will react and change their consumption. With IB DR however, consumers enter an agreement with the DSO or EVA or the operator, to allow or change their consumption.

Direct load control (DLC) has been offered to consumers before as (Mallette & Venkataramanan, 2010) state, where consumers allow the utility company to remotely shut off air conditioning in high demand hours. This type of DR gives the DSO much more control and thus more chance to optimise the load profiles. (Ghazvini et al., 2017) state that DLC is the most frequently used DR program since the 1960s, to quickly react to system load changes. According to (Ghazvini et al., 2019), the regulations in liberalised energy markets make it hard for DSOs to enter such contracts. This DR strategy, along with curtailment were by far the most frequent types of IBPs in the reviewed literature.

The other classical IB DR method, curtailment, is quite widespread and revolves around reducing or stopping charging when the system is overloaded. As stated before, EV charging is viewed as a shiftable load and thus curtailment with EVs is a good option. (Kumar & Tseng, 2016) studied the impact of interruptions by curtailment on the chargeability of EVs and found that a temporary interruption will have minimum impact on the chargeability. For the market based IB strategies, demand bidding is very much like the spot electricity market. Bidding is usually day-ahead and has both a demand and a price component (Rassaei et al., 2015). A popular strategy in this category is the ancillary services market, where EVs participate in maintaining the power grid's reliability (Rassaei et al., 2015).

DR implementation

These different DR strategies are though subject to market circumstances and infrastructure. The implementation of the strategies are often what is more complicated than the strategies themselves. How a proposed DR strategy will be implemented or carried out depends on what components are needed for it. Many strategies need accurate data transfers from smart meters or management systems. (Z. Wang & Paranjape, 2015) state that an effective DR implementation relies on DR-enabling technology. The most simple and easiest DR strategy is perhaps TOU, as it imposes a dynamic tariff scheme which is easy to implement. However, a smart metering infrastructure is necessary for its implementation. In Iceland for example, these smart meters have only recently been rolled out and it will take a few years to fully have a smart metering system.

But the IB DR strategies also have challenges in implementation. The market-based mechanisms need coordination and communication between different market players (Ghazvini et al., 2019). These market-based strategies also rely on a spot retail energy market where wholesale electricity prices vary over the day to fully utilise these strategies. In Iceland, the spot retail market is almost non-existent and the variance of the wholesale electricity price is very low. For the classical IB DR strategies there is another type of problem. As stated before, specialised infrastructure is needed to carry out direct load control or curtailable load. So in addition to the smart metering infrastructure as PB DR strategies rely on, there is another layer of technical difficulty, where two-way communication is needed between the consumers and the DSO or other operator of the DR.

Evaluation of DR strategies

As this project will create a model to evaluate the effectiveness of two different demand response strategies, the modelling formulation is very important. Many of the articles have a modelling element, where the different DRPs are measured. As stated before, some use a game-theoretical approach, while others use an optimisation algorithm. For this project, some results and findings from the reviewed literature can shed light on its application. (Dupont et al., 2014) finds that to realistically assess EV driving behaviour and thus EV load, real historical data is needed. The intended methodology of this project of implementing DR strategies to a case study has been done before according to (Sadeghian et al., 2019). The evaluation of DR strategies will however be very case-specific as technical system components, energy market characteristics and other variables play a big role as has been seen in the difference between DR strategies as discussed earlier.

3.3.2. Knowledge gap

From the exploration of this literature on demand response strategies, combined with the background knowledge on the environment and status of the Icelandic EV market and distribution grid, there emerges both an academic and a practical knowledge gap. From the literature it is clear that the DR strategies used depend both on the user group and necessary technology and infrastructure to achieve it. Price-based DR programs (PBDR) seem to dominate the literature and its studied cases. The different market players that will perform or coordinate the actual scheduling of the DR also vary between studies, but many propose that an EV aggregator (EVA) (Chen et al., 2019) do that. Furthermore, how the effects of different DR strategies are modelled and evaluated matters immensely to properly measure the impact on the distribution grid. As (Dupont et al., 2014) states, such analyses must be done over a full year of data.

The settings in the Icelandic energy market and the capital's distribution grid are different to most studied cases. There is a static electricity price over the day and year, almost non-existent spot energy market and a unique generation portfolio. Very few households if any, have HEMS systems and very few DSOs are active. Due to these unique circumstances there is no grounded understanding of what kind of DR strategies should be implemented for EVs in Iceland. Furthermore, the market players that can possibly participate in these strategies have to be analysed and possibly a new EV aggregator must be formed. Besides this academic knowledge gap on the implementation of these DR strategies, there is a practical knowledge gap on the modelling and evaluation of such strategies. Current analyses have been simple and only estimated yearly consequences. Furthermore, never before has EV specific behaviour data been available, but for this project a novel EV study dataset will be used, as described in detail in 5.1. Thus, in order to attempt to close this knowledge gap, the main research question emerges:

How can demand response strategies be used to coordinate the charging of a large EV-fleet to reduce the load impact on Iceland's capital distribution grid?

4 Conceptual model

The goal of this chapter is to formulate an approach towards a working model that will be used to gather insights into the behaviour of the distribution grid under different EV charging scenarios. As stated in the introduction of the research project, the main chosen methodology is modelling and simulation; first creating a model of the system that is being researched and then conducting simulations to see the effects of different scenarios and parameters. But before this computerised implementation can be done, the *conceptual model* of the system has to be formulated. Conceptual modelling is used in many fields; software development, product design, ecological system mapping and many more. But for modelling and simulation, conceptual modelling serves a specific purpose. According to Robinson et. al's influential book on the subject: "*...conceptual modelling is not about how to implement, or code, a model on a computer, but it is about how to decide what to include in a model and what to exclude from that model*" (Robinson et al., 2011, p. vii). In the book, the authors further state that there is no one correct way to perform conceptual modelling, as conceptual models are used in broad context in many fields. Even in recent years, the views on conceptual modelling for simulations are very different among researchers (Robinson et al., 2015).

As the field is essentially split on the specific properties of conceptual models, the conceptual model formulated for this thesis project will be built on the kind which best aligns with the type of the research problem. What is desired for the conceptual model for this project is to identify and describe the system's characteristics and properties of its modelled state; inputs and outputs, objectives and requirements. The role of the conceptual model is to formulate the system of interest based on these elements, and to make it possible to evaluate different system settings. Furthermore, the conceptual model elicits all assumptions and simplifications that have to be made when representing the system of interest and the processes within it. This is a very important step as it makes it possible to reflect on the model outputs and results and how they are shaped by these assumptions. Different system settings are derived by implementing the conceptual model technically, in a programming language. That makes it possible to alter values of inputs and observe the changing behaviour. The conceptual model thus guides the technical implementation, explained in detail in chapter 6 in detail.

In the earlier mentioned book, Robinson proposes a framework for developing a conceptual model, built on his experience of modelling and simulating operations systems (Robinson et al., 2011, p.74). The system of interest, i.e. the system which is to be researched in this project, is an energy system and can be viewed as an operations system or at least a system which is similar to the intended systems of the framework application. This proposed framework is essentially a sequence of activities to be carried out which together formulate a conceptual model. However, these activities can be carried out non-sequentially as this process is an iterative one. These activities are (Robinson et al., 2011, p.75):

1. *"Understanding the problem situation"*
2. *"Determining the modelling and general project objectives"*
3. *"Identifying the model outputs (responses)"*

4. *"Identifying the model inputs (experimental factors)"*

5. *"Determining the model content (scope and level of detail), identifying any assumptions and simplifications."*

In the following sections of this chapter, the conceptual model for the system of interest will be formulated, mainly based on the steps of Robinson's framework as described above. The subsequent chapters; *Data* and *Technical model implementation*, build on this conceptual model. In those chapters, the data used to create the technical model as well as the methodology of the technical model implementation are explained in detail, but the overall approach to the modelling part of this thesis comes from the conceptual model. Therefore, this chapter and the formulation of the conceptual model serves as an integral part of the research, as it is only after its creation that the technical model implementation can be done.

The first step of the conceptualisation of the model is to understand the problem situation. As discussed already in chapter 1.3.1 and 1.3.2, the thesis research question is about the effects of EV load on the distribution grid in Iceland's capital region and the missing knowledge on the performance of different demand response strategies. The overall research problem is reflected in this question, which is the problem of lacking understanding of the distribution grid system's performance under these different strategies. This overall problem will be solved through a series of sub-research questions that ultimately lead to the answer of the main research question. These questions, as put forth in chapter 1.3.3, are answered over the different chapters of this thesis project. The conceptual model will however answer two of the sub-research questions, namely number four and five:

4. **How can the effect of different demand response strategies be assessed and modelled?**

5. **How does EV charging affect the distribution grid under different DR scenarios?**

These two questions, answered with the use of the technical model, which is based on the conceptual model as well as the data, will contribute to the solving of the research problem and thus the main research question. But to be able to create this technical model, the problem that the model specifically will try to solve must be defined.

4.1. Problem situation

To define this problem, i.e. the problem situation according to the earlier mentioned framework, the system which is to be modelled - the system of interest - must be understood. As the famous quote on modelling states: "all models are wrong but some are useful", models are never a perfect depiction of reality but merely a representation of reality based on the modeller's perspective. Moreover, a model is twice disconnected from reality as it is a simplified version of the modeller's version of the real system (Dam, Nikolic, & Lukszo, 2013, p.51-52).

The conceptual model to be formulated is thus a simplified version of the system of interest; the capital region distribution grid, and more specifically, the part of the grid that is operated by the DSO Veitur. The physical boundary of this system are the five municipalities where Veitur is active in, as seen in figure 1.4 on page 5. Over these municipalities, the combined population is 196,120 (2020 Q2), or 53% of the country's population (Statistics Iceland, 2020). Car ownership is also very high in these municipalities, as half of the country's passenger cars are located there. Additionally, EV penetration is very high, with two of the municipalities having nearly 10% EV penetration. Combined, these municipalities have over 65% of all of the EVs in Iceland (Icelandic Transport Authority, 2020b). Apart from this physical boundary, the building blocks of the system can be seen in figure 4.1, where the infrastructure of Veitur is clearly specified.

Now that the system of interest has been determined, the problem can be situated within it. When identifying and confirming that there is a problem, the modeller's bias often comes to light, which might affect the modelling. But the problem that the conceptual model aims to solve is one that is grounded both in literature and practicality. This is explained in detail in chapter 3.3.2, where the knowledge gap that motivates this research is elicited. This problem situation is that *it is not known how large-scale EV charging affects the distribution grid and more specifically; at what levels in the grid, with varying EV penetration and under different demand response strategies.* The conceptual model is thus developed to obtain insight into the the performance of the distribution grid, the system of interest, under these unknown circumstances.

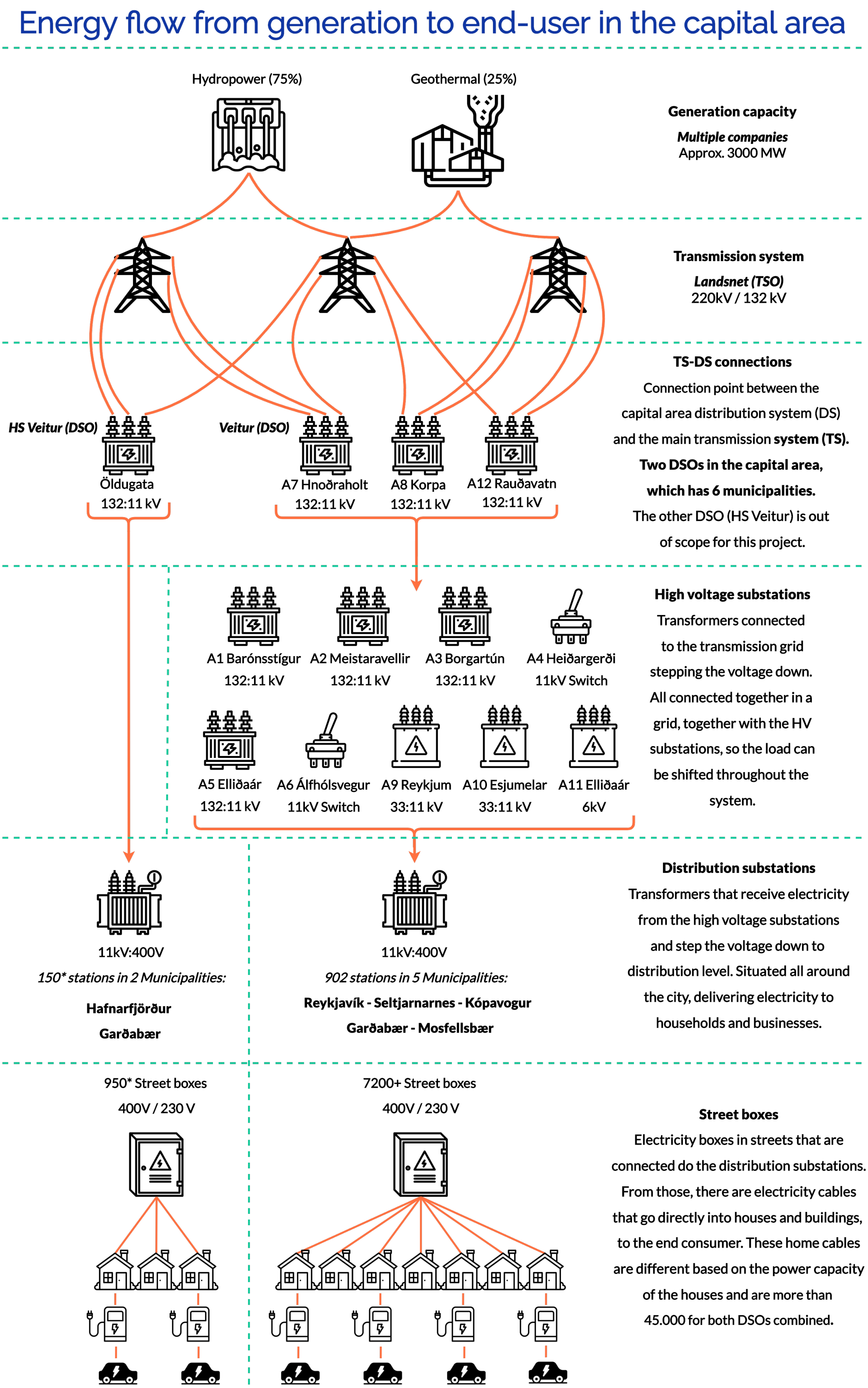


Figure 4.1: A visualised schematic of the energy market in Iceland from generation to end-user connection in the capital area. Numbers marked with * are estimated. Icons from www.flaticon.com

4.2. Modelling objectives and constraints

Now that the system to be modelled has been shortly explained as well as the problem that the model aims to solve, the objectives of the model can be determined. The overall motivation behind this conceptual model - which is subsequently implemented in a technical model - is to run the system in different settings based on charging scenarios, observe the behaviour and gather insights into the system's performance. This will ultimately provide answers to the research questions that apply to the modelling part of this thesis project and insights into a possible solution to the problem that the model tries to solve. According to Robinson's framework, the second step is determining the modelling and project objectives. As the name of this subsection suggests, for the conceptual model formulation in this project, design constraints are added to this part of the formulation as a separate entity. Robinson names three types of objectives; achievements, performance and constraints (Robinson et al., 2011, p.79). The difference between an objective and a constraint is that an objective is something that the solution or model *should* perform or attain whereas a constraint is something that *must* be done or cannot be violated. The objectives thus guide the functioning of the model and define what it should do, whereas the constraints create boundaries for it.

To identify and define the objectives and constraints of the conceptual model, the nature of the system of interest must be acknowledged. This system is both a physical system in terms of the distribution grid infrastructure, but also a market, where supply and demand must match at all times. This is one of the fundamental aspects of energy systems which makes their operation so challenging at times. With changing behaviour of consumers - in this case increased consumption based on EV charging - the supply side must match this rising demand instantaneously and at all times. The energy producers, TSO and DSO must all act to do this. As explained earlier, the modelling problem is that it is not known how large-scale EV charging affects the grid. This is a real problem, as this demand must be supplied at all times and predicting and forecasting the need for supply in various places in the system can be very challenging. This is a problem for all the energy industry stakeholders, but mainly the DSO, as explained in section 2.1, because the energy itself is not a problem but delivering this power supply to the consumers is.

The delivery of this power flows through different levels of the system, mainly three levels as illustrated in figure 4.1. These levels are based on voltage, where with each level the voltage decreases, starting at 132KV at the very top level and going all the way down to the household voltage level of 230V. The first level is the overall system capacity level, based on 12 high voltage substations, where there are transformers whose input voltage is 132kV at the highest but all transform down to 11kV. The next level of the system is the distribution level, which is based on roughly 900 distribution substations. These stations are connected by 11kV cables and spread across the capital region. These transformer stations step the voltage down from 11kV to 400V. The last level of the system is the street level, which is based on electricity street boxes. Each box is connected to a distribution substation and can operate on either 400V or 230V. To each distribution substation there are numerous electricity street boxes connected. From the street boxes themselves, there are cables that go into each house or building individually. The charging of EVs takes place at the bottom of this lowest level, as indicated in the figure. The power supply thus has to traverse through these different levels to match this demand. Congestion of this power delivery can happen on any of these levels in the system.

4.2.1. Objectives

Based on this more detailed explanation of the system of interest, the main objectives as well as the constraints can be elicited. One aspect to note here is that an overall objective of the modelling is that it should be over a full year. This could also be viewed as a part of the fifth step according to Robinson - on the model scope - but it is viewed as an objective for this project. This is due to the fact that according to the literature findings and identified knowledge gap, modelling over a full year of data is necessary in order to have a complete analysis (Dupont et al., 2014). This is because it is desired to find the peak load in the distribution grid, which can in theory happen anytime over the year. Modelling over a shorter time might therefore not showcase the true behaviour of the system. Therefore this time scope of the model is an important one to keep in mind before the objectives are defined. In the list below, the design and modelling objectives can be found. Following this listing, they will be explained in more detail and put in context.

1. **To determine the primary load in the capital region over a full year on a 15-minute basis**

2. **To determine the charging load of a scaleable EV-fleet over a full year on a 15-minute basis**

3. **To determine the capacity limits of the distribution grid on the three voltage levels**

4. **To calculate at what size of EV-fleet the capacity is exceeded under different charging scenarios**

5. **To determine how overall system load can be minimised under different charging scenarios**

6. **To determine the required consumer participation in different demand response strategies**

These objectives need to be elaborated on to fully structure the conceptual model. These modelling objectives are also reflected in the main research question of this thesis which essentially has two components as described in chapter 1.3.1. The first component is understanding how a large EV-fleet impacts the distribution grid and the second is to analyse the performance of the system under different demand response strategies. The first and second modelling objective aim to solve the first component of the question. First, the primary load - which is the base electricity demand of the capital region without any EV charging - has to be determined.

This makes it possible to model this primary load, which will not be affected in the modelling, and the charging load independently. This is vital to truly see the effects of the charging load and when combined with the unshiftable primary load causes problems in the distribution grid. The time specificity of these two objectives, modelling on a 15-minute basis, is based on available inputs for the conceptual model. The available inputs on charging load, as will be explained in more detail further on, are on a 15-minute basis. Therefore it was desired to model on 15-minute time intervals to fully see the effects of the load.

The second modelling objective however needs some additional clarification. As is mentioned in objective four, the size of the EV-fleet is a parameter which will be explored in the conceptual model. This size is the number of EVs situated in the system of interest. The goal of the second objective is to determine a charging load profile for an X-sized fleet, which can then be scaled to the desired fleet size or experimented with to ultimately attain objective four. The third modelling objective covers both components of the main research question and puts an important metric on the other modelling objectives. That is to determine the limits of the distribution grid in terms of power delivery capacity. The aim is to find and define limits at all of the three levels as described before to be able to quantify the load effects fully and the impact on the distribution grid. Achieving this objective is both very important for the next two modelling objectives as well as providing a metric to answer the sub-research questions that the conceptual model tries to answer.

The last three objectives employ an integral part of the conceptual model, which are the charging scenarios, based on different demand response strategies as previously discussed. In this context, a charging scenario means a specific implementation of a demand response strategy. For a certain demand response strategy, there exist many approaches and they can be carried out in different ways. The different detailed interpretations of the methods of getting consumers to alter their behaviour are nearly endless. Objectives four and five thus seek to first determine how many EVs can be allowed onto the grid, if so to speak, without breaking the capacity limits of the grid, and then explore how the system load effects can be minimised with the different demand response strategies. The fourth objective thus tries to see the effects and performance of the grid based on the chosen strategies and their various scenarios, whereas the fifth objective ultimately tries to approach a best solution given these strategies.

Lastly, the sixth objective explores what levels of participation in these different DR strategies is needed to make an impact and reach the minimised load and to allow the maximal EV fleet size. This objective thus explores how much of the charging load has to be shifted by affecting consumers behaviour to be the most effective scenario. Going over these objectives it becomes clear that these charging scenarios play a fundamental role in the conceptual model and are in fact at the very center of it. The choosing of the demand response strategies to incorporate in the model are not only very impactful on the model itself, but also a very important design choice for the conceptual model, as it will shape the possible model outputs. These two DR strategies make up the different charging scenarios in combination with the current state of the system, i.e. uncoordinated charging. These scenario can thus be viewed as the central modelling process or the model content. Their conceptualisation steps will be explained in further sections.

4.2.2. Constraints

Based on these objectives and the problem situation, some constraints can be identified, especially for the modelling of the DR strategies. In the same way as the objectives subsection was structured, the constraints will first be listed and then explained and discussed. The constraints for the conceptual modelling and project are:

1. **Model must run over a full calendar year**
2. **The primary load and charging load has to be based on actual values, i.e. historical data**
3. **The variability and heterogeneity of charging behaviour of EV consumers must be taken into account and validated**
4. **The annual total charging load of a given EV-fleet must be equal under any charging scenario**
5. **Existing charging preferences of EV consumers cannot be broken**

These constraints can be roughly classified into two types; the external modelling constraints and the implementation modelling constraints. The first type are the constraints that apply to the scope, inputs and other external factors affecting the conceptual model. These are the first three constraints. The model must run over a full year as already mentioned in the objectives. This has to be done as that is the only way to fully realise the effects of the charging load on the distribution system as well as the benefit of the different demand response strategies. The input data for these load values must also be based on actual data, as this is the only way that it will showcase the real behaviour of the system of interest. Additionally, the last external modelling constraint is about maintaining the diversity of charging behaviour of different consumer types. Based on the previous constraint, which specifies that real data must be used, this constraint ensures that the represent charging behaviour still portrays sufficient heterogeneity and thus captures the diverse charging profile of a large EV fleet. This again makes the modelling and subsequent analyses much more realistic and is necessary along with the other two constraints to attempt to close the knowledge gap make it possible to use the conceptual model to solve the problem situation.

The latter type of modelling constraints are the last two which both apply to the implementation of the DR strategies in the conceptual model. As was explained already in *Demand response* part in the literature review, DR essentially works by shifting or changing charging behaviour of consumers. To ensure that the modelling will generate the intended results, how this is implemented in the conceptual model must be constrained and guided. There will be many charging scenarios explored by the model, based on two distinct DR strategies as well as the current system scenario. For these different scenarios, consumer behaviour will be affected and thus the charging sessions will be shifted in time. This is the essence of the experiments with these DR strategies. But there is an important line that has to be drawn on how much the uncoordinated charging can be shifted in order to keep the strategy implementation comparable. For this reason, a constraint is defined which states that the annual charging load of a given EV-fleet size, must be the same for any implementation of the chosen DR strategies. This ensures that the charging sessions cannot be manipulated to an uneven level. This keeps the comparison of the different strategies more realistic and balanced.

The next and last constraint is also connected to the last one, which specifies that the preferences of the EV consumers cannot be overridden or broken. This means that the behaviour of the users, which make up the EV-fleet, have to be respected as the charging habits of users has to be put before the demand response strategies' performance. Similar to the former constraint, this means that the DR strategies cannot be implemented in a way that presents their performance out of proportion compared to the uncoordinated charging. Together these constraints, both external and implementation-specific, make up a boundary for the modelling objectives in the conceptual model.

4.3. Model content

Although this part of the formulation process was not listed after the identification of objectives and constraints, the formulation process is not sequential as earlier explained. At this point, the model content, centered around the two different DR strategy implementations, must be explained. To visualise the conceptual model formulation process, a flow-chart of the formulation steps can be used. This can be seen in figure 4.2.

In the figure, it can be seen that the model content, as well as the objectives and the constraints are derived from the problem situation. The simplifications and assumptions affect this central modelling process and will be explained in later sections, along with the inputs and outputs.

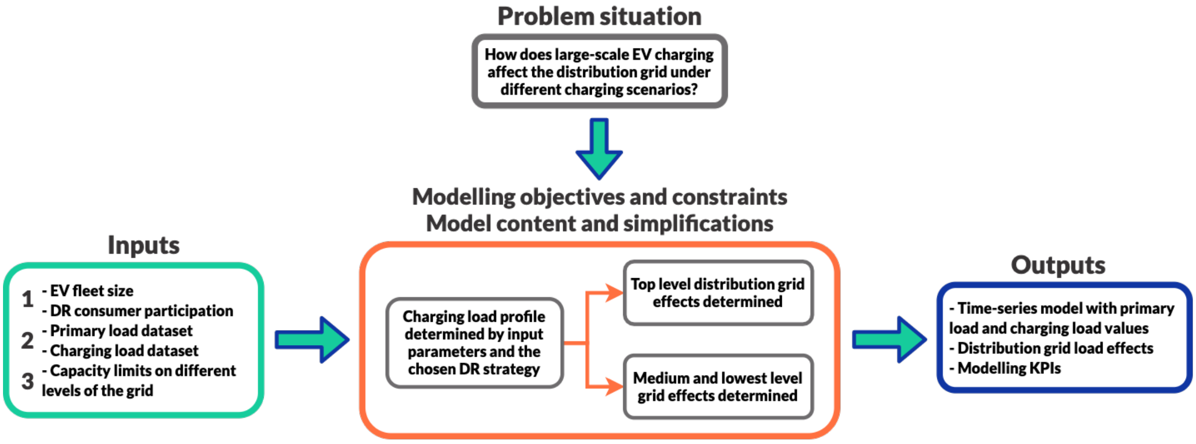


Figure 4.2: A visual representation of the conceptual model.

In this section, the motivation behind the choosing of the included demand response strategies is explained, as well as their conceptualisation in the model. In general, the main model content is a time-series based load model. This model is a representation of the system and is done on the three different levels of the system. Different charging scenarios are represented in this model, but they are derived from two DR strategies and the current state of the system. This current state, is defined as uncoordinated charging, as there is no implemented strategy in place to distribute or affect this load on behalf of the DSO. These three different settings of the system, uncoordinated and based on the two DR strategies can thus be seen as *the three main load scenarios*, as they represent the load of an EV fleet in the system. The first load scenario, the uncoordinated charging does not need much explanation as it is simply unaffected charging load based on the available charging behaviour input as will be explained later. However, the two DR strategies that are modelled were selected and implemented in a certain way. The explanation of that process will be described in the next section.

4.3.1. DR charging scenarios

Demand response is a field that has been immensely researched in past years and consequently a multitude of different methodologies, implementation variations and strategies exist. In the literature review conducted for this thesis, the main strategies that are widely used were explored and discussed. An overview of the different strategies can be seen in figure 3.2 on page 15. The differences between the roughly ten different strategies are discussed in detail in the *Literature findings* section of the literature review chapter, but without repeating the contents of that section some aspects of the different strategies can be mentioned that affect their suitability for the system of interest and thus the conceptual model. But before these aspects can be listed and discussed, some main points on the motivation behind the choosing has to be explained. First of all, the desired scope of strategies to model has to be mentioned. Because of the timeframe of this thesis project, running less than 6 months, it was decided that two distinct demand response strategies would be sufficient. By two distinct strategies, it is meant that two different strategies of demand response are used. By selecting only two, the analysis can be kept focused and rich but still gather insights into two different applications of demand response. Secondly, it was desirable to pick one strategy from each group of demand response strategies, namely one incentive-based and one price-based.

For the choosing of the two strategies, many things came into play. Many of those fall under the applicability of the strategy in the system of interest, as well as stakeholder interest and ease of modelling implementation and analysis. As has been declared earlier, this thesis project has been carried out in loose cooperation with Veitur, the DSO in the capital region. Veitur can certainly be viewed as a stakeholder in this project, having a major role in the system of interest, as well as having a somewhat active role in the research project. Along with guidance from an industry expert from Veitur, there was also another specialist from the rural and countryside DSO in Iceland, RARIK. These two specialist opinions and input on different demand response strategies affected the choosing procedure, as the chosen strategy has to be seen viable from the eyes of the market players.

First DR strategy
It quickly became clear that the first demand response strategy to be incorporated would be **time of use (TOU)**. This was largely supported by the literature findings, as this was one of the more prominent strategies found in the literature and is much simpler than the other popular price-based strategy, real time pricing (RTP). For RTP to work effectively, specialised infrastructure has to be in place which is lacking in Iceland, as well as a dynamic marketplace for the consumer side of the electricity market which is also not entirely the case in Iceland. TOU as a strategy has been widely deployed and is easy to implement as there only needs to be a time-dependent electricity metering system, which is being rolled out in Iceland in coming years.

However, as explained earlier, demand response strategies can be carried out in different ways with varying levels of complexity and complications. For the TOU included in the conceptual model, there are two price-periods determined inside the day. This is also the most widely used implementation of TOU, which is usually based on peak and off-peak pricing. With this type of TOU, the signal to the consumer is clear to understand, as there is simply a lower price later in the day or evening, hopefully making the user shift his consumption to that time. The other price-based DR strategies, as seen in figure 3.2, are based on critical peaks or extreme events and do little to alleviate charging load over an entire calendar year as this load shifting is targeted only on big extreme events. Those strategies were not very prevalent in the explored literature and also not very viable according to the industry experts that were consulted. These strategies are mostly based on predictions on when these extreme events will happen and have a limited number of days that the load curtailment or distribution can be performed. According to the experts consulted, these predictions tend to be unreliable and thus the strategies do not prevent major peaks.

Based on these characteristics of the different price-based DR strategies, the one to be incorporated is TOU. This is because the other strategies are not as applicable in the Icelandic energy market and therefore the system of interest. The different scenarios based on this strategy come from the specific implementation settings, which are mainly the time period of the day in which the price is lowered. The actual change in price is also an important setting, but for the conceptual modelling itself it does not change the implementation of the strategy in the model. It does however affect the likelihood of consumers' participation in the strategy, as the sixth objective explores. As there is no available data on the participation levels of Icelandic consumers, as explained in detail in the next chapter on Data, specifically the subsection on *Simulation input parameter data*, the most likely participation will be estimated based on available data on prices from current TOU strategies. Despite this, the actual prices do not matter so much, as the sixth objective does rather investigate the required levels of consumer participation. How realistic those levels are will be reflected on in the discussion and conclusion chapters of this thesis.

Second DR strategy
For the second demand response strategy, which is supposed to be an incentive-based strategy, roughly the same steps were taken to choose the best fitting strategy. Therefore, much of the rationale for choosing TOU can also be applied to the second chosen strategy. For incentive-based strategies, there are two categories; the classical strategies and the market-based ones. Based on input from the industry experts, the market-based ones seemed to be far less viable in application in Iceland. These types of IBP strategies were very absent in the literature and seem to be less applicable to EVs, as they require a well functioning electricity market and EVs often exhibit more volatile and random behaviour than conventional DR resources. The existing settings in the system of interest also make these types of strategies unlikely to be practical in application, as there needs to be a fairly complex electricity market with wholesale future markets as well as ancillary services or other grid services markets. For the capital region in Iceland this is not the case, as that energy market is fairly small and simple. For these aforementioned reasons, market-based strategies were considered to be unsuitable as a strategy to be implemented.

The other category, classical IBP strategies, were much more frequent in the literature. In simple terms, these strategies work in such a way that consumers or aggregators on behalf of consumers make an agreement with the DSO such that the DSO can curtail or interrupt certain loads in certain hours. This gives the DSO a high degree of control of the consumers' demand at these times. Under this classical type of IBP, there are only two strategies which are quite similar in many ways. It was decided to choose **direct load control (DLC)** which essentially gives the DSO control over the load of a consumer according to an agreement between the two parties. The choosing of this strategy was both supported by the industry experts as well as the literature as this strategy generated promising results when used with EVs. As with the TOU strategy, there exist many implementations of DLC, but the one that was formulated for the conceptual model was based on factors that make it more likely to be implemented and less disruptive for EV users. Similarly to the TOU discussion, there is an off-peak period which often experiences low charging load, as users charge their vehicles early in the evening as that is the time when they come home and plug in their vehicles.

The specific DLC strategy incorporated into the model is where the charging of EVs is shifted and distributed over a certain possible charging period so that the overall load of the system is minimised. That is, the charging is only done when it contributes the least to the overall system load. The start of this period varies for every single shiftable session and is based on when consumers arrive home and plug in their cars. The end of the shiftable period is also specified by the consumers, either when they leave in the morning or by default at a certain time in the morning. With this approach, the charging needs of the consumers can still be achieved, but the load can be shifted in time to match better to the system load. As with the TOU DR strategy, from this strategy there can be many charging scenarios. However, there are much fewer scenarios, or combination of parameters in the DLC strategy as the only thing that changes is the participation of consumers, as well as the size of the EV fleet.

With these two demand chosen response strategies, there are now three main load scenarios. This is the uncoordinated load, based on the charging behaviour of users without any DR strategies. This can be termed as the "business as usual" pathway of EV charging in Iceland. It can also be viewed as the "worst-case scenario" as the uncoordinated charging load will most likely affect the distribution grid in the most detrimental way. The second scenario is the TOU DR strategy, which is the more simplistic and easier to implement of the two DR strategies. This is therefore viewed as the "average-case scenario" or the middle-ground strategy. Third and lastly is the DLC DR strategy, which out of all possible DR strategies as shown in figure 3.2, will probably give the best results for the distribution grid, as with it the DSO has such a high level of control. Thus, this strategy is viewed as the "best-case scenario". From these three charging strategies, there comes a spectrum of charging load profiles, from the least intervention with the uncoordinated load to the most and perhaps overreaching intervention in the system with the DLC strategy. By choosing these two distinctively different DR strategies and incorporating them into the conceptual model and then subsequently implement them in the technical model, the effect of DR strategies on the charging of a large EV fleet can be explored.

4.4. Inputs and outputs

For this part of the conceptual model formulation process, it is vital to first focus on the intended outputs of the model. From there, the required inputs can be determined. As said before, the model will run over an entire year, on a 15 minute basis. Over this period, time-dependant values of both charging load and primary load are used to model the effects on the distribution grid.

4.4.1. Outputs

The main output of the conceptual model, and the one output which most of the other outputs are derived from, is therefore a time-series load model, with primary load and charging load values separated, over the entire model period. This output of the model will be different for every charging scenario, as the charging load part of the output will be different, based on varying consumer behaviour under these scenarios. Therefore, for every scenario, the output will be a full charging profile over the entire model period. From this main output, a multitude of outputs can be derived which will be used to measure the effects on the distribution grid on its three different levels. This main output serves as an overall indicator of the performance of each DR strategy scenario and is used to quantify the effects on the top level of the distribution grid, the high voltage substations. That is done by comparing the yearly load profiles to the capacity limits of the grid, which is an input that will be explained later on.

To determine the effects of the load on the lower levels of the grid, the same charging load values are used but to determine the primary load for those levels, another dataset has to be used. Therefore, to determine the load effects on the grid, there are essentially two steps; first on the overall grid and then the lower levels. These two steps are thus represented as two separate outputs in the model. Based on the main output, which is the time-series load model, metrics and information will be derived from. These outputs can be classified as modelling key performance indicators (KPIs) as they are used to quantify and compare the performance of the different scenarios that produce the main output. These KPIs in combination with the grid load effects outputs are used to determine which scenario or DR strategy can provide the best results. These KPIs are also largely based on the technical details of the model as it is implemented in a programming language which are discussed in detail in section 6.1.1.

4.4.2. Inputs

The inputs are not all of the same type. Some can be determined by the modeller, based on information or literature findings, whereas other inputs are datasets acquired from various sources. In the following *Data* chapter, the major datasets that were gathered and used for the model inputs are explained in detail and preliminary analysed. For the input identification for the conceptual model, the inputs will be shortly explained and what role they play, but their characteristics and specifics can be found in the chapter specifically on the data. The inputs can be generally classified into three different groups; the input parameters, the input dataset and capacity limts, as visualised in the overview of the conceptual model in figure 4.2.

1. Input parameters

Perhaps the first input to mention, is the EV-fleet size. This total number of passenger cars in the system of interest can be accessed online and based on that various penetration levels of EVs can be formulated. These penetration levels essentially mean how much of the vehicle fleet is electric. For a 50% EV penetration, every other passenger car in the system of interest will be an EV. This input for the model is explained in more detail in section 5.4. This input will be used in incremental values for different DR strategies to see the effects of the size of the EV fleet as well as determining the threshold EV fleet value based on the distribution grid capacity on different levels. Another input is the consumer participation in the DR strategies. To find concrete data for this is challenging, and as discussed earlier, the most likely participation level will be approximated based on predicted savings for an average consumer. Similarly to the EV-fleet size input, this input will be used in incremental values to see the effects on the load profiles and to approach solving objective six. More detailed explanation of this input can be found in chapter 5.4.

2. Input datasets

On to the dataset inputs, the two most prominent ones are the major components of the model itself; the charging load and the primary load values. These two inputs are very important as they are the foundation of the main output, but they are also regulated by the constraints, as the datasets have to run over a full year and be true values of actual load. Starting with the charging load, the dataset acquired for that input is actually one of the fundamental strengths of this research project as that dataset is based on a real-case EV study conducted in Iceland which has never before been used for academic purposes and thus offers a much better and realistic representation of the charging load of an EV-fleet. This dataset and how it is handled to represent a large EV-fleet is explained in detail in section 5.1. Based on this dataset, the constraint on capturing the variability of an EV-fleet to fully determine the distribution grid effects, can be met. That validation process is covered fully in section 6.1.1.

For the other major dataset - the primary load - two datasets were acquired for the project from Veitur. These two datasets are primary load values from different voltage levels of the distribution grid. For the top level, load values from all the substations are available, that together make up the overall load of the system of interest. However, as the DSO generally does not collect load data at lower levels of the system, primary load data on the distribution substation level was only available partly, from a handful of stations out of roughly 900. In this project, one station was used to represent a snapshot of the lower levels of the grid. Some of the available stations did not have the desired characteristics, i.e. were only based on business housing or other non-descriptive grid characteristics. This is certainly a simplification due to data availability and will be thoroughly explained in the *Simplifications* subsection. Additionally, how this primary load data from the substation is handled to approach the lower level grid effects determination is explained in detail in section 5.3.

3. Capacity limits
Besides these two major input datasets, the input on the capacity limits of the distribution grid on its different levels was acquired from the DSO. Similar to the primary load values, the capacity of all the high voltage substations was available, but based on the limited load data on the lower levels, the capacity data of the corresponding distribution substation was only acquired, also from the DSO. Additionally, to fully determine the effects on the lowest part of the level, where the EV charging itself takes place, information on the electricity infrastructure capacity was accessed online from a public source. This information makes it possible to map out the streets connected to the distribution substation with available load data and define the capacity of each cable coming from those stations. This way, the different levels can be represented in the model, despite the limited data for the inputs. This is also explained in more detail in section 5.3.

Central modelling process
As the conceptual model is quite complex and will guide the technical model implementation, it is important to have a clear overview of the flows of the aforementioned inputs and outputs as well as the central model process itself that is based on the modelling objectives and constraints. A visual representation of the conceptual model with its components was already provided in figure 4.2.

Now that the inputs and outputs have been described, as well as the model content, a summary of the modelling process can be provided. To explain the sequential steps of the conceptual model, it starts with the inputs as described earlier. These inputs are used in the central modelling process, which is essentially two steps; first modelling the combined load profile of the charging and primary load, based on the input parameters; the DR participation and the EV penetration. Then this load profile is quantified in terms of the capacity limits of the grid, first on the top level and then the medium and lowest level, in separate steps. From this process, the outputs are derived, and from them the results of the model use can be analysed and ultimately be used to compare performance of different charging scenarios. As can be seen in the visualisation of the conceptual model, the problem situation is the direct influence on the central modelling process, where the modelling objectives and constraints are used to guide the modelling process. But what is also an important factor in this process is the model scope, simplifications and assumptions. The scope of the model has been explained shortly before, with the constraint of it having to run over a full year. The simplifications and assumptions have an even bigger impact on the conceptual model.

Those are based on things that have to be decided, in order to carry out the conceptual modelling formulation. Some of these simplifications and assumptions apply to the scope of the model, both in terms of the modelling period but also to the amount of data used, details in the different processes or elements that make the process more manageable. They are made whenever something is not known or to simplify things in the modelling process. Both affect the conceptual model, as they limit what is carried out by it and can change the outputs or even the central modelling process. In the next two subsections, the simplifications will first be explained and subsequently the assumptions.

4.5. Simplifications

In the previous subsections the major components of the conceptual model have been formulated and explained. But as said earlier, the simplifications and assumptions made in this formulation process have an impact on all of these components. However, they also make the conceptual model more focused and targeted on the problem situation. The system of interest is based on the modeller's perspective on the real-world system, which is the distribution grid. Taking this system of interest and identifying the problem situation within it and subsequently formulating the conceptual model is essentially done by simplifying processes and assuming how specific steps should be implemented. In this section, the main steps that were taken to simplify the conceptual model are explained. These simplification steps focus on an entire part or process within the conceptual model, different to the assumptions which are more detailed and focus on specific formulation decisions.

One of the main simplifications is how the distribution grid system is represented in the model. As explained in the previous subsection on the inputs, primary load data was only acquired for one distribution substation. This means that only a fraction of the lower level of the grid can be modelled based on actual data, which was one of the modelling constraints. Although data on the capacity limits of the grid was available for more distribution substations, that would serve no purpose without actual load values. Therefore, a simplification was made; to represent the distribution grid as a combination of the complete overall grid level and a snapshot of the lowest levels based on the distribution substation.

Together, these two parts can represent the grid sufficiently to be able to compare the performances of different charging scenarios. For the lowest level of the grid - the street level - no load data is collected and thus not available. This however is the level of the grid where the EV charging load is situated and thus an important aspect to include in the model. Based on the available substation load dataset as well as the publicly available information on the street-level electrical infrastructure, a subgrid on this lowest level was formulated. This way, the three levels of the grid can be represented in the model. In figure 4.3 below, these three levels along with the simplifications made to make them work can be seen.

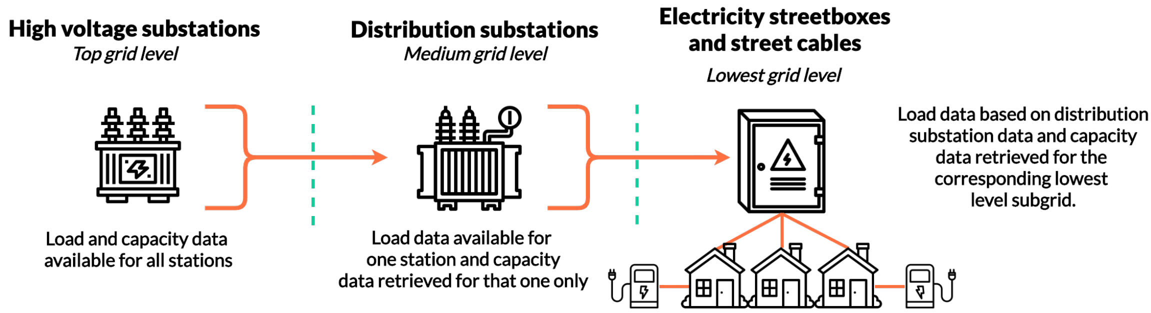


Figure 4.3: A flow of the three levels of the grid represented in the model. Icons from www.flaticon.com

These simplifications were made to make the model more realistic, instead of only using the overall top grid level, where exhaustive data could be acquired. This is also the reason why the grid determination in the conceptual model is a two-step process as seen in its visual representation in figure 4.2. By using this method, working with the data that was available, the effects of the charging load can be determined on all levels of the grid and thus the impact much more realistically assessed. However, the impact that this has on the modelling outputs is that these lower levels of the grid can only offer insights based on this one subgrid. As there are roughly 900 distribution substations in the system of interest and subsequently 900 such subgrids, this only offers a tiny glimpse into the effects of the different charging scenarios on the lower levels of the distribution grid. Therefore, this part of the results are less accurate than the grid impact on the overall system level. If the available datasets had been from any other distribution substation, the results would undeniably be different. The details of these datasets and the subgrid electricity infrastructure information can be found in the *Grid capacity data* chapter. The implementation of this approach in the technical model is explained in chapter 6.3.

Another simplification that was made is the way in which the charging load input is used and handled. In the dataset that makes up this input, the charging load profile is made up of individual charging values from an EV study as explained before. How to handle this input is an important step of the conceptual modelling process. This handling does not only apply to the base modelling, i.e. the uncoordinated load, but also the DR strategy implementation as they use these charging profiles and affect them by distributing or changing the load according to the strategies. A simplification was made in order to manipulate this input as little as possible for the most accurate depiction of the data behind it. This simplification is that only certain of the charging session properties can be affected. The charging power, duration and the total charging load of the session cannot be altered. The individual intervals of the session can be shifted in time and rearranged, but the charging power as well as the duration and inclusion of every interval in the session must be completed.

This still makes it possible to see the effects of the different DR strategies, but does so on an even ground, as the strategies still have to take into account realistic real-life charging behaviour. This simplification does also have effects on the modelling process and outputs. This essentially does provide a limited view of the performance of the different DR strategies, as when people shift their charging or change their behaviour, the charging settings as explained before; duration, power and other parameters can indeed be different than if the charging was uncoordinated. This of course impacts the results, as it might make the performance of the DR strategies less effective, as the sessions as they appeared in the EV study must be used in the same way.

4.6. Assumptions

As stated before, the assumptions are decisions that are made to be able to implement certain things in the conceptual model. As the two main simplifications as described before are quite broad, some of the assumptions are derived from the simplifications. These assumptions can be seen as the detailed design choices of the model; what to include and what not to. Most of these assumptions are related to the conceptual modelling formulation process, dealing with the handling of inputs or the central modelling process. They can be classified into main and minor assumptions, depending on how much they affect the conceptual model. The main assumptions affect the modelling steps and outputs significantly, while the minor ones are smaller assumptions that are made to deal with input inconsistencies or minor elements for the technical model implementation.

Both groups of assumptions will be described in this section, but only the main assumptions will be explained extensively. The motivation and reasoning behind them will be addressed and because the choices behind those main assumptions can indeed have big effects on the conceptual model formulation and the model results, their envisioned impacts will be analysed as was done previously done with the simplifications. These impacts will then be then be reflected upon in the discussion part of this thesis as mentioned earlier. In tables 4.1 & 4.2, the main and minor assumptions can be found.

#	Main assumptions	Motivation / Reasoning
1	Charging behaviour from EV study is made to represent an EV fleet	No other Iceland-specific EV dataset is available
2	Primary load adjusted by deducting EV charging load	To separate primary and charging load
3	Composition of EVs by residential type assumed to be same as in study	No known information on the actual composition
4	BEV and PHEV load profiles aggregated separately	They have different charging patterns
5	Charging sessions that can be shifted are only those who are thought to be at the home of the EV owner (after 14:00 and =< 11kW charging power)	This is a more realistic depiction of the DR strategies
6	Only the "last" charging session of the day can be shifted and at maximum towards the start of the next session or a trip	This ensures that the original charging behaviour is not broken
7	Shifting of charging sessions done at the same time for all participating EVs	Easiest, fairest and likeliest way
8	Charging sessions can be broken up and their intervals rearranged	Straight-forward and true implementation of DLC
9	Charging sessions are shifted to the intervals where primary demand is lowest	DLC implementation to distribute the load in an optimal way
10	Primary demand is updated in steps based on EV penetration, so that the EV charging takes that into account	Done to model more realistically and update load dynamically
11	Overall system capacity determined by N-1 rule	This is the way that the DSO determines the grid capacity
12	Number of EVs per building are based on EV penetration, building inhabitants and car ownership factor	Done to be able to model each house individually
13	Primary demand in each building based on proportional substation load	No house-level load profiles exist so this approach is used
14	EV charging profiles of each building based on EV quantity and building type	The EV charging study data is used as accurately as possible
15	EV charging taking place in each building assumed to be connected directly to the main building electricity connection cable	Assumed to be able to effectively use the subgrid data

Table 4.1: An overview of the main assumptions

#	Minor assumptions	Motivation / Reasoning
16	For buildings in subgrid that had missing values or strange values, an average number of inhabitants was assumed and used	Done to keep subgrid results consistent
17	Input data error over mid-year for subgrid primary load not treated specially	The missing data does not affect the overall system peaks
18	For EVs allocated to houses in subgrid, BEVs and PHEV were allocated alternately	Done to approach a 50-50 share of BEVs and PHEVs
19	For one of the EVs from the EV study dataset, trip data was unavailable and thus unable to be used in the shifting methodology for the shifting of sessions. To combat this, only nearest sessions were used for TOU and nearest sessions as well as the morning after were used for DLC, whichever was closer.	Only way to cope with this data error
20	The shifting limit for DLC DR was set to the morning after or the end of the dataset, whichever was closer, in the case that there were no further sessions or trips	Done to still comply with the modelling constraints

Table 4.2: An overview of the minor assumptions

4.6.1. Main assumptions

There is a big difference between assumptions and the programming steps taken for the technical model, where the conceptual model is implemented in a programming language. In chapter 6, these implementation steps will be explained in detail. The difference between those steps and the assumptions explained in this chapter is that the steps are either based on assumptions or applied straight-forward. But the assumptions are design choices made to be able to represent something in the technical model. In table 4.1 the main assumptions can be seen. In the table, the assumptions as well as the motivation or reasoning behind them are listed. These 15 assumptions can classified into four groups, based on which part of the technical modelling process they apply to. These four parts are the base modelling, TOU DR modelling, DLC DR modelling and the grid impact modelling. These are the four main steps of the technical model implementation and will be explained in detail in separate subsections chapter in 6.

Base modelling

The first four assumptions apply to the base modelling part, which generates the time-series load model, which is the main output of the model. This is where the load datasets are formulated into load profiles and the uncoordinated load is determined. Based on that uncoordinated load, the two DR strategies are implemented, so this part is the first step in the modelling process. The first assumption is on the charging load dataset. In this dataset, which is based on a limited number of EVs, a generic charging profile can be created. That profile is based solely on the cars included in the EV charging study. In this steps, Assumption #1 is made, by using that charging profile from the dataset. This is done as there is no other charging specific dataset and the only way to use this one to get specific charging values of a larger EV-fleet is to use this charging profile. This is the main concern for the validity of the modelling, and is validated and discussed in detail in section 6.1.1. How this affects the results is challenging to measure, as other data to formulate such charging profiles is very limited and hard to find. However, all of the results for the different scenarios will be based on this dataset and so if the dataset does not capture enough variability it limits and skews all results.

The second assumption is made to be able to use the primary load data for its intended purpose in the model. As said earlier in section 4.2.1, it is desired to have the primary load, i.e. the base electrical load in the capital region without any EV charging, and the EV charging load itself separate. As the primary load that is used does in fact contain EV charging loads - as it is the entire load of the capital region - the EV charging load had to be deducted. The assumption is that by using the yearly charging profile from the EV study dataset and deducting that load profile from the primary load based on the number of EVs in the system of interest over the modelling period, the primary load can be adjusted, and thus the primary load and the charging load be kept fully separate. This assumption is necessary to achieve the modelling objectives, but can affect the model outputs. As it is not completely known how many cars contributed to this primary load and so if this adjustment should be increased or decreased, it can have an effect on the overall system peak that is modelled. However, the reduction based on this assumption was made with the most accurate available data.

For Assumption #3, the residential types of the EVs in the dataset come into play. These types are family homes, apartment buildings and businesses. In the EV study dataset, there are different groups, but the composition of them is assumed to be the same in the modelling. These different groups are also explained and visualised in section 5.1.1 and table 5.1. This is assumed as there is no reliable information of what the actual composition is and the sample in the study is thus used as an approach. For the last assumption applying to this modelling part, the two main types of EVs; BEVs and PHEVs, are aggregated separately. This is done as they have different charging profiles.

For the modelling, the share between BEV and PHEV is assumed to be 50-50, i.e. for every EV fleet that is modelled, half of it will be BEV and half will be PHEV. Again, this is done as there is no known future fleet composition. According to the simple forecast done in section 2.2 and seen in figure 2.4, the composition is very close to 50-50 in 10 years time. For both of these assumptions, there is really no information on how the future values of the composition of the fleet will be, both based on these residency types as well as the PHEV and PHEV share. However, these assumptions affect how the charging profile of the EV fleet is determined and thus all of the charging scenarios that are modelled and therefore does affect the results of the modelling.

Time of use modelling

Assumptions #5 - #7 apply to the first DR strategy modelling part. They are therefore mostly concerning how the actual strategy is implemented. This implementation is largely based on these three assumptions. First, it is determining which sessions can actually be shifted. Only the charging sessions which are believed to be at "home" can be shifted. As there is no location information in the EV study dataset, this has to be approached by an assumption. Therefore, any session that starts after 14:00 and has a maximum charging power of less than 11kW - which is the maximum power of the most widely used home chargers - is believed to be at home. Additionally, only the last session of the day can be shifted and the shifting of the session has to take into account other charging sessions and trips as stated in Assumption #6. As TOU DR works based on a certain price changing time, all of the charging sessions are shifted to that time, as stated in Assumption #7.

As with the previous assumptions, the predicted impacts of these TOU assumptions can be laid out. They are largely based on the modellings constraints, which try to set a boundary for how the two DR strategies can be implemented. For the first one, the approach to the home sessions, this has the impact on the modelling that overall a bit fewer scenarios are shifted. This assumption is based on the particular implementation of the TOU strategy, which in itself is a big modelling assumption. For the Assumption #6, the same applies, fewer overall sessions are shifted as a result. This assumption is also made to comply to the modelling objectives and ensure that no sessions are overwritten when shifting the sessions. If the other sessions of the day could also be shifted, then the behaviour of the consumer would essentially be broken as it manipulates that recorded behaviour as presented in the EV study dataset. The last assumption is that all the participating EVs are shifted at the same time to the price-change hour. This again is based on the particular implementation of TOU in this thesis project and could have been implemented in another manner. This is also thought for future work and research, by using more price-change times for the same fleet.

Direct load control modelling

For the second DR strategy, there are also some important assumptions, which are Assumptions #8 - #10 and apply to the specific implementation of this strategy. Additionally, Assumption number five also applies to the DLC strategy, as the shifting and distribution of charging scenarios is only applicable to home sessions. The method of distributing the load essentially works by interrupting the load and allocating to the time intervals where it has the lowest impact on the distribution grid. As one of the main simplifications stated earlier, the input charging load profile can only be manipulated in certain ways. For this strategy, where the DSO has the main control over the charging, the individual intervals in a charging session can be interrupted and rearranged, but the load cannot be curtailed. This is reflected in Assumption #8. This means that the charging power itself cannot be changed or reduced. This simplification and assumption is made in order to keep the different DR strategies comparable in terms of performance. As with the TOU assumptions, this affects the performance of this DR strategy, but is made to comply with the modelling constraints. If curtailment would be allowed it could perhaps generate more favourable results, but would break the constraints.

The two second assumptions for this DR strategy depict how the shifting is done. They state that the allocation of the intervals of shiftable charging sessions is done by rearranging the intervals to the times where the system load is the lowest. This way, the overall system load is minimised. This is however done in steps, based on the EV penetration that is being explored in the model each time, as the times at which the system has the lowest load might change based on the EVs. Therefore, this process is done in steps, where the EVs are allocated in batches, based on the EV charging study dataset and the system load is updated after each allocation. This makes the process much more realistic and closer to how the strategy would be implemented in reality. How these assumptions were implemented in the technical model can be found in section 6.2.2. These assumptions are also made to represent this DR strategy in this thesis project. Different variations of the strategy could generate better or worse results, but these assumptions were made to comply to the modelling constraints, as with the TOU assumptions and to make it possible to have clear steps that can be compared between the DR strategies.

Grid impact modelling

For the last modelling part, which are the two central modelling process steps in the conceptual model as seen in figure 4.2, the last five assumptions apply. Assumption #11 depicts how the overall system capacity limit is determined. That is done by using the N-1 rule, which is the methodology the DSO uses. This rule essentially means that every high voltage substation must be able to run with N-1 of its transformers. Most of the 12 high voltage substations have only two transformers, so the overall limit is determined based on only the capacity of one of those transformers. There are many different ways to calculate this capacity number, but this one is used based on the DSO's recommendation. For the lower grid level modelling, there is no need for an assumption as then there are only one or two transformers, and the capacity of the station is simply determined by their combined power capacity. The impact of this assumption is that the theoretical limit of the grid is not used, but rather is approach. This might make the results of the modelling overvalued. This will be reflected upon and its sensitivity shortly analysed in section 8.2.1.

The last four assumptions #12 - #15 apply to the grid determination methodology of the lower parts of the grid. To find the number of EVs in each building in the subgrid, the input on the electricity infrastructure is used, as explained earlier. From the publicly available dataset on the street-level electrical infrastructure, there is also data on the number of inhabitants in each building. This data is explained and discussed in section 5.3. Based on that dataset, car ownership statistics from Iceland and the EV penetration input in the conceptual model, the number of EVs per building can be approached. This assumption is made as there is no other reliable information on this available. However, the accuracy of this can vary greatly between buildings. In some buildings, all of these inhabitants might be adults and thus this methodology is rightly assumed. However, in some buildings the majority of the inhabitants might be children or non-driving inhabitants. This might cause the EV numbers per building to be very overestimated. However, as this is done to all of the houses in the subgrid, overall it should be smoothed out, based on the car ownership statistic.

As explained earlier, there is no primary load data available on the lowest level of the distribution grid. As it is desired to still determine the charging load impact on this level, this load has to be approximated somehow. This is done in Assumption #13, using the distribution substation load profile and scaling that profile to each building proportionally based on the number of inhabitants as described before. This way, the total load of the system can be allocated to all of the buildings in this subgrid. Assumption #14 also applies to this level, on how to allocate the EV charging load. That is done by using the aforementioned data, the numbers of EVs per building and additionally the residency type and based on that allocating charging profiles from the EV study dataset. This makes the EV charging in each house more realistic as it is based on as many factors as possible.

Both of these assumptions approach the load in the individual buildings in the subgrid and do so with the information that is available. As with the EV number estimation in each house, this is merely an approach to these loads and can be a heightened or lower case of the actual load in these buildings. However, by using the substation load and allocating it properly to the houses, it can be ensured that the primary load in each house is not overvalued, as together they make up the substation load. The impact on the results in this case is that these primary values might be undervalued if anything. For the EV load estimation, the type of house, family home or apartment building was taken into account when allocating charging profiles to them.

The last modelling assumption is an important one for the load effects determination on these lower levels of the grid. It states that the EV charging is assumed to be located at each building's main electricity connection. To explain further, for every building in this subgrid, there is an electricity cable coming from the electricity streetboxes, as visualised in figure 4.1 on page 22. In reality, home charging of EVs might take place away from the houses themselves, in a garage or off-street parking next to the homes. Determining this would be very challenging and in most houses in Iceland there is a drive-way or a garage near the house, which is connected to the house itself.

This assumption thus states that the EV charging of a building is directly connected to the main electricity cable going into the houses. This will also be explained in more detail in the technical implementation of this part of the modelling, in section 6.3.2. This representation of the electricity infrastructure of each building might be over-valuating their capacity, as many houses in reality would charge in a garage or some other part of the properties. This is at least the case with the family homes. With the apartment houses however, this might be an under-valuation of the capacity as often times in those buildings there are additional connections added when EV charging is common.

As the subgrid modelling process is quite intensive and detail-oriented there are many additional minor assumptions that have to be made to implement the modelling. However, these assumptions do not affect the results in the same way as the critical ones as described before. The minor assumptions will be shortly explained in the next subsection.

4.6.2. Minor assumptions

The minor assumptions can be seen in table 4.2, presented earlier. These will be shortly described and explained, but as said before, they are mostly made to deal with input discrepancies or made to be able to implement certain modelling steps. The first three minor assumptions apply to the subgrid modelling. In the publicly available information on the street-level electrical infrastructure, which is used to formulate the subgrid, as described before, the number of inhabitants per building in the subgrid could also be found. This is also a part of main Assumption #12. However, some data discrepancies were found in that input dataset and missing numbers or faulty numbers were found. To deal with this, an average number of inhabitants were used instead. The input for the substation primary load also had some faulty data, as data for three months or so was missing over the modelling period. However, these months were spring and summer months, which have much lower load and thus peaks. Since all of the results and outputs are based on peaks, this should therefore not affect the model outputs. The last subgrid minor assumption is how the allocation of EVs is carried out. As stated in the main assumptions, the number of EVs per building are calculated. As the composition of EVs is assumed to be always 50% BEVs and 50% PHEVs, EVs were allocated to buildings in the subgrid alternately, to approach this equal number of BEVs and PHEVs.

The last two minor assumptions are based on the methodology of the two DR strategies. First, Assumption #19 deals with missing trip data of one of the EVs from the dataset. This trip data can be viewed as a part of the consumer charging behaviour which cannot be broken, as stated in modelling constraint number five, earlier defined in this chapter. To deal with the missing data, the nearest sessions were only used to limit the shifting this particular EV for the TOU, as is also done with other EVs. For the DLC DR strategy, nearest sessions were also used to find the limit of the DLC period, in combination with the morning after at 9:00, whichever was closer. The next assumption, number twenty, also deals with shifting limits of the DLC DR strategy. The charging sessions are broken up and rearranged over a certain period which is marked by a limit. When a certain session was either the last one of the year or had no trip data after its start, the morning or the end of the modelling period was used to determine this limit, whichever was closer.

5 Data

This chapter is dedicated to the explanation of the data and information used to formulate the technical implementation of the conceptual model. These are essentially the inputs of the conceptual model, numbered from one to three, with the data connected to the different inputs being discussed in the subsections below. Subsection 5.1 describes the input datasets of the conceptual model (2), subsections 5.2 and 5.3 refer to the capacity limit data (3) and finally subsection 5.4 corresponds to the input parameters (1). The specific properties of these datasets shape the technical model, as explained in the earlier *Simplifications*. As explained in the literature review, subsection 3.3.2, the data used in this thesis project is a major part of the approach of closing the identified knowledge gap. Never before has EV charging data specific to Iceland been available. Therefore this acquired data indeed plays a central role in the research and makes it possible to model much more accurately then before and to make more use of different demand response strategy simulations. Models are only ever as good as their input data and for this project it is certainly true. To get an accurate depiction of the system of interest, accurate data is important. The following subsections of this chapter are dedicated to the datasets used for the creation of the modelled system. These datasets will be described, preliminary analysed and their intended use cases explained.

5.1. Charging data

Arguably the most important dataset for this thesis project is the charging dataset which comes from a study conducted in 2018 and 2019 on behalf of Samorka, the association of the electricity industry, district heating, waterworks and sewage utilities in Iceland, founded in 1995. All district heating and electric providers and utilities in the country are members as well as most sewage and waterwork utilities (Samorka, n.d.-a). The study was in carried out in cooperation with these member companies, intended to gather insights into EV charging behaviour for future decision-making on the distribution grid and charging infrastructure.

5.1.1. Charging data properties

The study itself was conducted by using a tracking device in the vehicles which measured and collected various performance and behaviour metrics (Samorka, n.d.-b). For every trip the vehicles made over the study period, various metrics were collected such as; distance, driving time, start and end state of charge (SOC), electricity consumption as well as fuel consumed (for PHEVs). These metrics do not only provide valuable information for the model as will be explained later on, but give important insights into how the EV users behave. For charging specific metrics, data was collected in data-slices, which were recorded in 15 minute timeslots over the timestamp hour, only when the EVs were actually charging. However, the first slice of charging sessions is rarely exactly 15 minutes and thus most often shorter. Similarly, many things were collected for the EV charging such as; duration of the charging slice (most often 15 minutes), maximum charging power, charging energy, start and end SOC.

The study period was an entire year, from December 1st 2018 to November 30th 2019. In total, 194 vehicles participated, classified by thirteen different subgroups. These groups are based on the type of EV, area and residency type. In table 5.1 these subgroups can be seen. For the subgroups, there are three EV type vehicles. First is BEV short, which means a BEV type vehicle with a range of equal or less than 300km. Second is BEV long, which means a BEV vehicle with more than 300km range. The last EV type group are PHEVs, all in one category. These EV groups are then also categorised by the area in which they are situated and the type of residency or housing. With this information, EVs in the capital region can be modelled more accurately.

Group	Area	EV type	Housing type	No. of vehicles
1	Urban outside capital area	BEV short	Single family home	15
2	Urban outside capital area	PHEV	Single family home	14
3	Urban outside capital area	PHEV	Apartment building	15
4	Urban in capital area	BEV short	Single family home	16
5	Urban in capital area	BEV long	Single family home	15
6	Urban in capital area	PHEV	Single family home	15
7	Urban in capital area	BEV short	Apartment building	15
8	Urban in capital area	BEV long	Apartment building	15
9	Urban in capital area	PHEV	Apartment building	15
10	Urban in capital area	BEV short	Business housing	15
11	Urban in capital area	PHEV	Business housing	15
12	Rural	BEV short	-	15
13	Rural	PHEV	-	14

Table 5.1: Overview of the different EV subgroups of the EV charging dataset. Based on information from the EV study dataset.

To properly utilise the data it had to be handled and formulated. As described earlier, charging data in the study was only collected when vehicles were charging. To derive the charging load per 15 minute timeslot as described before, the slice duration and the charging energy were used. By dividing the charging energy with the slice time duration as the share of an hour, the charging load was calculated. With this methodology the charging of each individual EV in the study could be calculated. This charging load data was then formulated such that each EV was represented in a column with the charging session appointed to the correct timestamps. A visual representation of this can be seen in table 5.2, where the first lines of this data table for a few EVs from the study can be seen. The charging values seen in the table are straight from the dataset and showcase how this formulation method maps the charging load to the correct timestamps. With this data table, the EV load can be aggregated into load profiles based on the different EV subgroups.

Timestamp	EV #5	EV #19	EV # 21	EV #25	EV #39	EV #41	EV #60	EV #74	EV #156
12.1.2018 00:00	-	1902	-	2876	-	1814	1540	-	7677
12.1.2018 00:15	-	1900	-	2887	-	116	1116	-	7084
12.1.2018 00:30	-	1900	-	2888	-	567	884	-	5951
12.1.2018 00:45	-	1902	-	2895	-	299	741	3059	6132
12.1.2018 01:00	-	1900	-	2892	-	-	656	3056	6107
12.1.2018 01:15	-	1902	-	2892	-	-	525	2993	5384
12.1.2018 01:30	-	1900	-	2895	2102	-	600	-	3996
12.1.2018 01:45	-	1900	-	2888	2092	-	618	-	3872
12.1.2018 02:00	-	1902	-	2883	2088	-	-	-	2143
12.1.2018 02:15	-	1900	-	2880	2086	-	3095	-	-
12.1.2018 02:30	-	1900	-	2879	2076	-	3412	-	-
12.1.2018 02:45	-	1902	-	2880	2094	-	3007	-	-
12.1.2018 03:00	-	1900	-	2891	2072	-	2087	-	-
12.1.2018 03:15	-	1900	-	2888	2090	-	-	-	-
12.1.2018 03:30	-	1902	-	2891	2088	-	-	-	-
12.1.2018 03:45	-	1900	-	2888	2094	-	-	-	-
12.1.2018 04:00	-	1902	-	2889	2084	-	3266	-	-
12.1.2018 04:15	-	1900	-	-	2094	-	3252	-	-
12.1.2018 04:30	-	1900	-	-	2030	-	-	-	-
12.1.2018 04:45	1937	1902	-	-	-	-	-	-	-
12.1.2018 05:00	1971	1900	-	-	-	-	2965	-	-
12.1.2018 05:15	1972	1900	-	-	-	-	3100	-	-
12.1.2018 05:30	1974	1902	-	-	-	-	3082	-	-
12.1.2018 05:45	1976	1900	-	-	-	-	-	-	-

Table 5.2: Example of the charging load data

For the technical model creation, which is explained in-depth in the next chapter, chapter 6, it was desired to only select the EVs situated in the capital region. Therefore only EV groups 4 - 11 were included for the technical model creation, as seen in table 5.1. In the next subsection, the trip and charging data based on these selected data groups will be preliminary analysed in order to gather some insight into charging behaviour and the data itself.

5.1.2. Charging data analysis

As discussed above, the charging study data essentially comprises of two parts, the trip data and the charging data. Based on the selected EV subgroups, i.e. those situated in the capital region, 76 BEVs and 45 PHEVs were used for the creation of the load model. When these EVs are formulated into the data table as discussed before, the charging behaviour can be investigated. Average time between charging sessions and the mean charging session duration as well as the mean charging power can give a good insight into how substantial the load of charging an EV is. In table 5.3 below, these metrics can be seen, based on the mean values of the different EV types.

EV type	Average time between charging sessions [hh:mm]	Average charging session duration [hh:mm]	Average charging power [W]
EVs (overall)	33:20	3:05	2759
BEV long	47:30	3:44	4163
BEV short	31:56	3:20	2463
PHEV	24:17	2:23	2125

Table 5.3: Overview of the major charging behaviour characteristics of the studied EVs

However, this is excluding a part of the data that was deemed abnormal. Most EVs in the dataset showcase very similar times between charging sessions, coming from regular use. A few EVs had extremely long times between charging sessions. This can be seen in the figure 5.1. These EVs are either very rarely used or have faulty data collection. Either way, these EVs, specifically those with higher than 700 hours average time between sessions, which can be seen where the line rises most aggressively in the graph, were excluded from the calculations for the mean as presented in table 5.3. What can be seen in that table is that PHEVs charge more frequently than BEVs and longer-range BEVs need less frequent charging. Note that this is the time between each finished charging session, so the time between plugging the car in is actually the time between sessions in addition to the duration of the sessions themselves. So EV users plug in their BEV long, BEV short and PHEV on average roughly 3, 5 and 6 times a week respectively. Same goes for the charging power which is by far the highest for the bigger range cars and then lowest for the PHEVs.

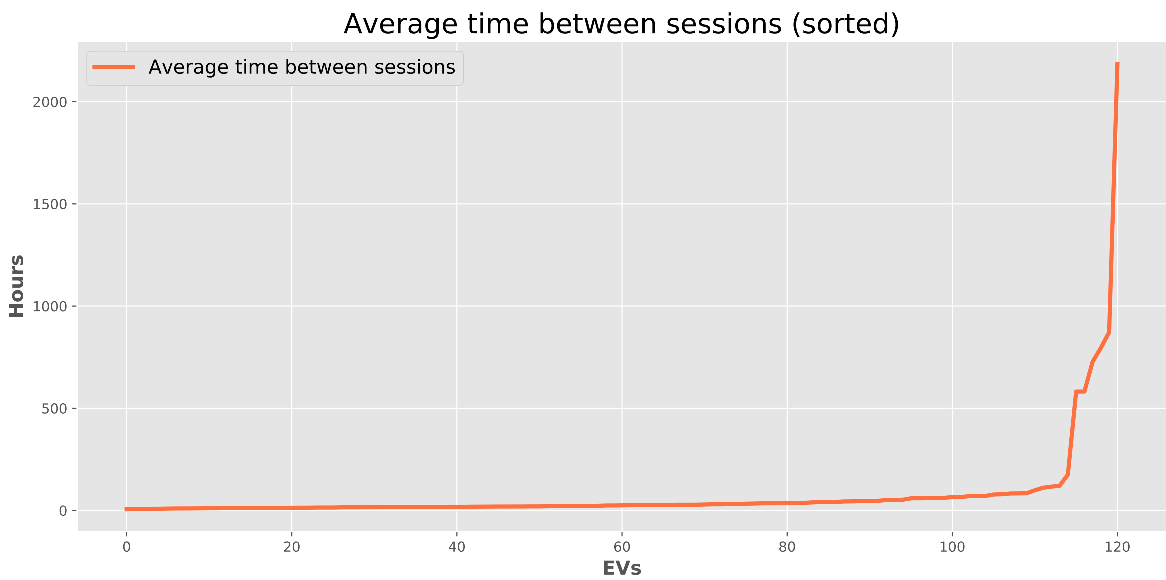
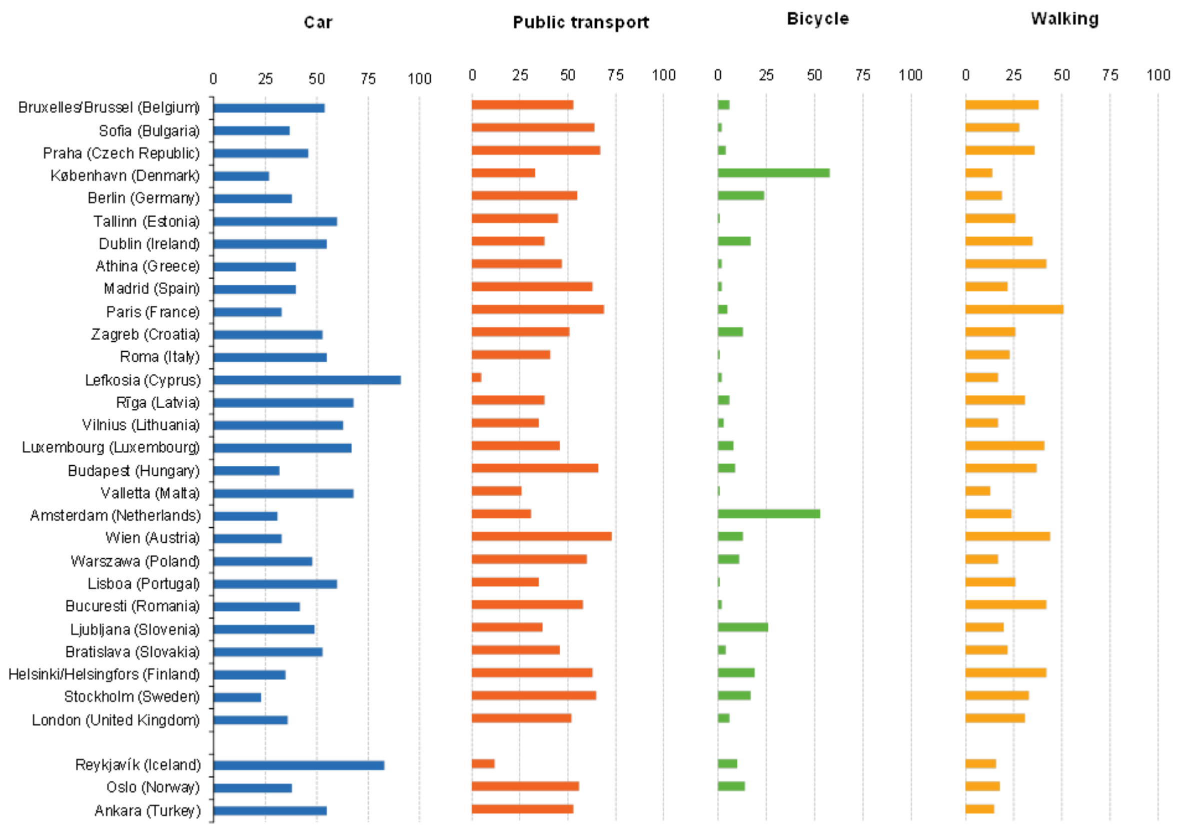


Figure 5.1: Average time between session of all EVs used for the model creation. Values were sorted from lowest to highest.

The other part of the dataset, the trip data, can also provide good insights into the charging behaviour of users. As explained earlier, this part of the dataset was collected when EV users drove their cars. When it comes to driving and especially commuting in Iceland's capital region, the behaviour is drastically different to other European cities. Partly explained by the harsh climate; long winters with sub-zero or near-to-zero temperature, the majority of the population in Reykjavik, Iceland's capital, commute by private car. This is also explained by the high car ownership in Iceland, which is around 0.75 passenger vehicles per inhabitant (Statistics Iceland, n.d.). The lack of trains and substantial public transportation is also a big explanation factor. Figure 5.2 taken from Eurostat (Eurostats, 2017), shows the breakdown of commute by type of transportation in EU countries in 2015. Iceland is remarkably different than most countries, with the second-highest share of commute by car. It can also be seen that public transport use for commuting is extremely low in Iceland compared to the other EU countries.



Note: respondents were given the option to mention more than one means of transport for going to work (as such, the shares may rise to over 100 %). Athina (EL), Paris (FR), Lisboa (PT) and London (UK): greater city.
Source: Eurostat (online data code: urb_percep)

Figure 5.2: Breakdown of commuting types of transportation. Image from (Eurostats, 2017)

What is also very different in Reykjavik is travelling time. In major European cities many commuters drive dozens of kilometers and up to an hour each way to work. However in Reykjavik, which is fairly small, travel times are much shorter and distances likewise. From the trip data from the EV study, for the selected subgroups in the capital region as described earlier, the average travelling time of all the trips are roughly 12 minutes and the average driving distance is 6.9 km.

What is also interesting to see - and indeed affects charging load - is when people leave for work in the morning and when they arrive again home. In figure 5.3 a histogram of the leaving time of trips can be seen. The two rush hours of the day can be seen, 7:30 until 9:00 in the morning and 16:00-18:00 in the evening. In this graph there is also an overlaid line, which is the mean charging profile of all the selected cars from the study. This means that for every 15 minute period over the year, the mean charging load of that period is calculated. These two datasets together show how the trip leaving time affects the charging. If the graph is examined left to right, it can be seen that in the morning when people leave for work, they turn on their cars and might even charge a little in the morning.

This takes the charging power up from the charging sessions that were gradually finishing over the night. After most people have left their house, the charging power stays relatively the same over the day, from around 8:00 to 14:00. This constant charging power is most likely due to some people still being at home and charging or others charging at work or other places during the day. This load is still much lower than the peak charging later in the day. Nearing the second rush hour - when people leave work or school at the end of the business day and arrive back home - the load starts to ramp up and peaks when the load accumulates when people arrive after this rush hour.

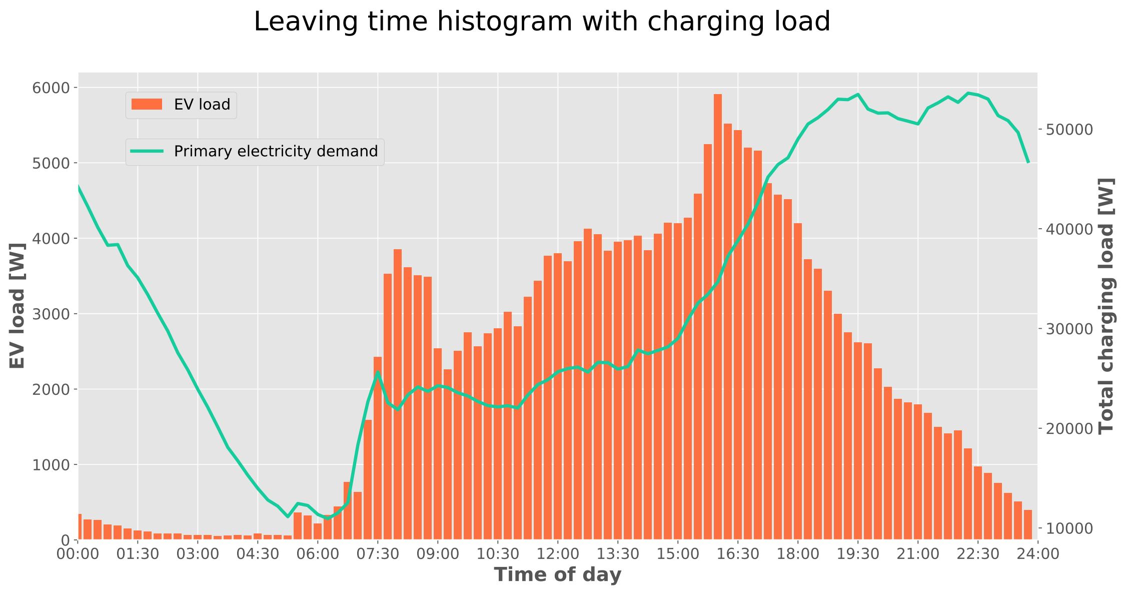


Figure 5.3: Histogram of the leaving times of EVs according to the EV study data. Overlaid is the mean charging load profile.

5.2. Primary load data

Together with the charging data it was desired to acquire data on the primary load for the whole of the capital region in order to model separately the primary load and the charging load. The capital region's electrical distribution grid consists of a few voltage levels as explained before in section 4.2 and visualised in figure 4.1. In the figure, the three major levels can be seen. The high voltage substations, which are either connections from the TSO or connected internally, have varying size of transformers but as a rule transform the voltage down to 11 kV. The voltage level below that are the distribution substations, which count roughly 900 for the DSO Veitur. These substations are connected to the high voltage substations and transform the voltage from 11kV to 400V. Lastly, there are street boxes which are either 400V or 230V and are connected in series to the distribution substations. From each street box, several houses are connected by separate cables.

For the main primary load dataset, only the data from the highest level of the distribution grid was available fully. This data, provided by Veitur, is time-series data from all of high voltage substations in the capital region and combined represents the entire load on the area. The dataset spans a few years back in time and is in 5 minute time intervals. It is thus possible to find the primary load in the same period as the EV study dataset, December 1st 2018 to November 30th 2019. In figure 5.4 the load-duration curve of the primary load over this period can be seen. The peak is approximately 222 MW and the curve seems to follow a regular pattern, where it falls with frequency of load values. The mean load over this period is 141.3 MW which is exactly in the middle of the load-duration curve. The different substations also exhibit different energy flows. As explained before, these high voltage substations are either connected to the TSO and thus the high voltage transmission system, or connected internally. Additionally, some stations are bigger than other in terms of capacity. This will be explained in more detail in the next subsection on the grid capacity data. For the load characteristics of each station, the mean, maximum and minimum values can be seen in figure 5.5.

Additional to this primary load data from the high voltage substations, load data from one distribution substations was acquired. That data will be used together with the capacity data on the lower levels to create a snapshot of these lower levels of the distribution grid. However, as it is only available from one station, this

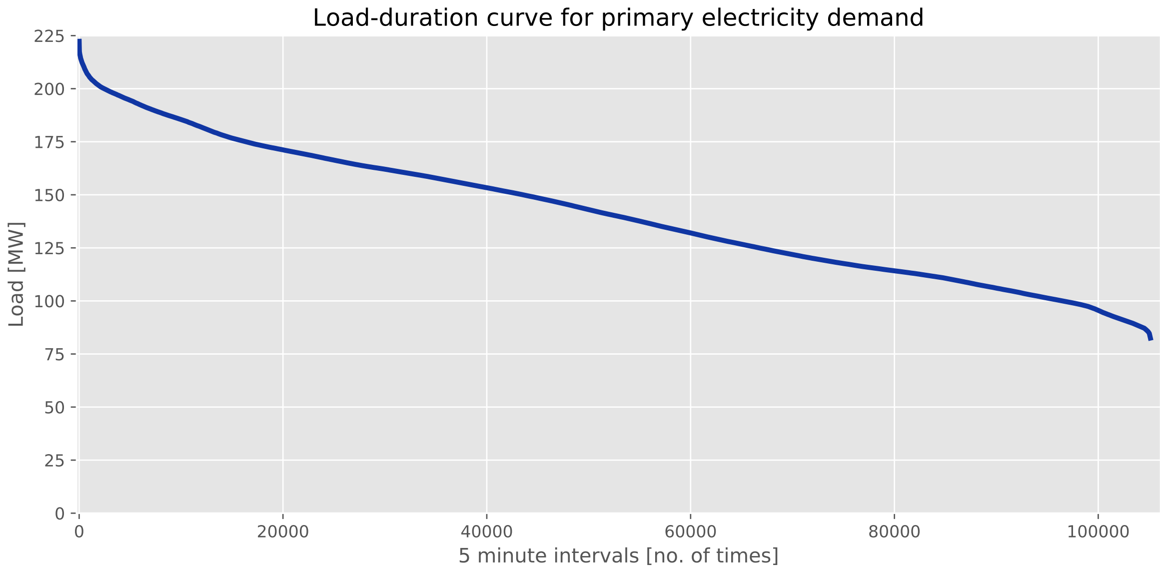


Figure 5.4: The load-duration curve of the primary load over the modelling period. Based on the primary load dataset.

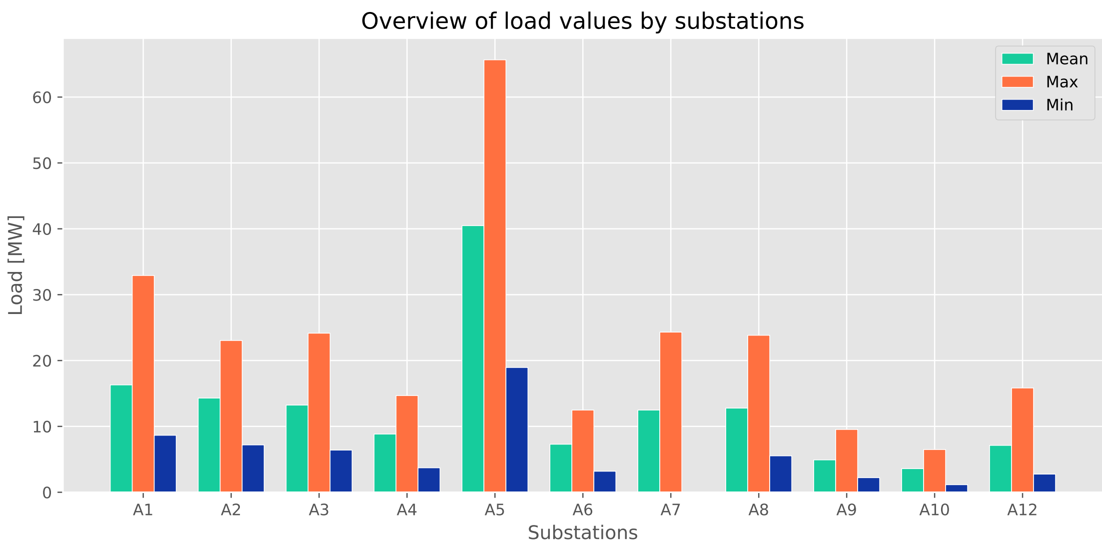


Figure 5.5: Load values from the different high voltage substations over the modelling period. Based on the primary load dataset.

data cannot serve as the primary load data for the whole capital region. These two load datasets, i.e. the top level and the subgrid level, are on different voltage levels and serve different purposes. This lower-level, more detailed data will act as an exploration tool for the local parts of the grid, and will be explained in more detail in the next subsection.

5.3. Grid capacity data

To be able to synthesise the results of the charging and primary load data when put into a model, data on the capacity of the distribution grid must also be acquired. This is necessary to quantify the load effects on the distribution grid. This grid capacity data serves as a load limit on the distribution grid on its different levels as visualised in figure 4.1. This capacity data supplements the load modelling based on the primary load data and the charging data and serves as a metric to quantify the modelled load values. The approach towards the grid capacity is essentially two-fold, a global overview approach and a local sample approach. This way, both large-scale distribution grid problems can be identified and measured as well as local grid effects from the EV charging load.

First, the global overview approach determines the system capacity based on the high voltage substations and thus is the overall system capacity limit. There are many ways to exactly calculate the maximum load that can be sustained by these stations, but it revolves around defining in what state the system should be able to run. The most common rule according to the DSO Veitur and the one that they use, is the N-1 rule. This means that for every station, each station has to be able to run on N-1 one of its transformers. So for a station with two 25 MVA transformers, the N-1 determined capacity is $(2-1)*25 = 25$ MVA. The capacity unit that is most commonly used is MVA or megavolt-ampere. This is the unit for apparent power in an electrical circuit. This value can be converted to watts to get the power capacity. To do that the power factor, which is the ratio between the real power and the apparent power must be estimated. Based on a recommendation from the DSO, this factor is 0.95. This means that the MVA values can be multiplied by 0.95 to get capacity limit in MW.

In figure 5.6, the connections between the different high voltage substations can be seen. In this schematic the connections between those stations can also be seen, but they are connected in a loop. Out of the twelve stations, two of which are purely switches, seven form the capacity limit which are indicated in the figure. One of the stations, station A11 as seen in the figure, has no transformer and thus more acts as a connector rather than a station. Therefore it does not contribute to the system capacity and is also not included in the primary data as it does not represent that. Using the N-1 rule as explained before, their combined capacity of those stations is thus 275 MVA $= 0.95 * 275 = 261.3$ MW.

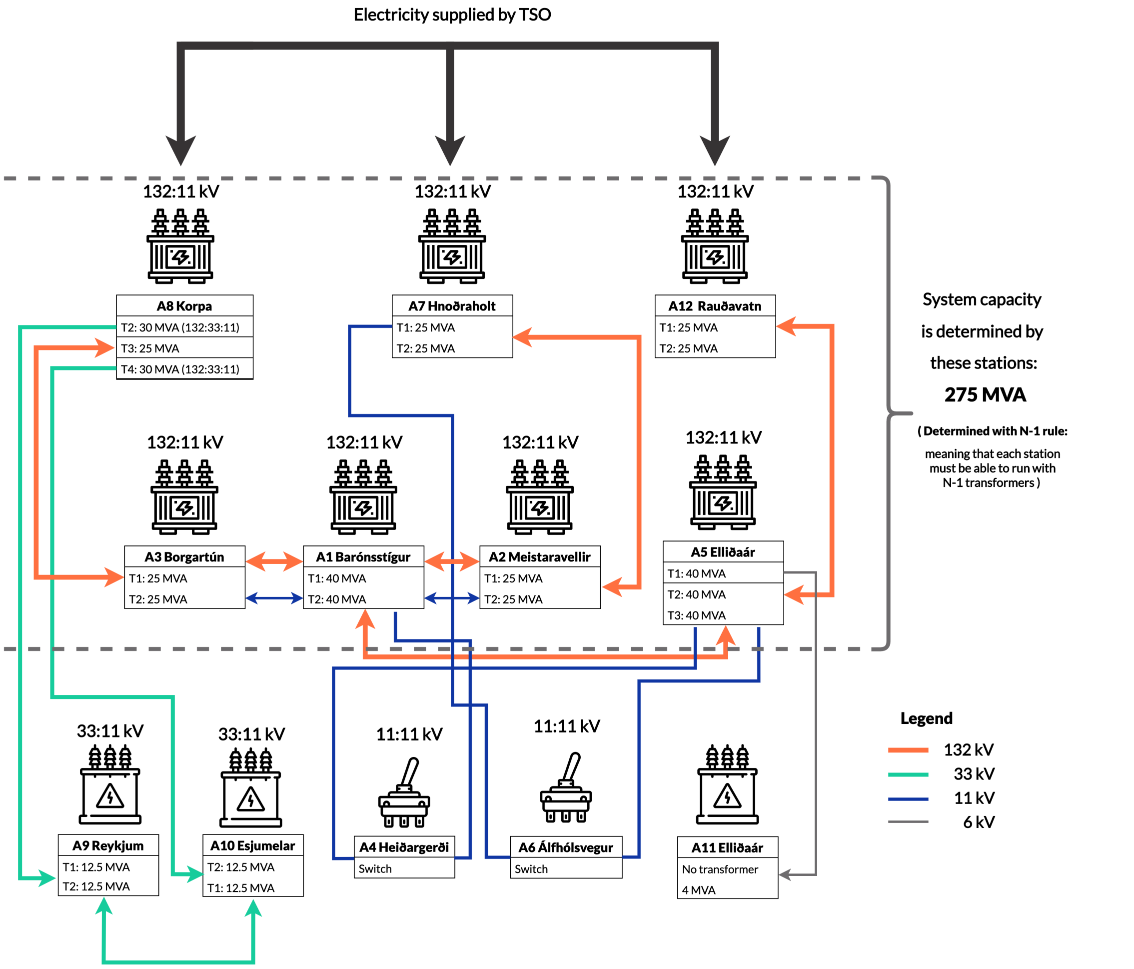


Figure 5.6: Overview of the connections between the high voltage substations and how the global distribution grid capacity limit is determined. Based on a system schematic provided by the DSO. Icons from www.flaticon.com

However, there are also other ways to determine this system capacity. Another, more aggressive approach, would be to allow only two of the biggest stations to exercise the N-1 rule, i.e. station A8 and station A5. This would result in a higher system capacity of 415 MVA or 395 MW. For the purpose of determining the capacity for the load simulations, the first method will be used as that is the preferred method of the DSO.

For the second part of the approach, the local grid sample, the load data discussed in the previous subsection is used as a guide towards measuring the effects on that part of the grid. This available data is actual consumption data from a distribution substation. This data makes it possible to accurately model load behaviour of individual households and therefore see where the load effects happen in these local grids. But to do this additional data is needed. Available online is a geographic information system (GIS) of the capital region area from the city's online data portal. In this system (Reykjavik City, n.d.), there are drawings of the electrical grid and cables for every building in the capital region. With this data, the connections of the distribution station could be mapped out and a local grid can be visualised and formulated into a model. In figure 5.7 the buildings that belong to distribution substation no. 670, the distribution substation which is used, can be seen. The location of the station itself can be seen as well. With the drawings of the electrical grid, the connections can be formulated as an electrical circuit and the load effects calculated. This can be seen in figure 5.8.

Figure 5.7: Distribution substation no. 670's area. In the right upper side the location of the substation can be seen. Original picture from Google Earth.

Along with the information on the electrical connections in the online data portal, additional information is available that facilitates determination of load effects in these local grids. The number of inhabitants in every house can be found and based on that the load behaviour of each building can be approximated. From the load consumption data of the distribution substation, the proportional load of each house can be found with the share of inhabitants of each house compared to all houses connected to the station. Additional to this, the number of vehicles per house can also be approximated based on average car ownership, which is 0.75 passenger vehicles per inhabitant (Statistics Iceland, n.d.) as stated earlier. With the primary load approximated for each house and the number of vehicles at each house, the charging load can also be approximated based on the EV penetration, i.e. how much of the car population is electric. With this data and the subgrid - based on the consumption data for the distribution substation - simulations can be run and load effects measured at a more detailed level. Together these two distribution capacity datasets, the global effects as well as the local effects, will give insights into how the added load of EV charging affects the distribution grid. How this is implemented in the technical model is explained in more detail in section 6.3.2.

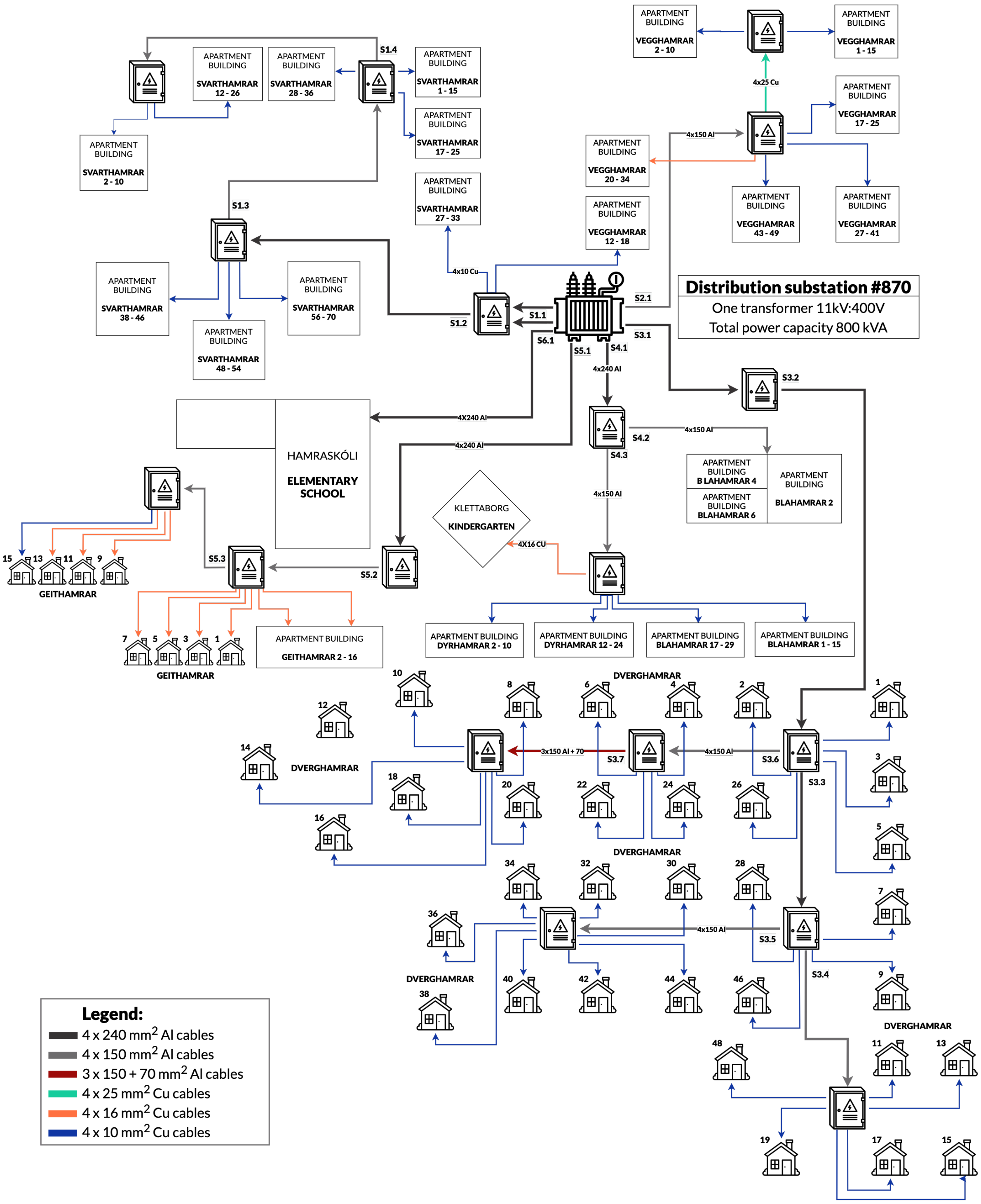


Figure 5.8: Visualised schematic of the local grid behind distribution substation 670. Different colors of cables mean different materials and thus capacity. These cable materials are explained in the legend in the figure. Icons from www.flaticon.com

5.4. Simulation input parameter data

Besides the three types of datasets already explained, which are the last three inputs in the conceptual model, the simulation input parameters still have to be explored. Those parameters are the EV fleet size, based on EV penetration, and the consumer participation in the DR strategies. As explained in the conceptualisation, the different values of these parameters, as well as the DR strategy specific settings, make up the different charging scenarios. The technical model implementation, based on the conceptual model, thus uses different values of these parameters to perform the simulations. The setup of these simulations will be discussed in detail in section 7.1. However, in this section the available data for these two parameters will be described, as the values for the simulations will be based on that data.

To define the EV penetration input it is required to know the population of passenger vehicles in the capital region area. That data was acquired from the Icelandic Transport Authority and includes statistics on the numbers of vehicles by type and municipalities. As was explained earlier, the system of interest is the distribution grid in the capital region where the DSO Veitur is active, which is in five municipalities as seen in figure 1.4. The number of passenger cars in these municipalities on December 31st in 2019 can be seen in the table below (Icelandic Transport Authority, 2020b). It should be noted that for the municipality of Garðabær, only half of the total passenger cars were used, as Veitur is only party operating in that municipality, along with the other DSO in the capital region.

Municipality	**Passenger cars**
Reykjavík	90,796
Kópavogur	24,419
Seltjarnarnes	2,698
Garðabær	4,922
Mosfellsbær	8,125
Total	**130,960**

Table 5.4: Overview of the number of passenger cars in the system of interest (Icelandic Transport Authority, 2020b)

In the system of interest there are thus roughly 131 thousand passenger cars. Based on this number, EV penetration levels can be calculated. Furthermore, the composition between BEV and PHEV are assumed to be equal, as already explained.

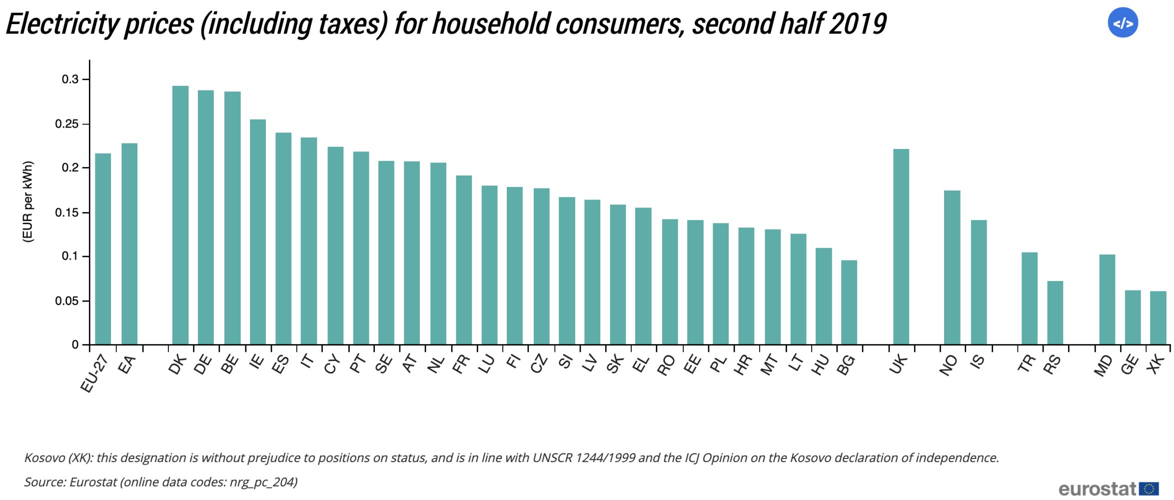


Figure 5.9: Overview of electricity prices in the EU and a few other European countries. Image from (Electricity price statistics, 2020)

The other simulation input parameter, demand response participation, is more challenging to gather data for. The willingness of consumers to participate and with that, change their behaviour is relatively unknown. It is well known that demand elasticity of electricity is very low, in that it is very inelastic. That essentially means that a big change in the electricity price will not alter the demand for electricity in a big way. Electricity is a necessity product that people have to use and do not change their consumption of as much as other products. The consumer electricity price is very cheap in Iceland compared to other countries in Europe, as can be seen in figure 5.9.

This property of electricity consumption makes it more likely that people stick to their behaviour as opposed to altering it. The price responsiveness of Icelandic electricity consumers is unknown, i.e. how they will respond to demand response strategies that depend on pricing changes or changing charging behaviour. In the same way as the EV penetration parameter will be used, different values for this parameter will be explored in the different charging scenarios. However, it is desired to find the most likely DR participation in both of the DR strategies that are to be modelled. To approach this, the average electricity cost savings of a participating consumer, based on the EV study dataset, will be calculated. Based on that saving, an estimation on the most likely participation level will be made. As well as using this value as an input parameter for simulations, incremental participation values will also be explored to see the effects. This calculation process and participation determination is carried out in section 7.1, where the details of this parameter for the simulations is also explained.

6

Technical model implementation

This chapter is dedicated to the methodology of the technical model implementation. In chapter 4, the conceptual model was formulated and explained. As explained in that chapter, to be able to use the conceptual model for problem-solving and answering of its correlating research questions, it has to be implemented in a technical manner. In the last chapter, *Data*, the conceptual model inputs and datasets that are needed for the technical implementation were explained.

The conceptual model was implemented in the programming language Python. As was explained in the conceptualisation process, the modelling process has three main parts. First, it is the base modelling, then the implementation of the DR strategies to be simulated and lastly the grid impact determination. These parts can then be used together to simulate various charging scenarios based on the different DR strategies and their specific settings. The model results are thus derived from those simulation runs, which are explained and listed in the next chapter; *Results*. In the following subsections, the methodology behind the formulation of the three technical modelling parts will be explained.

6.1. Base modelling

The first step of the technical modelling process is the base modelling. This process essentially takes the inputs and datasets, formulates and handles them so they can be used for modelling. This is called the base modelling as it is the technical foundation for all of the subsequent modelling steps. The two main input datasets - as described in the conceptual model - the primary load and the charging load are put together in a time-series load model. Based on that model, different charging scenarios can be used to shift the time-dependant load values. For the first main load scenario - the uncoordinated charging - this base modelling process is used.

This part of the modelling process is the only one that can be properly validated. The two other modelling parts are based on assumptions and state-of-the art knowledge from literature or expert inputs. However, the base modelling, where the EV study dataset is used to represent a large EV-fleet, can be measured and quantified and thus validated to a certain extent. Additionally, the modelling KPIs as mentioned before in the conceptual model chapter are defined in this part of the modelling process, as in this step the technical capability of the model is determined. In this section, the methodology of this base modelling process is explained. After that, the validation steps and results are shown and lastly the modelling KPIs are defined and explained.

This first part of this base modelling process is the handling of the input datasets. As explained in the previous chapter on the data, the EV study period was between December 1st 2018 and November 30th 2019. For that reason, the modelling period is set as the same period. Therefore, the primary load data used was also from the same period. However, the charging data has intervals of 15 minutes, whereas the primary load data has 5 minute intervals. To cope with this, the primary load was aggregated into 15 minutes intervals by finding the average of three 5 minute intervals. The next step was to select and include the relevant EVs to create the charging profile. As explained in the data chapter, namely table 5.1, the EVs in the study were divided into 13 different subgroups based on geographical area, EV type and residency type. As the system of interest is the capital region, only the EVs situated in that area were included. This means that subgroups 4 to 11 were included, with 76 BEVs and 45 PHEVs thus being used for the charging load profile creation. This is exactly the aim of the validation process, to see if this sample size of EVS displays enough heterogeneity and variability to be able to model an entire EV fleet based on it.

The next part of the base modelling process was to formulate the selected EVs into workable load profiles. As already explained in the data chapter, each EV was assigned a specific column in the time-series load model. This way, the overall charging profile can be determined by simply combining the charging load of all the included EVs for every interval, or using batches of specific EVs based on their EV type or residency type. However, as explained in the assumptions of the conceptual model, the representation of these different subgroups of EVs is assumed to be a good enough representation of the system of interest. Therefore, for all of the simulations, only BEVs and PHEVs were handled separately, and a ratio of 50% BEVs and 50% PHEVs were used.

In this time-series base load model, the EVs are thus aggregated into two load profiles, one for BEVs and one for PHEVs. As it is known how many EVs of each type are in the dataset, an average charging profile for EVs and BEVs can be determined by simply dividing the combined charging value by the quantity. A visualisation of this model can be seen in table 6.1 below, where the first 25 lines of the actual model values are shown. All of the values are in kW. It can be seen that at many times, only a few of the EVs are charging. By finding the combined charging power of all of the EVs for every single interval, the behaviour of the entire fleet in the study can be approached more accurately.

Timestamp	Primary load	#3	#4	#5	#6	#7	#8	#9	#11	#18	#19	...	#187	#188	#189	#191	#194	#196	#199	#201	#202	Aggregate BEV load	Aggregate PHEV load
12.1.2018 00:00	136,042	-	-	-	-	-	-	2.09	-	-	1.90	...	-	2.45	-	-	-	-	-	-	-	33.62	11.30
12.1.2018 00:15	133,250	-	-	-	-	-	-	2.03	-	-	1.90	...	-	2.42	-	-	-	-	-	-	-	32.57	5.75
12.1.2018 00:30	129,493	-	-	-	-	-	-	2.19	-	-	1.90	...	-	2.48	-	-	-	-	-	-	-	30.76	8.98
12.1.2018 00:45	127,363	-	-	-	-	-	-	1.93	-	-	1.90	...	-	2.48	-	-	-	-	-	-	-	33.41	3.93
12.1.2018 01:00	125,016	-	-	-	-	-	-	1.22	-	-	1.90	...	-	2.50	-	-	-	-	-	-	-	31.13	3.17
12.1.2018 01:15	123,537	-	-	-	-	-	-	0.68	-	-	1.90	...	-	2.50	-	-	-	-	-	-	-	30.11	0.84
12.1.2018 01:30	121,314	-	-	-	-	-	-	0.75	-	-	1.90	...	-	2.47	-	-	-	-	-	-	-	25.72	4.57
12.1.2018 01:45	119,272	-	-	-	-	-	-	0.30	-	-	1.90	...	-	2.52	-	-	-	-	-	-	1.88	27.65	4.89
12.1.2018 02:00	117,792	-	-	-	-	-	-	-	-	-	1.90	...	-	2.52	-	-	-	-	-	-	1.91	24.76	5.50
12.1.2018 02:15	117,313	-	-	-	-	-	-	-	-	-	1.90	...	-	2.52	-	-	-	-	-	-	1.90	25.73	4.24
12.1.2018 02:30	116,496	-	-	-	-	-	-	-	-	-	1.90	...	-	2.53	-	-	-	-	-	-	1.90	23.55	4.22
12.1.2018 02:45	115,217	-	-	-	-	-	-	-	-	-	1.90	...	-	2.53	-	-	-	-	-	-	1.90	23.20	4.09
12.1.2018 03:00	113,780	-	-	-	-	-	-	-	-	-	1.90	...	-	2.54	-	-	-	-	-	-	1.94	22.33	4.02
12.1.2018 03:15	113,132	-	-	-	-	-	-	-	-	-	1.90	...	-	2.55	-	-	-	-	-	-	1.94	20.16	4.17
12.1.2018 03:30	113,063	-	-	-	-	-	-	-	-	-	1.90	...	-	2.56	-	-	-	-	-	-	1.92	19.30	3.90
12.1.2018 03:45	112,293	-	-	-	-	-	-	-	-	-	1.90	...	-	2.04	-	-	-	-	-	-	1.91	18.26	4.45
12.1.2018 04:00	111,936	-	-	-	-	-	-	-	-	-	1.90	...	-	1.34	-	-	-	-	-	-	1.90	20.56	2.87
12.1.2018 04:15	111,299	-	-	-	-	-	-	-	-	-	1.90	...	-	0.98	-	-	-	-	-	-	1.90	17.08	3.87
12.1.2018 04:30	111,520	-	-	-	-	-	-	-	-	-	1.90	...	-	0.77	-	-	-	-	-	-	1.93	13.23	4.13
12.1.2018 04:45	111,890	-	-	1.94	-	-	-	-	-	-	1.90	...	-	0.59	-	-	-	-	-	-	1.97	13.48	1.96
12.1.2018 05:00	111,445	-	-	1.97	-	-	-	-	-	-	1.90	...	-	0.44	-	-	-	-	-	-	1.96	15.89	1.54
12.1.2018 05:15	112,204	-	-	1.97	-	-	-	-	-	-	1.90	...	-	0.36	-	-	-	-	-	-	1.95	15.92	0.86
12.1.2018 05:30	113,113	-	-	1.97	-	-	-	-	-	-	1.90	...	-	-	-	-	-	-	-	-	1.95	15.52	0.26
12.1.2018 05:45	113,652	-	-	1.98	-	-	-	-	-	-	1.90	...	-	-	-	-	-	-	-	-	1.94	12.41	0.92
12.1.2018 06:00	114,595	-	-	1.98	-	-	-	-	-	-	1.90	...	-	-	-	-	-	-	-	-	1.92	10.22	0.00

Table 6.1: An example of the first 25 rows of the time-series base model. All load values are in kW.

For the primary load, an adjustment was made as depicted in modelling assumption #2, as seen in 4.1. The primary load, aggregated into 15 minute intervals as described earlier, was lowered by taking the aggregate profiles of all of the BEVs and the PHEVs from the charging study and multiplying them with the number of EVs active over the model period. The data on the EV numbers by municipalities was acquired from the Icelandic Transport authority. These statistics can be seen in table 6.2. The average number of EVs from year end of 2018 and 2019 was used as the model period is over that period. For the municipality of Garðabær, only half of the EVs were used, as the other DSO in the capital region is also active there. It was thus assumed that half of the EVs would be charging on the distribution grid operated by Veitur. These statistics result in an average of 2087 BEVs and 4218 PHEVs over the modelling period. This means that the primary load profile is thus lowered by taking these numbers and multiplying them by the BEV and PHEV aggregate profiles. The comparison between the adjusted and the non-adjusted primary load profile can be seen in figure 6.1. In the graph, the mean primary load profile - i.e. the mean value of every interval of the modelling period - before and after the EV load profile adjusted can be seen.

Based on this adjusted primary load, which is then independent of EV charging, the combined load of the primary load and the uncoordinated charging load can be determined. This uncoordinated charging is calculated by simply scaling up values from the EV study in the way it was implemented in the base time-series

	BEV		PHEV	
	31/12/18	31/12/19	31/12/18	31/12/19
Reykjavík	1109	1512	2213	2759
Kópavogsbær	348	502	753	1020
Seltjarnarnesbær	56	77	144	182
Garðabær	95	126	279	351
Mosfellsbær	145	203	198	267
Total	1753	2420	3587	4579

Table 6.2: The historical number of EVs in the five municipalities in which Veitur is active. Statistics acquired from (Icelandic Transport Authority, 2020b).

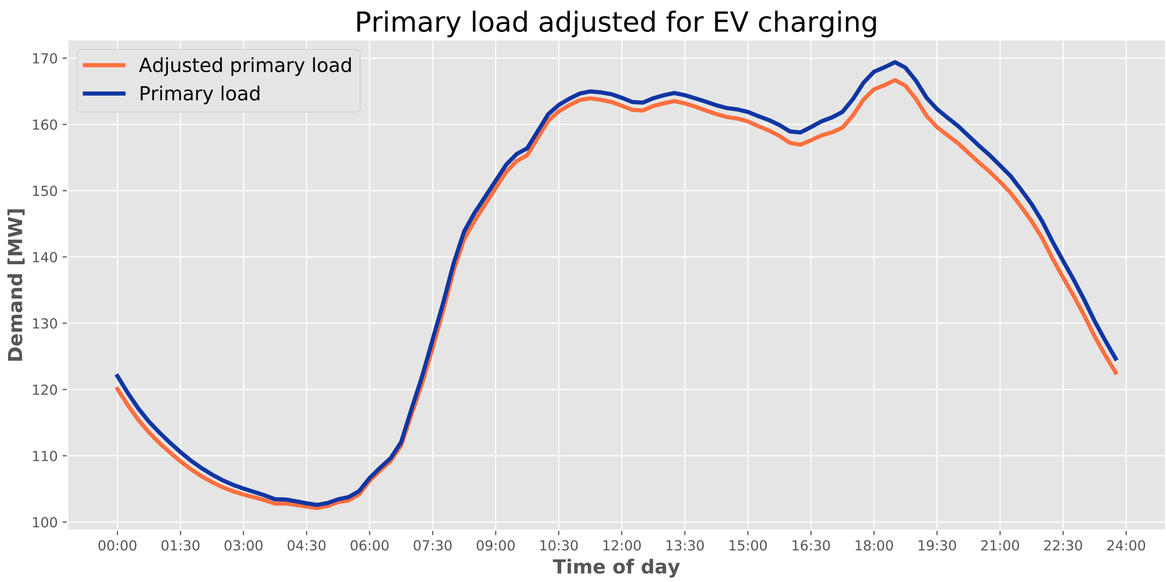


Figure 6.1: Comparison between the adjusted primary load and the original primary load data

load model. The aggregate charging profiles of BEVs and PHEVs, as seen in table 6.1, can be scaled up to represent a fleet of any size. In section *Scenario 1 - Uncoordinated charging*, the results and simulations of the uncoordinated charging are listed and explained.

6.1.1. Validation

For the validation of the technical implementation of the model, only the base modelling steps can really be validated. This is mainly due to the nature of the other modelling steps. As has been discussed before - and is in fact a large part of the knowledge gap - that is the missing knowledge on the nature of DR strategies for EVs in Iceland. As such, it is very challenging to validate the conceptualisation and technical implementation of those strategies. Likewise for the grid impact modelling, there is no previous solution or benchmark that the modelling implementation can be compared to in order to validate. For the base modelling, the charging load representation can indeed be validated, which is also the most important modelling step, as the two other steps; DR strategies implementation and grid impact determination are based on that.

This validation process aims to measure how well the EV study dataset captures the behaviour of a large EV fleet. If the dataset does not generate diverse enough charging behaviour, this modelling step and thus the resulting charging load profile will not be able to sufficiently represent a large EV fleet. There are undoubtedly many ways of validating this charging profile formulation, but the one that was chosen is based on the *coincidence factor* of the fleet. This factor is often used to measure the validity of load or charging profiles in load modelling. This validation method is based on input from an industry expert from the rural DSO in Iceland and is further supported by literature, as it is widespread both in regular load modelling and forecasting and more recently in EV specific applications. The aim is to quantify the behaviour of the EVs from the study and to determine if their combined charging characteristics can be scaled up for a larger EV fleet, based on the 121 observed cars.

This coincidence factor explores the ratio between diversified and non-coincidental demand (Richardson, Flynn, & Keane, 2010). In other words, it explores the ratio between individual EVs' peaks and the combined charging peak. For almost any size EV fleet, it is highly unlikely that all of the EVs will be charging at the same time, at the highest available charging power. Most of the time, roughly 90% according to the EV study data, the EVs stand idle. The coincidence factor can be used to track the development of the behaviour of the fleet with an increasing sample size, thus validating the sample size of the EV study data. For this approach, the formula that is used for calculating the factor is:

$$\text{Coincidence Factor} = \frac{\text{Total charging load}_{peak}}{EV(1)_{peak} + EV(2)_{peak} + ... + EV(N)_{peak}} \tag{6.1}$$

, where N is the total amount of EVs included. This method works for any size of EV fleet. First the highest combined charging load is found, i.e. Total charging load$_{peak}$, which is the combined load profile based on the individual charging values of the EVs. This is for example the BEV and PHEV aggregate profiles as seen in table 6.1. For the denominator of the equation, the peaks of each individual EV are found and added together. This value thus becomes much larger, as it takes the peak of each car independent of the time at which that peak occurs. What can be observed by using this formula is how the factor develops with an increasing fleet size, i.e. the value of N. In theory, it should decrease with an increasing value of N (Quiros-Tortos, Ochoa, & Lees, 2015). When N=1, i.e. a fleet with only one EV, the coincidence factor is 1. For two EVs, the factor might come close to 1 but never reaches as high as with only one EV. This keeps on developing, and the factor keeps lowering, until there is almost a stagnation in its development.

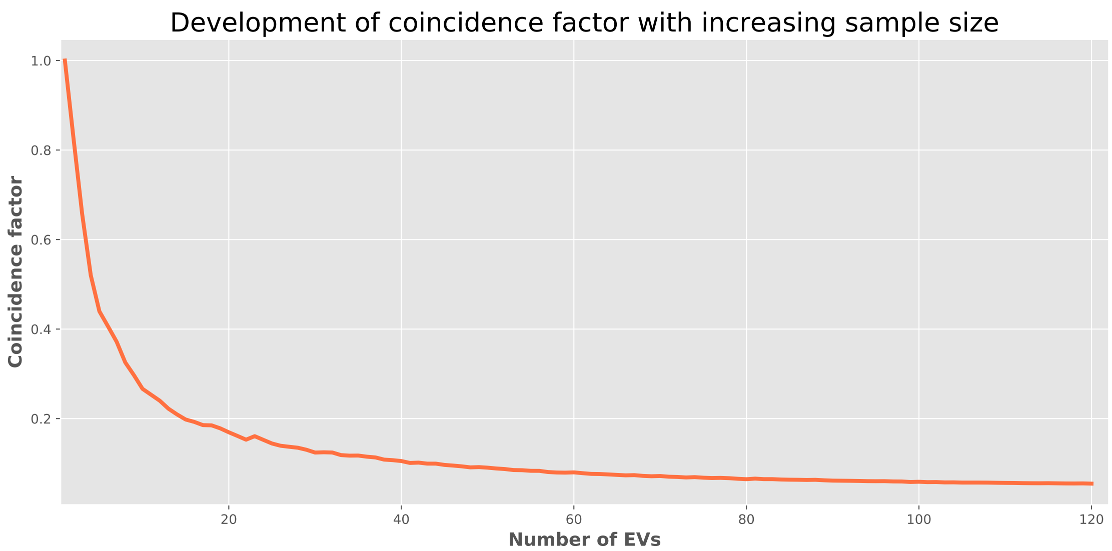


Figure 6.2: The development of the coincidence factor with increasing sample size.

That is essentially what is desired in this validation process, to see if the stagnation of the curve happens before the number of EVs used for the charging profile creation run out. For this process, the methodology was thus to go over the entire EV study dataset, with an increasing sample size. Equation 6.1 was used to calculate the coincidence factor for a sample size from 0 to 121, with 100 iterations for every sample size value. The mean factor was calculated over the 100 iterations and plotted. In figure 6.2 this can be seen. For every sample size N, a random N-EVs were selected and their coincidence factor calculated. This was then carried out a 100 times for each sample size, N, so all of the behaviour could be explored for every sample size.

As expected, for only one EV, the coincidence factor is 1.0. Increasing the sample size however, it quickly decreases, and is roughly 18% at 20 EVs. What can also be seen is that the change is quite drastical in the beginning and then becomes much more gradual. For the last 20-30 EVs, there is almost no change. The coincidence factor for the 121st car is also fairly low, so the changes to the factor for more EVs is expected to be very minimal. From this it can be concluded that the dataset from the EV study, which is used to model a large EV fleet, captures enough diversity to be able to represent this large fleet. However, as this is only one validation technique and deemed acceptable by the researcher, this method will be reflected upon in the discussion part of this thesis, namely section 8.2.2.

6.1.2. KPIs

In this subsection, the key performance indicators (KPIs) will be explained. They were briefly touched upon in the conceptualisation of the model, as they are an output of the conceptual model. However, they are perhaps different than regular outputs, as they are not necessarily something that comes out of the central modelling process, but rather metrics that are used to quantify and measure those outputs. They are however built on and are often themselves outputs of the model. The modelling KPIs were determined throughout the implementation of the all the three main modelling steps; base modelling, DR strategies' implementation and the grid impact modelling. Still, they are introduced here in the base modelling section, as their determination also shapes the technical implementation of the subsequent modelling parts. The KPIs are also the elements that guide the storyline of the *Results* chapter, as they are used to display most of the results of the modelling part of this research project.

In the determination of these modelling KPIs, the main motivation was to translate the outputs of the model - which are simulations of different charging scenarios over an entire year - into usable results. These KPIs can be classified into two main categories. First, it is graphical and visual indicators and then numerical indicators. The latter type is also in some cases used as a guide towards what specifically should be visualised and graphed. For the three main load scenarios; uncoordinated, TOU DR and DLC DR, there exist many scenarios based on the two input parameters; EV penetration and DR participation as well as the specific settings of the two DR strategies. To combat this, a heat map can be used as an indicator into which specific regions of parameters should be looked at closer. This will be explained better in the actual results chapter; *Results* where these heat maps will be used for some of the numerical KPIs.

Visual KPIs

For the first type of the KPIs, the graphical results, there are four main indicators:

1. 24 hour load graph of the primary load as well as the charging load **for an average day** with the system limit capacity
2. 24 hour load graph of the primary load as well as the charging load **for the worst day of the year (highest peak)** with the system limit capacity
3. Bar graph of the peak loads for every building as well as the capacity limits for each building
4. Map illustration of the cable load

All of these KPIs essentially combine the three main modelling parts; uncoordinated load, strategy DR implementation and the grid impact modelling. They take the simulation outputs and put them together with the grid capacity, both on the overall system level as well as the lower level grid snapshots. For the first two KPIs, the outputs of the simulations on the overall system level are used. The first one finds the mean charging profile over a 24 hour period, by finding the average charging value of every interval at a certain time over the entire model period, a full year of data. The primary load and the charging load are plotted separately and stacked on top of each other, so the combined effects of the two can be seen. Additional to this, the capacity limit of the system is plotted on this graph. For the second KPI, the same graph is used, but with the "worst" day of the year, i.e. the day in which the highest peak occurs. This is the primary method of the DSO to determine the performance of the system and thus an important measurement of the performance of the different scenarios.

For the latter two, the focus is on the lower levels of the distribution grid. As was explained in the data chapter, in the section on the *Grid capacity data*, a subgrid on this level will be modelled. These KPIs focus on that grid. The third KPI plots the peak load of every building in this subgrid, as well as the individual power capacity of each building. This can be done for any charging scenario. The fourth and last visual KPI is simply the visualisation as seen in figure 5.8, but with a display of the loading of each cable in the subgrid. This is done with using three colours, green, yellow and red, representing the load of each cable. Green means that the load on the cable is less than half of its capacity, yellow more than half and red means that the load has exceeded the cable capacity.

This makes it easy to see where in these subgrids the load has the most impact. For the loading of the electricity streetboxes, the cumulative load is determined. As can be seen in figure 5.8, where this subgrid is visualised, the boxes are connected in series based on an outgoing connection from the distribution substation. Going from the outermost box in each of these series and inward, the load of each building adds up. The representation of the cables between the streetboxes is thus based on the cumulative loading of each of the boxes in such a series. This way, it can be seen when there will be an overloading in any of the boxes.

Numerical KPIs

The latter type of the KPIs are based on numerical values. Some of those KPIs are based on the outputs of the central modelling process as described in the conceptual model chapter and illustrated in figure 4.2. These numerical results are also used to find out which scenarios should be used for the visual KPIs as described before. For the TOU DR strategy for example, there are the two input parameters; EV penetration and DR participation, and additionally the settings of the strategy itself; the price changing time. There are therefore almost endless combinations of these parameters, i.e. different charging scenarios. To figure out which parameter values should be used for the visual KPIs, the numerical KPIs can be used. As opposed to the visual KPIs, the numerical ones mainly apply to the overall system level. In the list below, the KPIs can be seen.

5. Peak load of combined primary and charging load
6. Most peak reduction compared to uncoordinated charging
7. Size of EV fleet at which capacity of the overall system capacity is exceeded
8. Size of EV fleet at which capacity of the distribution substation is exceeded

The first two numerical KPIs, number five and six, apply to the overall system level, i.e. the high voltage substations. The first one determines the maximum load, the peak, of the combined primary and charging load. This can also be done with all of the scenarios. For the second one, KPI six, the overall system level is again used, but this determines how much the peak is reduced compared to the uncoordinated charging. This is based on the combined load of the primary and charging load for a given EV fleet size and the corresponding charging scenarios based on that size can then be compared to the peak of the uncoordinated charging. This again is another indicator that translates the outputs of the simulation runs into usable results. This KPI will also sometimes be displayed in a heatmap, which is a graph, but is essentially a number matrix. Therefore, it is not classified as a visual KPI, but numerical.

The last two KPIs derive from the objectives of the conceptual model, namely modelling objective four as seen in section 4.2.1. That objective aims to calculate at what size of EV-fleet the capacity limit would be exceeded. Compared to the other numerical values, which can be viewed as more exploratory values, these two values are more detailed than the others. These two KPIs essentially do the same, but they work on different levels of the grid. One at the overall system level, and the other one at the lower level subgrid. The number of EVs, based on a specific charging scenario, that can be "allowed" onto the grid, i.e. without breaking the capacity limits is determined. This indicator is good for a quick and effective comparison of the performance of each scenario.

As has been explained before, these modelling KPIs which are described in this section also guide the results chapter; *Results* and how the different simulations are presented and compared. These eight different KPIs can thus be seen as a sequence in the storytelling of the results. First, KPIs five and six are used to see which parameter regions and thus scenarios are interesting to look into and where the best results for the DR strategies might be. Based on that, the visual KPIs, 1-5, can be used to offer a more detailed look into the possible scenarios. However, from these visual results it might be difficult to accurately determine the performance between multiple scenarios. For this step, the last two KPIs come into play as they can numerically compare the performance. This setup of the KPIs is good to have in mind when navigating the *Results* chapter and the results from the simulation runs.

6.2. DR modelling

The demand response modelling process is essentially a two-step process, as there are two distinct DR strategies that are implemented. Each one called for a separate implementation, and at the center of both of the strategies is a Python function which takes the base modelling output - the time-series load model - and affects the charging sessions. As was visualised earlier in the *Base modelling* section, the first step of the technical modelling process was to formulate and handle the two inputs and create the base model, which is visualised in table 6.1. This time-series load model is the representation of all of the charging sessions from the EV study dataset. This can thus be viewed as a dataset of 121 charging profiles over an entire year.

The main methodology for both of the DR strategies is to select X-many cars, based on the EV penetration parameter, and shift their charging sessions based on different rules and settings of the strategies. These rules, i.e. how the two different strategies are interpreted and implemented in the model are explained in the conceptual model chapter; specifically sections *DR charging scenarios* and *Simplifications*. Those modelling steps were conceptualised there and in this section the technical implementation of these steps are explained. Both of these methodologies use more data from the charging study dataset than the base modelling and are more detailed and complex in implementation.

6.2.1. Time of use

The first DR strategy that was modelled is time of use (TOU). The specific implementation of this strategy was conceptualised in the conceptual model chapter, where the assumptions behind it were also explained. Those assumptions are largely what dictates how the specific settings of the strategy were determined. They guide the programming steps of this strategy. As explained earlier, the starting point for both of the DR strategies is the base time-series model. In this section, the modelling steps of the TOU DR strategy are explained.

To explain the modelling approach and methodology, it is first good to explain the overall modelling steps. The application of the strategy itself is centered around a Python function, that actually shifts the charging session of the EVs. This function has two inputs that are the specific settings of the strategy. Those are the start of the shifting range and the end of the shifting range; i.e. the shifting range parameters. This shifting range was explained in the conceptual model chapter, but that is the time period between when EVs are thought to be arriving home and the price change hour. In this function, there are two loops, an outer one that runs over each of the EVs in the time-series model, and then an inner one that iterates over the charging sessions of each EV and shifts them based on a set of rules. This function can thus be run with different values of these input parameters. The output of the function is a another time-series model, similar to the base model, but with the shifted values.

Additional to these shifting range parameters, the function has an input on the consumer participation, i.e. what share of consumers actually respond to these price changes and change their behaviour. This is called DR participation. For a 10% participation level, 10% of the 121 cars will be selected and their sessions shifted, while the other 90% will remain uncoordinated. However, there can be large differences in the behaviour between individual consumers and which consumers are participating can generate different results. Some cars always charge at low charging power, while others may charge more frequently and on higher power.

Therefore, an iterative approach must be taken in the modelling process to combat this. In figure 6.3 below, the inputs, main modelling steps and the output of the TOU DR modelling can be seen. In the figure, this iterative process is illustrated. For a given value of the DR participation, EVs are selected randomly and their sessions shifted as explained earlier. The charging load of all of the cars, both shifted and unshifted are then aggregated into BEV and PHEV load for every interval, exactly the same way as in the base modelling.

Based on the known numbers of BEVs and PHEVs in the study dataset, the charging load can then be scaled up to represent the charging load of a given EV fleet size, based on the EV penetration input. This process; selecting EVs, shifting their sessions and aggregating and scaling up the charging profile is done 10 times, each time randomly selecting the participating EVs. An average charging load profile can be determined by finding the average charging profile over the 10 iterations, for BEV and PHEV separately. Then this profile can be combined with the primary load to calculate the different modelling KPIs as explained earlier. These iterations make it possible to determine the performance of this DR strategy, based on the different parameters and settings. This number of iterations was deemed sufficient to capture the variability of charging behaviour between the different EVs in the study dataset. However, this will be reflected on and analysed in section 8.2.3. The main Python function that applies the strategy's rules is represented by the first two gray boxes inside the modelling steps box, while the last one is a separate function that iterates and determines the final output.

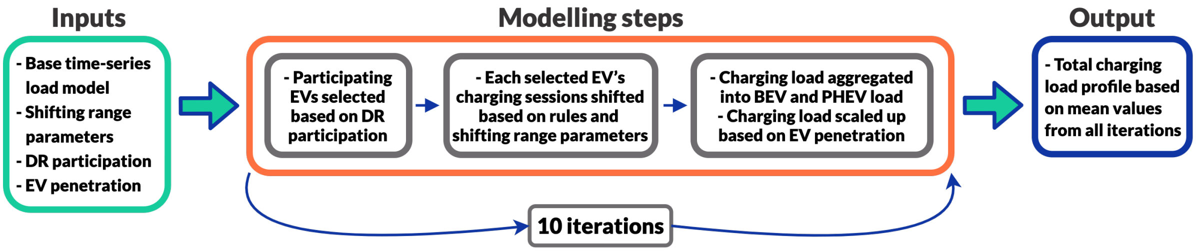


Figure 6.3: An overview of the modelling steps for the TOU DR strategy.

Now that the overall modelling methodology has been described, the methodology of the main function can be described. The first step is to input the time-series model, as seen in the inputs in the modelling overview figure. As explained earlier, the function then iterates over all of the EVs in the model. Therefore, in this explanation, the inner iteration is described, as it is the same for every EV. The first step in that inner loop is to figure out a way to find the individual charging sessions of each EV. Then an iterative loop is formulated, that goes over every charging session. In this iteration, the shifting rules as described before are applied. These rules are essentially based on the modelling assumptions as described in section 4.6, and can be seen in the list below.

- The end of the session after shifting cannot "overwrite" another session or a trip made
- The session can only be shifted if its maximum charging power is lower than 11kW
- The session can only be shifted if it is the last session of the day
- The total charging load over 24 hours has to be the same

For the first rule, additional information from the EV study dataset was used, which is trip data. This data was briefly explained in section 5.1.1. This rule not only ensures that the DR strategy is correctly carried out, but also that the charging profiles are not manipulated. This makes it possible to respect the fifth modelling constraint as defined in 4.2.2; that the existing charging preferences of EV consumers cannot be broken. As was explained in the previous section on the modelling validation, the modelling implementation of the DR strategies can be challenging to validate and will therefore not be done for this project.

However, the last rule as seen above combined with the first rule, can at least validate that the shifting of the sessions is done in the correct way. As the session cannot overwrite any other session, if the rules are implemented correctly, and the charging load for every 24 hour period must be the same, a quick validation can be done for this modelling implementation as well as conforming to modelling constraint four; that the annual total charging load must be equal under any charging scenario. When comparing the annual total charging load of all of the EVs between the uncoordinated base model and any TOU model based on different price changing hours, the difference in total charging load is about 0.4 %. This difference is considered negligible for the results of the model, i.e. the modelling KPIs and is most likely due to faulty data in the datasets. This will however be reflected upon in more detail in the *Discussion* chapter.

6.2.2. Direct load control

For the direct load control (DLC) DR strategy, some of the same modelling steps apply. Again, there is a central modelling process which is affected by the input parameters. However, for the DLC DR strategy, there are no strategy specific parameters. There is no price-sensitive time period or price changing hour. The shifting of the charging sessions is done by the DSO according to an agreement between the consumer and the DSO, as shortly explained in the literature review. The modelling of the DLC strategy is again mostly based on the modelling assumptions around this strategy, as explained in section 4.6. This strategy essentially means that when sessions are applicable for DLC, the individual charging intervals can be interrupted and distributed over a time certain time period so it best matches the overall system load.

In the same way as the TOU was explained, the overall modelling steps are explained first. As said before, the input parameters affect the modelling steps, and these inputs are exactly the same as for the TOU DR strategy, however there is no specific parameters to the strategy itself. The application of the strategy itself is carried out by a Python function that finds the charging sessions of each EV and rearranges the intervals of the charging session so it best matches the system load. This function is built in the same way, with an outer and inner function. However, the modelling process for this strategy is very different in one way. The scaling of load based on the EV fleet is not only done in the end as for the TOU, but it affects the process from the beginning. The overview of the modelling process can be seen in figure 6.4.

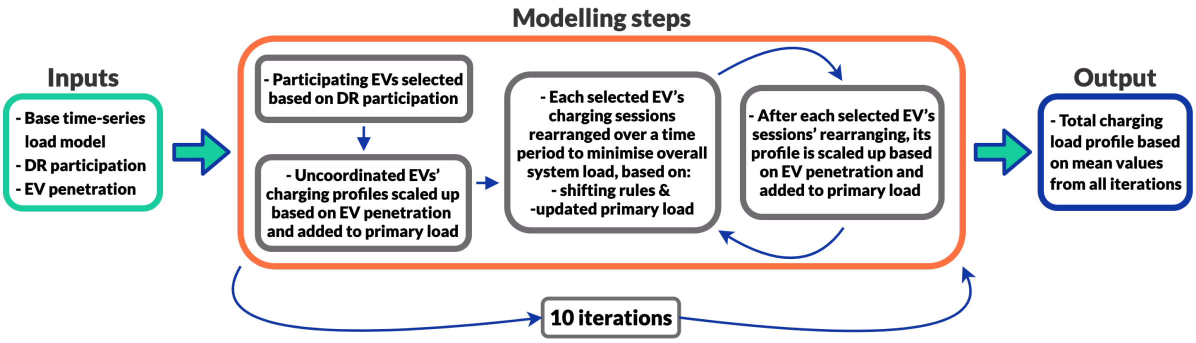


Figure 6.4: An overview of the modelling steps for the DLC DR strategy.

In the same way as the TOU DR strategy did, participating EVs are selected based on the DR participation input parameter. This is the first step of the central modelling process. The uncoordinated EVs, which are not participating in the DR strategy, are however scaled up, based on the EV penetration parameter and their combined charging profiles are added to the primary load. The primary load is thus updated, based on the EV fleet size which is being considered in each scenario. If there is 10% DR participation, then 90% of the EVs will be uncoordinated and those cars will be aggregated into a load profile, which is then scaled up to represent 90% of the EV penetration parameter value. The remaining 10% participating EVs are then modelled based on the new, updated primary load. This is done in order to accurately minimise the overall system load.

After this step, each selected EV's charging sessions are examined and rearranged over a time period. This step will the explained in more detail later on. This rearrangement of the charging session's intervals is done in order to minimise the effect that the session has on the distribution grid. The arranging itself is based on shifting rules, similar to the TOU strategy and the new updated load as explained before. Lastly, after each EV has been shifted, its new profile is scaled up proportionally according to the EV penetration parameter and added to the primary load, just as was done for the uncoordinated EVs.

These two last steps are then iterated over all of the selected EVs, so each subsequent EV takes into account the updated primary load. This ensures that for each EV the charging load is controlled in truly the best way for the system. This iterative process can be seen highlighted as a circular process inside the modelling steps in figure 6.4. Lastly, all of these modelling steps are iterated over 10 times, as the participating EVs are also selected randomly as with the TOU DR strategy. The average charging profiles for BEVs and PHEvs over the iterations are found and from that the main model output is determined.

The rearranging of the intervals inside a session are as said before based on shifting rules and the primary load. The shifting rules ensure that only the right sessions are affected and that the charging behaviour is not broken as the modelling constraints outline. For the DLC strategy, exactly the same rules apply as for the TOU strategy. These rules, already put forth in the previous section, are listed below.

- The end of the session after shifting cannot "overwrite" another session or a trip made
- The session can only be shifted if the maximum charging power of any interval is lower than 11kW

- The session can only be shifted if it is the last session of the day

- The total charging load over 24 hours has to be the same

For the rearranging however, the approach is completely different. The first step is to find the time period for which the interval can be distributed over. The start of this interval is the start of the charging session and the end is determined either based on the nearest trip, nearest charging session or at 9:00 in the morning, whichever is the closest. As the shifting rules state, only the last session of the day can be shifted. Additionally, the session has to start after people arrive home, much like the start of the shifting range for the TOU strategy. This time is determined to be 14:00, based on the trip data analysis, as explained in section 5.1.2, but that time is when the charging load begins to increase when people begin to arrive home.

When a session is applicable for rearranging, the intervals in the session are then ordered in descending order by charging power. As the time period for which the rearranging can be applied has been found, all of the primary load intervals inside that period are ordered in ascending order. Then a loop is iterated over all of the charging session's intervals, beginning with the highest charging power, where the charging session intervals are allocated to the intervals where the primary load is the lowest.This way, the overall system load is minimised. This is done for all of the applicable sessions and in the end a new charging profile is determined. As explained in the overview of the modelling steps, this profile is then scaled up and added to the primary load. For the next EV, the same rearranging steps are done, but will then be based on the updated primary load and with that the system load is effectively minimised.

Although this strategy implementation can hardly be validated as is the case with the TOU strategy, the same methodology as mentioned there can be used, to compare the annual total charging load betwen the DLC implemented charging profile and the uncoordinated base model. For some reason, the DLC method seems to have even less of a difference, or no noticeable difference at all when comparing all 121 EVs uncoordinated and all 121 EVs affected by DLC DR. This difference can truly be considered negligible, but as with the TOU, will be reflected upon in combination with the overall strategy, in the *Discussion* chapter.

6.3. Grid impact

The last step in the technical modelling process is the grid impact modelling. This is the third main modelling part with the base modelling as explained earlier being the first, and the two DR strategies' implementation the second step. This last step is mainly focused on taking the simulation runs of these two previous steps and modelling how they affect the distribution grid, both on the overall system level, as well as the lower levels of the grid. Many of the modelling steps for this part of the modelling process come from the KPIs as described earlier in section 6.1.2. It can be seen that all of the visual KPIs are based on simulation runs and the grid capacity limits in some way. Additionally, KPIs number seven and eight are also based on the system capacity limits, on these two different system levels.

The grid impact modelling does not generate any new load profiles, like the base modelling and the two DR strategies do, but takes the generated load profiles and inputs into a grid model. This process is done in two separate parts, one for the overall system level and another one for the lower level subgrid. The conceptualisation of this process was done in the *Conceptual model* chapter, and these two distinct steps can be seen highlighted in figure 4.2. The determination of the grid impacts are also dependant on the modelling assumptions applying to this modelling steps, namely assumptions 11-15 as seen in table 4.1. For the overall system level, the process is quite simple, as there is only one limit, which is the combined transformer limit of certain high level substations. Which substations make up this overall system limit were explained in the data chapter, namely section 5.3. For the lower levels however, the last three modelling assumptions apply, as the process is far more complicated. Based on available primary data from the DSO on these lower levels, as well as available public data on electricity infrastructure in the capital region, a subgrid can be formulated. The data handling and overall ideology was also briefly explained in section 5.3, where the subgrid was explained. In this section, the modelling methodology behind those two steps of determining the grid impact based on the three main load scenarios is explained.

6.3.1. Overall system level

For the overall system level, the methodology is quite straight-forward and mostly focused on plotting. As explained in the *Grid capacity data* section, the N-1 rule is applied to determine the overall system capacity limit. Based on that and a 0.95 power factor, the overall limit is determined to be 261 MW. The modelling process for this system level is thus mainly to implement the KPIs that apply to this overall view of the grid. Those are KPIs number 1, 2 and 7. For the first two, the process is to find the mean charging profile over a 24 hour period and then the worst charging profile over a 24 hour period, which is determined by the highest peak. These profiles are then plotted in a stacked area chart, where the primary load is first added, then the BEV load and lastly the PHEV load. With this method, the combination of the charging profiles can be seen, as together these loads create the peaks. To be able to determine the impact on the overall system grid level, the capacity limit, 261 MW, is also plotted in this graph. That makes it possible to see when the combined load profile of the primary and charging load exceeds the system capacity. This graph is then first used to find the mean value for every interval of the year - the average day - and then find the day where the highest total system peak occurs. This essentially generates visual KPIs 1 and 2.

For the last KPI that applies to this level, the capacity limit is again used. The aim is to determine the maximum size of the EV-fleet that can be allowed onto the grid. This is done by finding the highest system peak of the different scenarios for the two DR strategies and the uncoordinated load. For the fourth KPI, the peak load of the combined primary and charging load is found based on these different scenarios. So in modelling the highest EV fleet size, the scenario which achieves the lowest peak load is the most effective. This modelling process is done in two steps.

For the uncoordinated charging and the TOU DR strategy, the same methodology can be applied. For the uncoordinated charging, the scaling function as explained in section 6.1 is used to find at what EV fleet size the system peaks exceeds the capacity. For the TOU strategy, first the "best" performing scenario is found, i.e. which DR participation and what time of the price change hour. This is also something that is done in the earlier KPIs. The best performance for a given EV fleet can be determined by using KPI number four, in its heatmap form, and based on the "optimal" scenario for the TOU DR strategy, the same methodology can be used as for the uncoordinated charging. That is scaling up the EV fleet size and finding the system peak. This is possible as the scaling of the float is linear for the case of TOU and the EV fleet size does not affect overall charging load profile.

For the DLC strategy however, the EV fleet size is an input parameter, as explained earlier. However, a similar methodology as for the TOU DR strategy can be used. By calculating KPI number four, the different scenarios of the DLC strategy for a given EV fleet size are illustrated. By again finding the "best" performing scenario based on the input parameters, which in this case is only the DR participation, that scenario can be rerun until the system capacity limit is exceeded and an approximation of the maximum EV fleet size for this strategy can be determined.

6.3.2. Subgrid level

The overall approach for determining the grid impact on the lower levels of the distribution grid is similar to the overall system load, which is to generate the KPIs and translate the simulation outputs into results. This part of the grid modelling is however more complicated than the overall system load, as this part involves several modelling steps and uses another dataset for the primary load. To start with, it is good to indicate which KPIs this subgrid level aims to calculate. For the visual KPIs, it is KPI 3 and 5, which are the peak loads of every building and the map illustration of the cable load in the subgrid. For those two KPIs, different capacity limits are also applied to the graphs. As explained before, the distribution grid can be classified into three voltage levels; high voltage, distribution and street levels. This is also visualised in figure 4.1 on page 22. The subgrid which is examined in this modelling step includes the two lower levels.

Additionally, to make this analysis more detailed, an even lower level is analysed, which is the individual building level, by finding and using the cable capacity to those houses from the electricity streetboxes. This makes it possible to find the effects of the charging load in detail, on the individual household level. In the same way as for the overall system capacity, the size of the EV fleet that can be allowed onto this subgrid is also calculated as stated in KPI 8. The approach towards finding the loads on the individual building level as well in the grid itself is largely based on the modelling assumptions as explained in section 4.5. There are four critical assumptions which guide this modelling process which together cover the approach towards determining the load on this individual building level. That approach is mainly based on what data is actually available and working around that. Those data handling steps were explained in section 5.3. In this subsection here, the methodology of working with that data and modelling this subgrid is explained.

The first step in the modelling process for the subgrid is to make a visualisation of the grids. This does not only help to clarify things but is also used as a KPI, as it represents the map illustration as stated in KPI number four. This was done for the subgrid which will be used in the *Data* chapter, section 5.3. That subgrid was based on distribution substation no. 670. In that figure, the power capacity of the transformer was given, which is 800 kVA. Based on the 0.95 power factor as explained earlier, the power capacity of the station is thus 760 kW. In the map visualisation of the subgrid, the different levels of the subgrid can be seen; the distribution station itself, electricity streetboxes and lastly individual buildings.

There are different type of electricity cables connecting these levels together. As explained in section 5.3, these cables are made from different materials and based on that have different capacity limits. In the figure, different types of cables are marked with different colors and a legend is placed in the illustration to explain the materials used in each cable type. Additionally, next to each building there is a house number and street names are also displayed next to the houses. The different series are also displayed, with the letter S and a numbers. These are the series-connected electricity streetboxes which will be analysed in the grid impact modelling.

When the map illustration has been formulated the next modelling steps can be implemented. As this illustration is done by hand, based on the available information from the geographic information system from the city's online data portal, this information has to be formulated into usable data for modelling. The next step is to determine the cable capacity of the different cables in the subgrid. Based on the type of cable, the maximum current value for each cable was provided by the DSO. From that current, the power capacity can be determined. As these local grids operate on alternate current (AC) they have three-phase power. As most of Europe, the Icelandic distribution grid operates on 230V voltage. The power capacity of the cables can thus be calculated based on Joule's law and Ohm's law:

$$\begin{aligned} P &= I^2 * R \text{ (Joule's law)} \\ V &= I * R \text{ (Ohm's law)} \\ \text{where} & \\ R &= \frac{P}{I^2} \\ \text{leading to} & \\ V &= I * \frac{P}{I^2} = \frac{P}{I} \\ \text{and thus} & \\ P &= V * I \end{aligned} \tag{6.2}$$

The maximum power capacity in the cables can thus be found by multiplying the operating voltage with the maximum current, but that is still only the power for each phase. To determine the total cable power capacity, that power has to be multiplied by three. In table 6.3 below the maximum current and the calculated power capacity based on equation 6.2 (multiplied by 3) can be seen. The values for the maximum current based on the cable types was provided by Veitur.

Cable type	**Maximum current [A]**	**Power capacity [kW]**
4x10 mm$^2 Cu$	77	53.1
4x16 mm$^2 Cu$	100	69
4x25 mm$^2 Cu$	130	89.7
4x150 mm$^2 Al$	290	200.1
3x150 + 70 mm$^2 Cu$	370	255.3
4x240 mm$^2 Al$	375	258.8

Table 6.3: Overview of the cable types and their maximum current and based on that, power capacity. Cable types identified in the geographic information system (Reykjavik City, n.d.) and capacity values provided by Veitur.

It can be seen that for the most common connections to individual buildings, which are the two smallest ones, 4x10 mm^2 and 4x16 mm^2 copper cables, the power capacity is quite significant or 53.1 and 69 kW respectively. As the mean charging power of EVs based on the study dataset is around 3 kW, as explained in section 5.1.2, it is highly unlikely that regular family homes will exceed their capacity, even with several EVs. This is one of the reasons why the KPIs are so exhaustive for this lower level snapshot of the distribution grid, as the KPIs will dive further into the connections between each houses and the cumulative loading of the electricity streetboxes.

Next in the modelling process is as explained before, is translating the map illustration into a load model. To represent the characteristics of each building in the subgrid, a data table is made, which holds the available information on each building. This data table holds the information needed to determine the primary load, charging load as well as the capacity data as calculated earlier. An example of this table for the subgrid based on substation no. 670 can be seen in table 6.4.

For each building, the cable power capacity is determined and the number of inhabitants in the building are stated. This variable is very important as the primary and charging load are derived from that. As explained before, this subgrid is chosen specifically as there is available consumption from its substation. As laid out in the assumptions, it is desired to translate that data into primary load data for each individual building in the subgrid. It is also desired to find the number of EVs per building and from that the EV charging load, based on the EV penetration. The number of inhabitants in each house thus plays an important role in that process. As stated in the *Grid capacity data* section, information on the number of inhabitants in every building in this subgrid can be found in the city's online data portal.

To find the primary load profile of each building, the share of the population in that particular building divided by the total population in the subgrid is used. For the first entry in table 6.4 to take an example, which is Blahamrar 2, an apartment building, as seen in figure 5.8, the number of inhabitants are 71. The total population in the subgrid is 545, and thus the primary load in Blahamrar 2 will be 71 / 545 multiplied by the primary load profile. This is done for all of the buildings in the subgrid, so the combined profile will match the overall primary load of the station.

Building ID	**Building type**	**Cable type**	**Cable power capacity [kW]**	**Inhabitants**
Blahamrar 2-6	Apartment building	4x150 mm^2 Al	200.1	71
Blahamrar 1-15	Apartment building	4x10 mm^2Cu	53.1	16
Blahamrar 17-29	Apartment building	4x10 mm^2Cu	53.1	21
Dyrhamrar 2-10	Apartment building	4x10 mm^2Cu	53.1	10
Dyrhamrar 12-24	Apartment building	4x10 mm^2Cu	53.1	21
Geithamrar 1	Family home	4x16 mm^2Cu	69	3
Geithamrar 3	Family home	4x16 mm^2Cu	69	2
Geithamrar 5	Family home	4x16 mm^2Cu	69	4

Table 6.4: An example of the subgrid's building characteristics data table

This primary load profile for each building is then put into a new data table, or model, much like the base time-series model as explained in section 6.1. Each building in the subgrid is represented by a column, and there are rows for every interval of the year. The primary load profile is calculated for all buildings using the aforementioned method and put into their respective columns. The next step is to model the charging load. In table 6.4, there is a column which states the type of building. As the EV study dataset has different subgroups as explained before, the charging profiles which are based on family homes or apartments can be used to get a more accurate representation of the charging load. To find the charging load per building, the number of inhabitants are again used. Based on the average passenger car ownership in Iceland and the inhabitants in each house, the number of passenger cars in each building can be determined. The average ownership is 0.75 passenger vehicles per inhabitant (Statistics Iceland, n.d.), so for the example building, Fludasel 2, with X inhabitants, Z passenger cars are associated with that building.

This new subgrid model as described before, is another time-series load model and can thus take any charging profile, based on the different simulation runs from the uncoordinated load or the two DR strategies and add these profiles on top of the primary load of the buildings. These simulation runs will be based on the input parameters as explained before, the DR participation and the EV penetration. For the grid impact model, there is no need to define the DR participation or iterate 10 times as with the DR strategy modelling. This is because the average profiles based on all of the iterations will be used.

However, the EV penetration input is used to scale up the EV charging profile of each house based on the estimated number of EVs. So for a 50% EV penetration, the EVs per building will be $0.5 * 0.75 *$ no. of inhabitants. To be able to assign the "correct" type of EV to each building, the full time-series load output from the simulations will be used, where the charging load will be aggregated into four groups; BEV and PHEV in apartment buildings and BEV and PHEV in family homes. These four aggregate charging profiles will then represent an average profile for these types of cars based on the charging scenario. For every EV represented in the subgrid, each of these four profiles will be assigned, based on the number of EVs per building and the type of house. As with the DR strategy modelling process, an equal number of BEVs and PHEVs are assumed, so half of the EVs in the subgrid will be BEVs and the other half PHEVs.

By adding the charging load on top of the primary load, the peak of each building can then be determined, based on different charging scenarios. These peaks can then be plotted for every single building in the grid, as well as their capacity limits, based on the building characteristics datatable. This is essentially KPI number 3. With this visual KPI, it can be seen which share of the buildings will exceed their cable capacity under which scenario and which EV penetration.

However, this only tells half of the story of the grid impact on the subgrid. As said before, the cable capacity going into every house is quite substantial. But as the subgrid is essentially made out of a series of electricity streetboxes, the load behind every streetbox can be found. From the distribution substation there are a number of outgoing connections. They connect to different electricity streetboxes which are connected in series and make up the subgrid itself. The load of every electricity streetbox adds up, when going from the outermost box towards the substation. Thus for an outermost streetbox, only a few buildings will be connected to it. But going up the series, the load of every streetbox's connections add up. This is the cumulative loading which is represented in the map illustration, KPI four. It is far more likely that this will be the part of the subgrid that will break under the load. An overview of the modelling steps and process for this grid impact determination can be seen in figure 6.5.

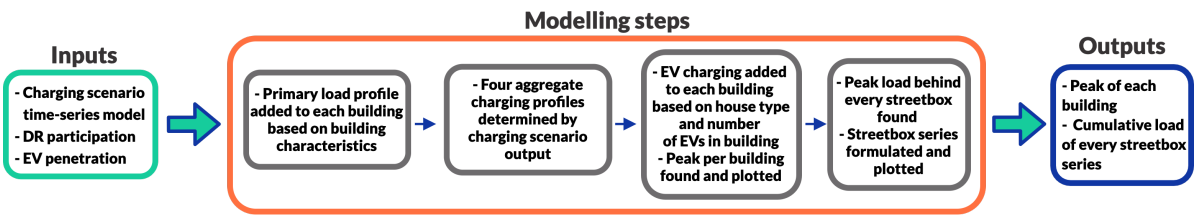


Figure 6.5: An overview of the modelling steps for the grid impact modelling

For the last step of the grid impact modelling, the peak load behind every streetbox is determined. This load is however determined differently than the individual peaks of each house as calculated for KPI three, as the different peaks can be at any time of the year. For the peak behind every electricity streetbox, the maximum combined load of its outgoing connections is determined. Then another smaller model is made, which formulates the different streetbox series in the subgrid. An example of such a series are the streetboxes connected to family home neighborhood on the lower right side of the subgrid, as illustrated in figure 5.8. Going from the outermost box in the series, the lowest box, which cable is marked S3.4, that streetbox is connected to six family homes. Going to to next one above, which cable is marked 3.3, another four homes and all the homes connected the streetbox on the left add up. Therefore, cable S3.3. holds the load of all of the houses connected to the three streetboxes below it. To represent the capacities of the streetboxes, the cable capacities of the cables between them are used. This modelling is done for all of the streetbox series and are displayed in the map illustration. This makes it possible to see when the capacity is exceeded, i.e. where the system breaks. As with the individual building impact model, different scenarios can also be used in this small streetbox model.

Combined, these two approaches towards determining the effects on the subgrid make it possible to see the effects on every single cable in the grid. For the individual buildings, the individual peaks can be found and for the streetboxes the combined load of the connected buildings. This makes it possible to display KPI number four, the map illustration of the cable load. This illustration will be based on the illustration already presented as seen in figures 5.7.

However, the loading of each cable will be represented with different colors. For a loading of 0 - 50% of the cable capacity, a green color will be applied to the cable. For a 50 - 100% loading, a yellow one will be applied and lastly with a load that exceeds the cable capacity, a red color will be applied. This will thus show where in the grid the cables fail and where the load has the most impact. Lastly, based on these two approaches, the total number of EVs that can be allowed onto the grid, based on the EV penetration share, can be determined. This can both be done on the individual house level and the streetbox level, as well as the overall station level. This thus calculates the last KPI, number eight.

7
Results

This chapter is dedicated to the results of the technical model use, which are mainly simulations based on the different charging scenarios. As described before, there are three main load scenarios; uncoordinated charging, charging load based on TOU DR and charging load based on DLC DR. Therefore, this chapter will cover the results of each load scenario separately, before comparing the results in the end. Most of the results presented are based on the eight modelling KPIs that were defined in section 6.1.2. As stated in that section, those KPIs are also used as a guide towards finding the most important results for each load scenario, where the best performance is achieved.

For each load scenario, numerous different charging scenarios can be generated, based on the two input parameters; EV penetration and DR participation, as well as the strategy-specific settings. To make the reporting on the results clearer, a few values will be chosen for the simulation runs. These will be explained in the next section. For the three main load scenarios' results, the main approach will be to first explore the behaviour of the load based on the scenario, then assess the impact of that load on the distribution grid. That will first done on the system's top level and then on the subgrid level. For each scenario, comparative values for the scenarios will be used, which will then be summarised in the end of this chapter.

It is important to note that all of the results of the DR strategies displayed in this chapter are based on the mean charging profile, which is determined by the 10 iterations that are run for each scenario. This was described in the methodology of the technical model implementation in chapter 6. Displaying the mean values only is done in order to keep the results more focused and comparative. This is especially the case for the visual KPIs. Including the results of all iterations makes the graphs hard to read and even harder to compare between scenarios. The same goes for the numeric KPIs, where a range would have to be supplied instead of a single number. However, to support this main results chapter and offer more details of the technical model use, extended results can be found in Appendix A.2. In that appendix, the standard deviation and spread of the KPIs that are displayed in this main results chapter can be found. This is also done for the comparative values as described before.

7.1. Setup of input parameters

The two input parameters are both formatted as a percentage number. EV penetration is the share of the passenger vehicle fleet that is electric while the DR participation is the share of consumers that participate in the DR strategies. Based on that, any number between 0 and 1 could be used to generated simulation outputs. The available data on these parameters was described in section 5.4. In this section, the choosing of the values to simulate and thus present in the results will be explained.

7.1.1. EV penetration

The total number of passenger cars in the system of interest, the municipalities of the capital region where the DSO Veitur is active in, is 130,960 as stated in section 5.4. Based on this, the numbers of EVs based on different EV penetration values can calculated. Incremental values of 0,25 will be used, i.e. 25%, 50%, 75% and a 100% EV penetration values will be used. In table 7.1 below the corresponding EV numbers can be seen.

EV penetration	25 %	50 %	75 %	100 %
Number of EVs	32,740	65,480	98,220	130,960

Table 7.1: Overview of the chosen EV penetration values for the simulations

The viability of these values, i.e. when the EV population in the capital region area will be equal to any of these values is unknown. However, it can be noted that the EV prediction from power-industry working on the energy transition in transport predicts 145,440 EVs in 2030. Based on the current share of EVs within the five municipalities in the system of interest and the total EVs in Iceland, this would result in around 86,000 EVs in the system of interest, or roughly 66% EV penetration.

These four incremental values will be used to simulate charging scenarios for all of the three main load scenarios. Those values will both be used for the visual KPIs, namely number one and two as defined in 6.1.2 and the numerical KPIs, number five and six.

7.1.2. DR participation

The consumer participation in the two DR strategies is harder to define as there is hardly any data available on it. As reported on in section 5.4, Icelandic electricity prices are also relatively low when compared to other EU countries. This means that the potential savings of consumers participating in the DR will most likely be quite low. For this reason, the main chosen values of this parameter will be more comprehensive than the EV penetration and incremental steps of 10% will be explore for the numerical KPIs 5 and 6. With this range, the effects of the different participation levels on the load profiles can be explored in more detail.

However, it is still desired to find a likely participation level for the two DR strategies. As was briefly explained in section 5.4, the potential savings can be estimated based on the outputs of the DR strategy modelling. Estimating this participation still requires some estimations on two different metrics, price reduction for DR-based hours and how consumers react to costs savings.

For the first one, pricing schemes based on TOU DR have been deployed in different variations and with different methods in many places. In this thesis project, a single TOU price has been proposed which is effective every day, essentially shifting the day into two price periods. In many implemented cases, more periods for each day are used, such as valley price, off-peak and on-peak. Acquiring historical data on different prices for two periods of the day was challenging but some sources were found. In the US and the UK, TOU has been ongoing for several years. Historical prices from (Ontario Energy Board, 2020), often have a difference of more than 50% for the off-peak and on-peak price. From (Hawaiian Electric, 2020a), the differences between these two periods seem to be near 30%. For the popular energy plan in the UK, Economy 7, which has 7 cheaper hours over the night time, the difference can be up to 50% (Hawaiian Electric, 2020b). For the DLC pricing, it is really challenging to find any historical data. For the cost savings estimation, the same price difference is thus assumed for DLC as is with TOU.

By using these price numbers and the electricity in the capital region, the cost savings of consumers can be estimated. This was done by using the full outputs of the TOU and the DLC DR strategies, i.e. where every consumer participates. For the TOU strategy, a price change hour of 23:00 was assumed, and as the limit to shifting is until 7:00 in the morning, the lower price period is thus between 23:00 and 7:00. For the DLC, only the charging intervals that were actually rearranged were calculated to have a lower price. For both of the strategies, the difference between the cost of uncoordinated, where there is only one charging price, can thus be compared to the DR strategy costs, based on different historical values found as described before. The results of these calculations can be seen in table 7.2.

	30 % price difference	40 % price difference	50 % price difference
TOU DR	12.9 % cost savings	18.6 % cost savings	24.3 % cost savings
DLC DR	20.6 % cost savings	27.5 % cost savings	34.4 % cost savings

Table 7.2: An overview of the savings between uncoordinated charging and DR strategy charging based on different price reductions

It can be seen that the DLC DR strategy seems to offer more cost savings than TOU DR. This was based on an Icelandic energy price of 15,46 ISK kWh (Orkusetur, 2017), by using the distribution price of Veitur and the electricity price from ON, the biggest energy supplier in the capital region. Based on these approximated savings, participation levels can be estimated. Though, this is also very challenging as little data is available on it. However, a study was performed in Norway - a country which also has really high EV penetration and a similar energy market to Iceland - on DR participation with EVs. The results from that study stated that if the shifting of charging would not inconvenience the user in any way, 90% of consumers would be willing to postpone their charging (Saele & Petersen, 2018, p.3).

Furthermore, the study's results stated that willingness to shift charging from daytime to nighttime would be around 38% if the cost savings were 200 € yearly and 26% if it would be 50 €. For both of the simulated DR strategies in this research, the cost savings were quite moderate. For the 50% cost difference, the savings (assuming 1 € = 160 ISK) were 56.5 € and 78 € for the TOU and DLC DR, respectively. However, based on these study results, the most likely DR participation can be defined. For the TOU, where the cost savings are less, this value is assumed to be 25 % and for DLC 30 %, based on the results of the Norwegian study. These parameters will thus be used together with the incremental values, as the most viable participation levels with a viable implementation of the simulated strategies.

7.2. Scenario 1 - Uncoordinated charging

For the results of the first main load modelling scenario; the uncoordinated charging or the "worst-case scenario", there are very few input parameters. There is no participation parameter as this is based on the same charging profile as presented in the EV study. This also means that there were no iterations needed for this modelling part and thus no extended results as explained earlier. The only parameter for this load modelling scenario is the EV penetration. Because of this, there is no need for a comparison of the numerical KPIs, as the uncoordinated charging essentially has only one charging scenario per EV penetration value. To be able to fully grasp the results of the uncoordinated charging, the behaviour of the distribution grid without any EV charging must be defined and can be used as a benchmark to compare this uncoordinated charging as well as the two other DR strategies to.

As was explained in section 6.1, the primary load was adjusted for EV charging. Based on that adjustment, the peak over the modelling period; December 1st 2018 to November 30th 2019, is 217.3 MW. In section 6.3, the overall system capacity was defined as 261.3 MW. Therefore at the beginning point of the distribution grid without any charging, there is only room for a peak increase of 44 MW. The peak of this primary load, can thus be used as a comparative benchmark for the different charging scenarios.

To quickly grasp the effects of the uncoordinated charging on the overall distribution grid, the peak system load can be calculated for the four predefined EV numbers. This can be seen in table 7.3 below.

	25 % EV penetration	**50 % EV penetration**	**75 % EV penetration**	**100 % EV penetration**
System peak	239.6 MW	269.3 MW	298.9 MW	334.1 MW
% of system capacity	92 %	103 %	114 %	128 %

Table 7.3: An overview of the system peak and share of overall system capacity for the uncoordinated EV charging

It can be seen that for the 50 % EV penetration value of roughly 65,000 EVs, the new system peak exceeds the system capacity. The addition of more EVs into the system is entirely linear for this scenario, so with increasing EV penetration the peak grows higher and higher. This charging behaviour is also interesting to see visually and when during the day it affects the system the most. For this, visual KPIs 1 and 2 can be used. In figure 7.1 below, the mean load for the uncoordinated charging can be seen, based on 50% EV penetration.

What is concerning to see is that the charging load profiles follow the primary load profile, so that the peaks of the two add up. This increases the impact of the charging load. The differences between BEV and PHEV charging can also be observed. As stated before, all of the simulations are based on equal ratio between BEVs and PHEVs. Overall, the BEV load is higher and more even throughout the day. However, the PHEV load also reaches its peak late in the day, when the primary load is also at its highest. These are the consequences of uncoordinated consumer behaviour. EV owners arrive home from work around the rush hour, as illustrated in figure 5.3 from the *Charging data analysis* section.

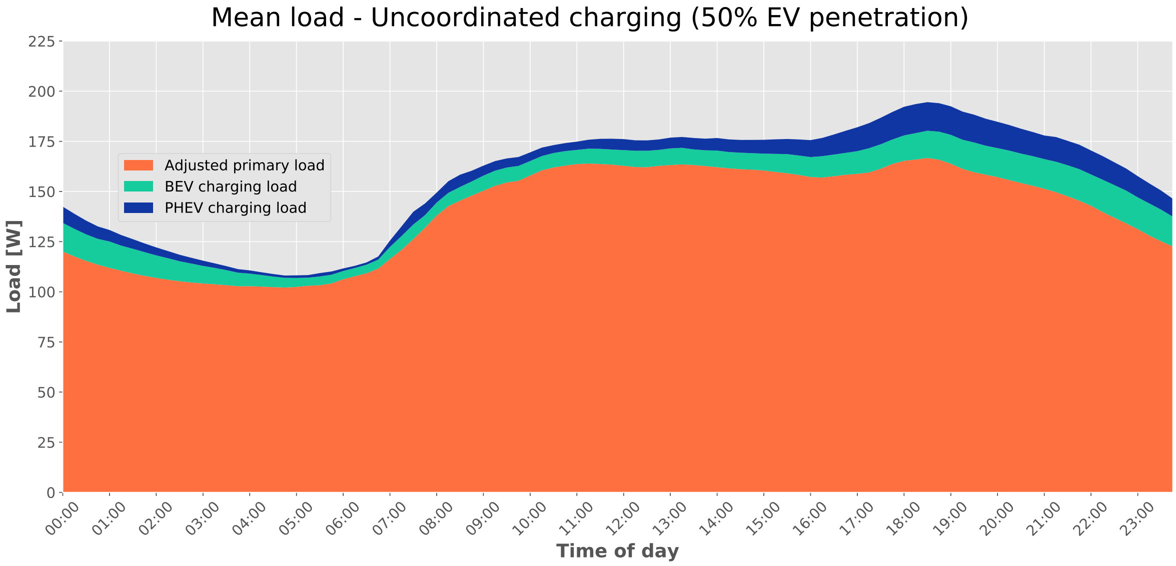


Figure 7.1: The combined load of the primary and the uncoordinated charging load for the mean day based on 50% EV penetration

At this time, home appliances get turned on and the small increase in primary load occurs between 17:00 to 19:00 as seen in figure 7.1. The charging load thus occurs at the worst possible time for the system, which exaggerates the peaking effect of the load. A more extensive insight into how the charging load stacks on top of the primary load can be seen in figure 7.2, which shows the weekly mean values.

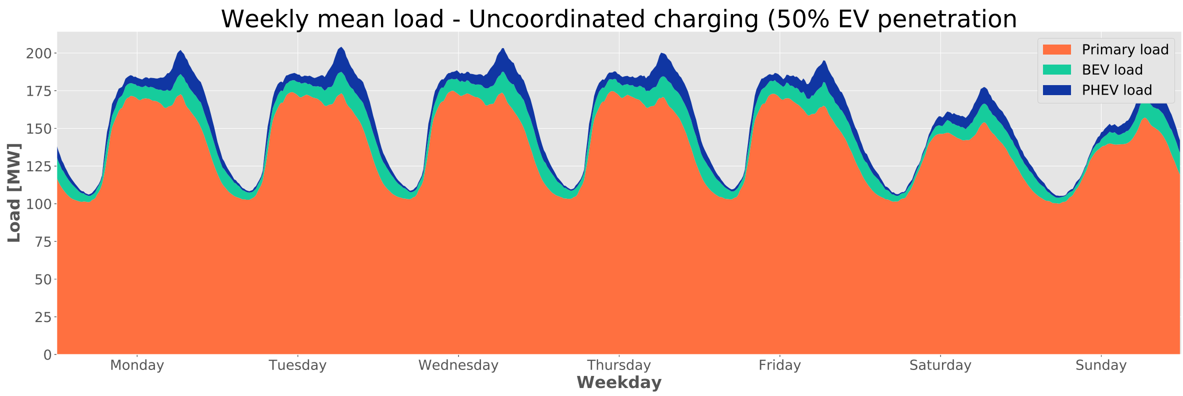


Figure 7.2: The combined load of the primary and the uncoordinated charging load for the weekly mean based on 50% EV penetration

First of all, it can be observed that both the primary and the charging load lower slightly towards the weekend, and are much lower on Saturday and Sunday. This is expected behaviour, as activity is reduced over the weekend. What can though be seen clearly in this graph is the major potential for shifting this uncoordinated charging load. For the BEVs, the charging load is more spread over the day than the PHEVs, but the nights are still largely unused. This can be seen on the left side of the peak profile for each day. For the PHEV charging load, there is less overall charging but more concentrated only over the peak hours. This can be seen in the blue sharp towers in the load profiles of each day. With DR strategies, this peak amplifying effect of the charging load can be reduced.

Up to this point, the mean values over the year have been shown. They give a good overall indication of how the load contributes to the overall system load, but is still a moderate depiction of that impact. However, plotting the worst day of the year really shows how hard the system is hit by this added charging load. This is essentially KPI number 2 and the DSO's preferred way of measuring the impact of load. In figure 7.3, this can be seen. Unsurprisingly maybe, the peak load happens exactly at the same time as the primary load peaks during this particular day. The system load is amplified by the charging load. In this scenario, based on a 50% EV penetration, there are only a few intervals over the modelling period which exceed the system capacity of 261 MW. However, if the higher EV penetration levels are explored, this number is much higher.

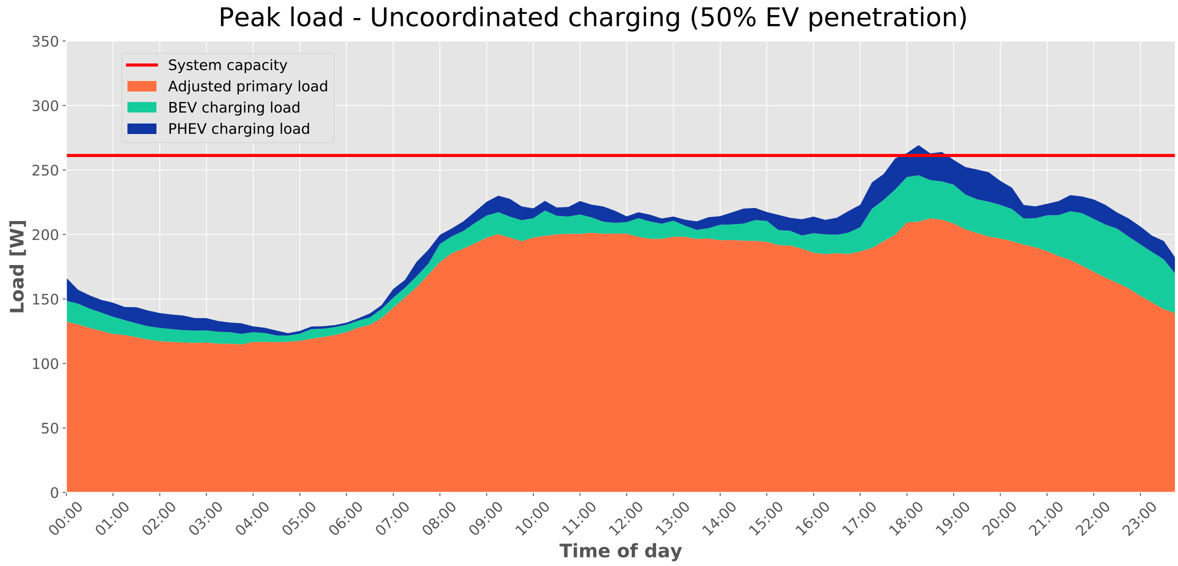


Figure 7.3: The combined load of the primary and the uncoordinated charging load for the worst day based on 50% EV penetration

With a 100% EV penetration, the system peak is almost 75 MW higher than the system capacity. This can be seen in figure 7.4 below.

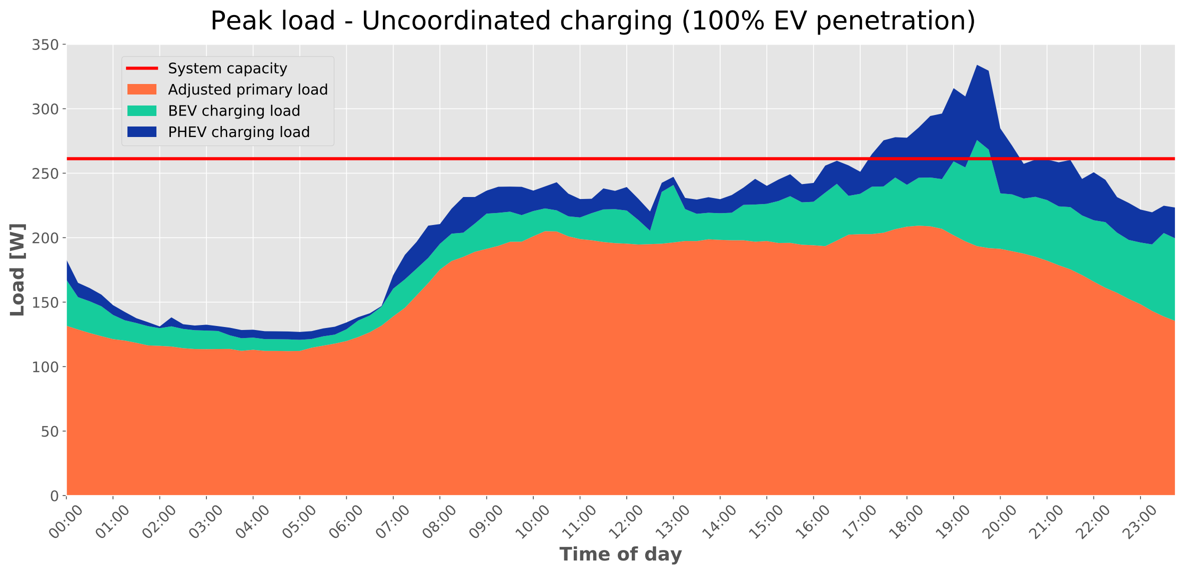


Figure 7.4: The combined load of the primary and the uncoordinated charging load for the worst day based on 100% EV penetration

The same trend can be seen, the peak load happens late in the day when the primary load is still pretty high. For this scenario, there are over 900 hours where the system load is higher than the capacity, which is more than 10% of the year. Summarising the impact of this uncoordinated charging load on the top system level can be done with KPI 7, which calculates the amount of EVs that can be "allowed" into the system without breaking its overall capacity. This is easily done as this uncoordinated profile scales linearly. The result is that 56,626 can be active in the grid and charging based on the EV study data without going over the system capacity over the modelling period. This comes out to a EV penetration of around 43%.

To analyse the load effects further, the subgrid approach can be used. As explained before in section 5.3, the total population in the grid behind distribution substation no. 670 is 545 inhabitants. Similar to the overall system load determination, this level can also be simulated with varying EV fleet sizes. Again, there are a few KPIs that capture the results of this modelling part. The overall approach to report the results of this is to go over the three components in these grids; the individual buildings, the electricity streetboxes and the distribution substation itself. By going over these systematically an overview of the load impact can be given and then summarised by the map illustration.

Beginning with the individual buildings; as KPI 3 states, the peaks of individual buildings can be seen. In figure 7.5 below, three scenarios for the uncoordinated charging can be seen. That is the peak load of each building based only on primary load, 50% EV penetration and a 100% EV penetration. It is important to note that for the 100% EV penetration, meaning that every single car in that subgrid is either BEV or PHEV, no building exceeds its cable capacity. It is thus clear the this part of these lower parts of the system are not in sudden jeopardy and have more than enough slack. In fact, the average load share, i.e. the peak divided by the maximum cable capacity, is less than 50%.

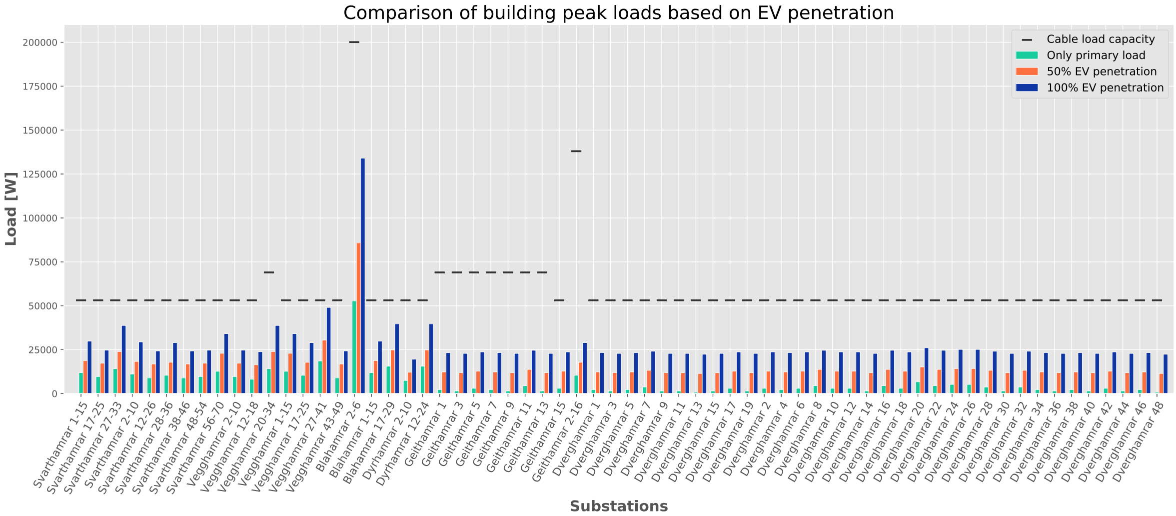


Figure 7.5: The individual building loads for uncoordinated charging for both 50% and 100% EV penetration

But this still does not tell the entire story. As explained before, the electricity streetboxes that connect these buildings to the distribution substation are connected in series. For this subgrid, there is one series which has seven streetboxes. The cumulative load from the outermost one towards the station ramps up significantly and it is likely that this will be the part of the system that breaks. By using KPI 8, the map illustration of the grid, the overall effects of the grid can be seen. As the cable connecting each house to the streetboxes in the grid seem to hold up fine under a 100% EV penetration, it is interesting to see the impact on other cables in the grid. This can be seen in figure 7.6.

In this map illustration, the load of every cable can be seen based on its maximum capacity. This is based on a 100 % EV penetration. It becomes clear that indeed the higher aggregate level in the grids, the electricity streetboxes are the bottleneck in power delivery. Although the building connections can handle the load of every single passenger car being electric, this electricity supply cannot be delivered to all places in the subgrid. The entire family home neighborhood, based on series 3 is congested. In these cables, the overloading is at its highest, 300% of the cable capacity. This is the case for the first two streetboxes in series 3. Additionally, the overall peak load on the distribution substation itself for this maximum EV penetration level, is 80% over the stations transformer capacity, or 1.36 MW.

Even with the more realistic load scenario of 25% EV penetration, the cables between the first two streetboxes, i.e. S3.1 and S3.2 are overloaded by 10%. Although the building connection hold up quite well, the subgrid as a whole does not. What has to be kept in mind also is that there are over 900 of these subgrids in the operating area of the DSO. Based on this varying performance of the subgrid based on its components, KPI 8 can be approached and a EV penetration value can be calculated. This can be seen in table 7.4 below.

	Distribution substation	**Electricity streetboxes**	**Individual buildings' cables**
Maximum EV penetration	43 %	18 %	119 %

Table 7.4: The maximum EV penetration threshold of the different subgrid components for uncoordinated charging

These values show the gross imbalance between the components of the subgrid. It is clear that the biggest bottleneck are the cables between the streetboxes, which carry the load of multiple buildings and sometimes whole streets. The value in the table, 18% is calculated by finding the maximum EV penetration value. The substation itself is also quite limited in terms of capacity and can experience 43 % EV penetration while the cables connecting individual buildings have a large slack in capacity. This way of showing the load impact on individual components of the grid is also a good benchmark when comparing the performance of the two DR strategies.

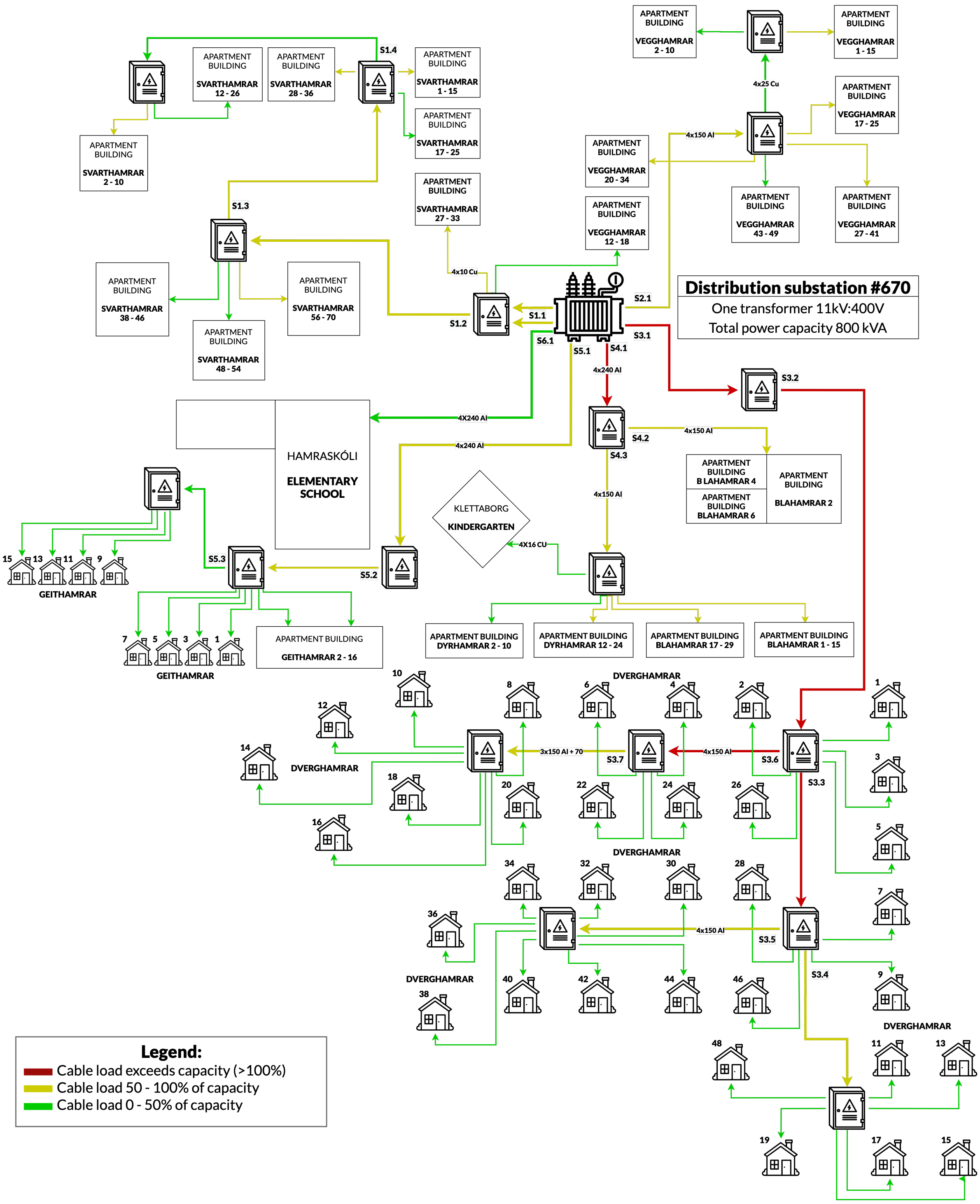


Figure 7.6: The map illustration of the subgrid based on a 100% EV penetration for the uncoordinated load scenario. Icons from www.flaticon.com.

7.3. Scenario 2 - Time of use

The TOU modelling has the most number of scenarios as this DR strategy has additional parameters over the two input parameters. Those parameters are the settings of the shifting range, which is the period when sessions can actually be shifted. The start of this range is assumed to be 14:00 as explained in Assumption 5 as seen in table 4.1. However, the end of this range, which is the price-change time, can be variable and thus simulated with various values. Eligible charging sessions are shifted to this time, and are therefore delayed in time. The goal is to alleviate some of the charging load over the peak hours and thus reduce the overall system load. Which sessions are actually shifted and the rules applied to shifted sessions are mainly based on the assumptions behind the TOU DR strategy, as discussed in section 4.5 and laid out in detail in the *Technical model implementation*, section 6.2.1.

TOU load profiles

To understand this shifting effect it is good to visualise it. In figure 7.7 below an overview of these different price-change hours can be seen, based on a 100% DR participation and the mean of every interval of the day over the full year, similar to KPI 1.

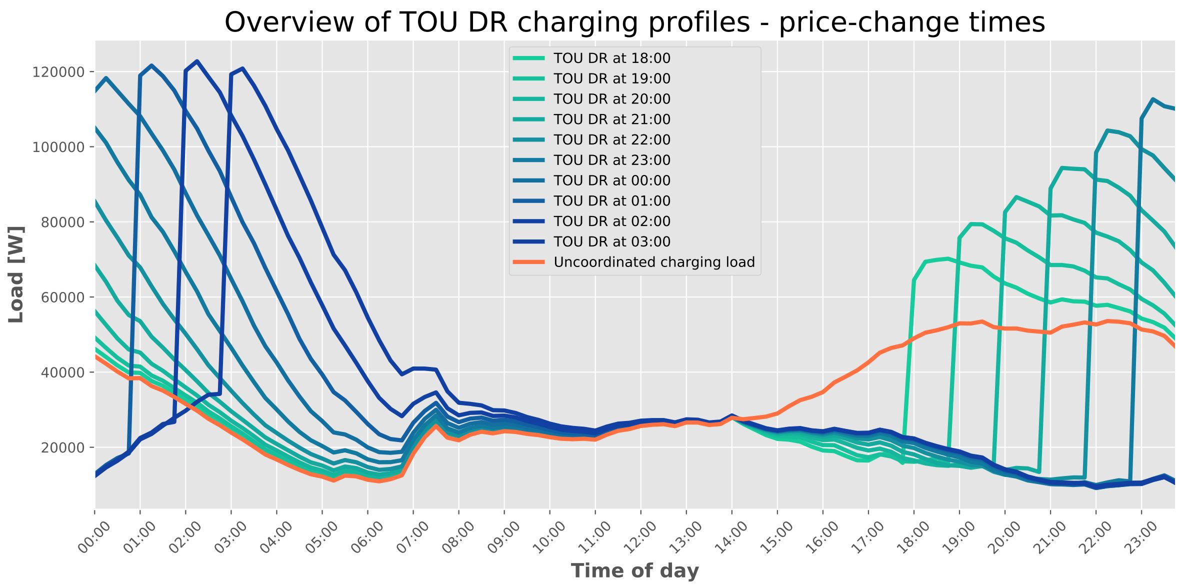


Figure 7.7: An overview of TOU charging profiles based on different price-change times

In the graph, it can be seen that from the shifting range start, majority of the load is shifted until the time when the price changes. This is the aggregate charging profile of all of the 121 EVs combined, meant to best show the effects of the DR strategy. The general rule seems to be that the later the price change is, the higher the new peak of the shifted charging profile. This is because there is a bigger and bigger cumulative charging need when the charging is increasingly delayed. The uncoordinated charging can also be seen, which rises from 14:00 and peaks in the evening and then lowers significantly over the nighttime. Most of the charging sessions end in the morning around 7:00 - 8:00 when other sessions or trips limit the shifting amount. This was explained in the technical implementation of the strategy, but if there is another session or trip, the shifting of the session is adjusted, so as much of it as possible falls within the lower price period. However, some sessions end later, especially when the price change hour is very late, as can be seen with the 03:00 price change hour, which has some sessions ending around noon.

It is also interesting to see the effects of the consumer participation. As described in the methodology, participating EVs are shifted while the rest remain uncoordinated and the overall charging profile is determined by combining the load of all the EVs. With less participation, less EVs will delay their charging and thus less sessions will thus be shifted in time. In figure 7.8 the effects of varying consumer participation can be seen, based on a price changing hour of 23:00. With less participation the new charging peak is lowered. However, this means that there will be less reduction of the charging load over the peak hours in the evening and also less valley filling in the night.

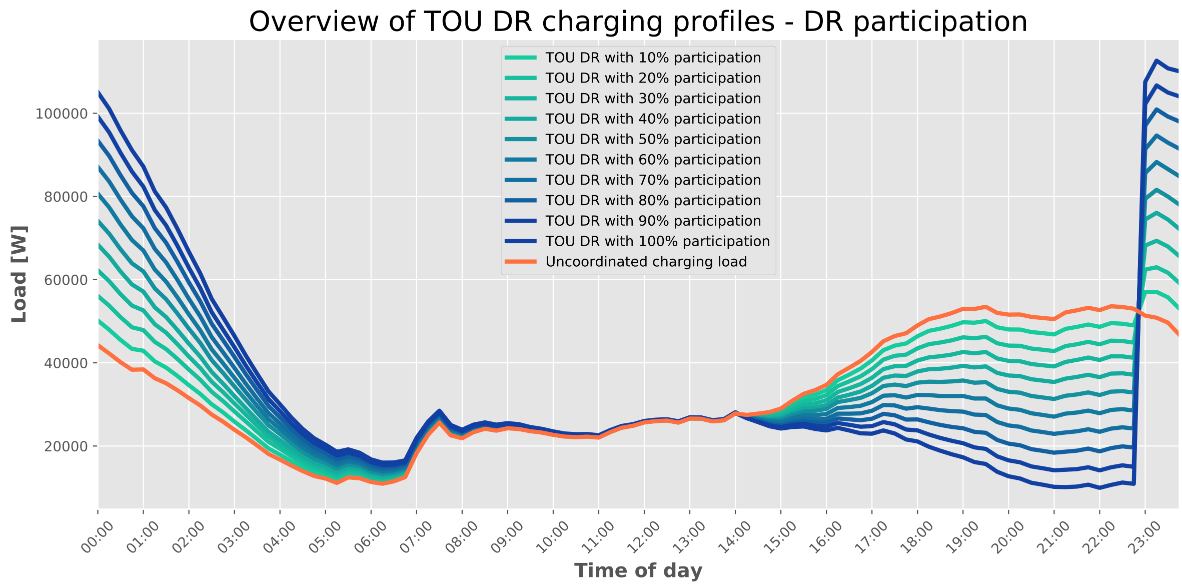


Figure 7.8: An overview of TOU charging profiles based on different participation levels

But the charging load on its own does not convey the effects that this strategy has on the overall system load. How it combines with the primary load is the main concern and the goal of this DR strategy. In figure 7.9, this can be seen. This is essentially KPI 1, where the mean profile over the day is plotted. To fully see the effects of the change, the uncoordinated charging load is also plotted in the graph. For a big part of the day, or from around 6:00 to 14:00, the TOU profile and the uncoordinated profile are identical. However, after 14:00 the TOU strategy begins to delay the charging, but then experiences a sharp peak at 23:00.

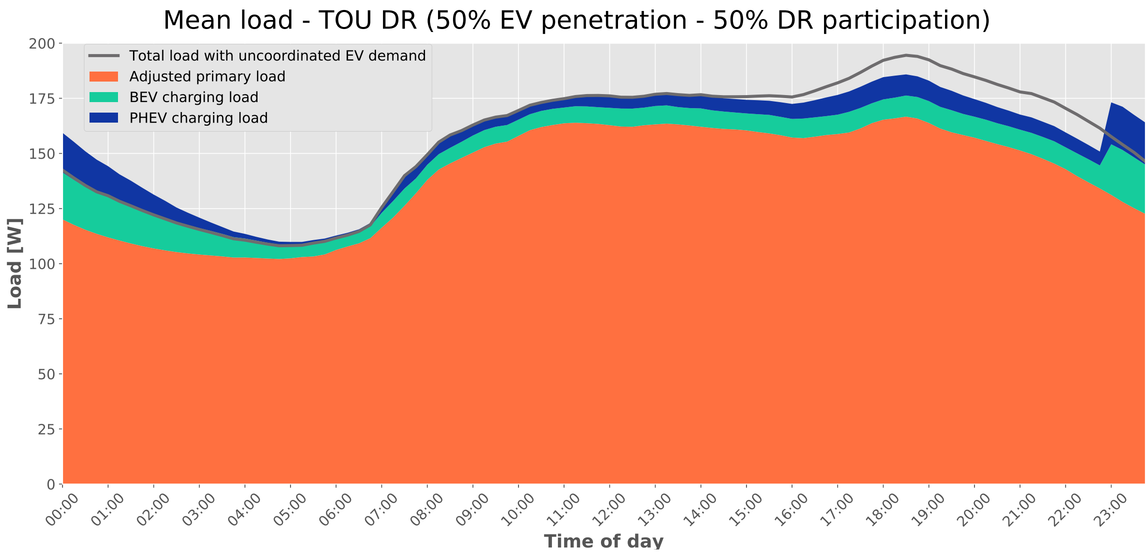


Figure 7.9: The combined load of the primary and the TOU charging load for the mean day based on 50% EV penetration and 50% DR participation

Overall system load impact

What is perhaps more interesting to see is the worst day based on the uncoordinated charging load for a 50% EV penetration, as visualised earlier in figure 7.9. This can be seen in figure 7.10. This should not be confused with KPI 2, which is based on the peak load of the DR strategy itself, whereas this graph shows the peak load of the uncoordinated load. The former uncoordinated peak of roughly 270 MW, has been reduced, as the majority of the charging load over the peak hours has been shifted to 23:00 and over the night. This example scenario is based on 50% EV penetration, price change hour of 23:00 and 50% DR participation and has a peak of 250.9 MW, That is almost 20 MW less than the uncoordinated charging based on the same EV penetration, as stated in table 7.3. Although there are secondary peaks when applying this strategy, it can indeed lower the overall system peak.

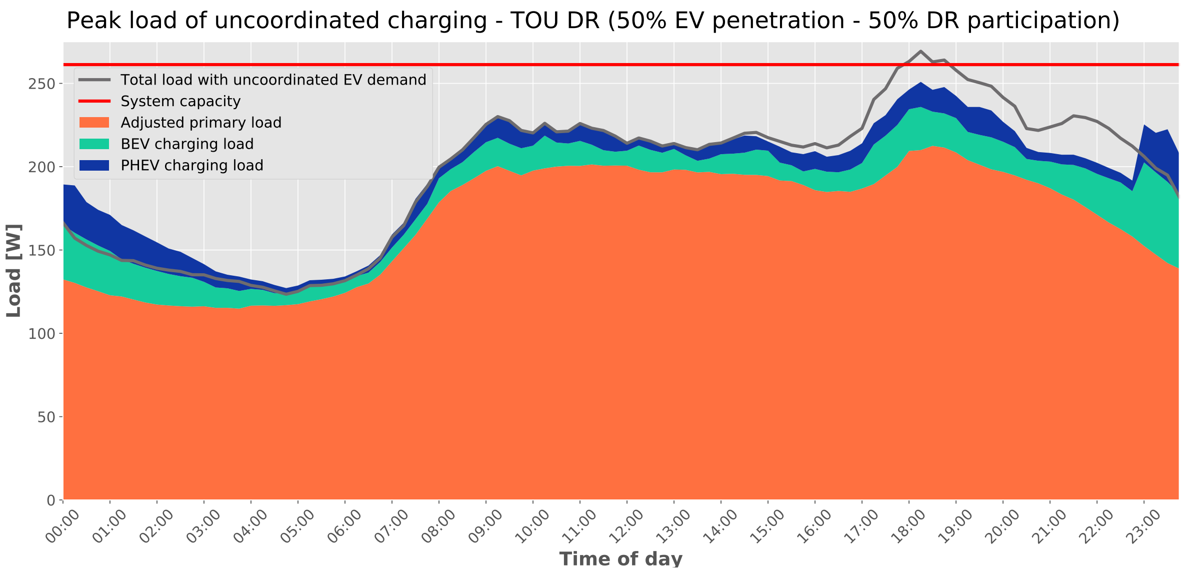


Figure 7.10: The combined load of the primary and the TOU charging load, based on 50% EV penetration and 50% DR participation, plotted for the worst day of the uncoordinated charging load

As this DR strategy does not take into account the EV penetration in its shifting methodology, the characteristics of the charging profiles based on different scenarios do not change with increased EV penetration. As was illustrated in figure 7.7, the charging profile peak becomes higher as the price-change time is later in the day. However, as was showcased with 50% EV penetration as an example, how this charging profile interacts with the primary load is the main concern.

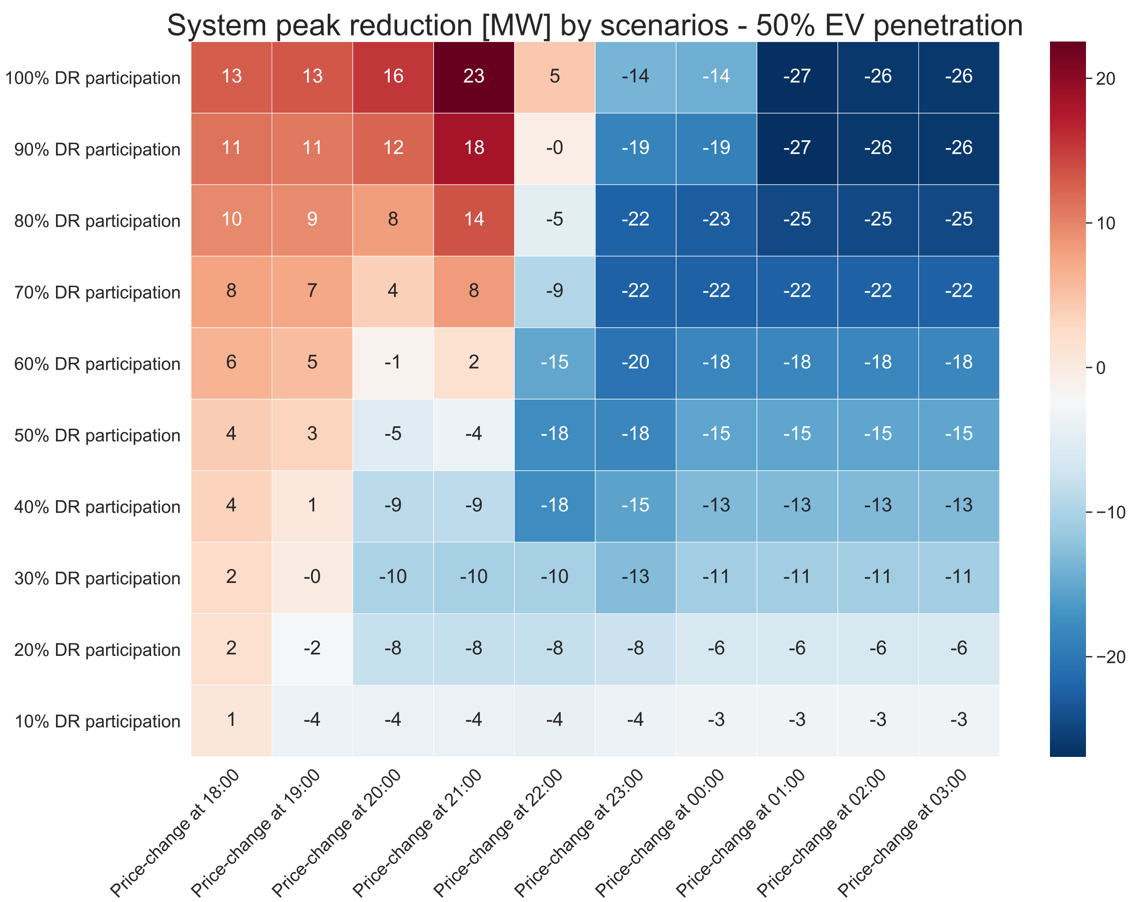


Figure 7.11: Heat map illustration of TOU scenarios for 50% EV penetration. The values in the graph show how much the peak can be reduced compared to the uncoordinated charging peak.

Therefore when the charging profiles are scaled up based on EV penetration and added to the primary load, the best overall performance of the TOU DR strategy is not necessarily based on the scenario which has the lowest peak charging load, but the one which minimises the overall system peak. This best performing scenario will vary with different EV penetration values. With increasing number of EVs, the charging load is proportionally bigger compared to the primary load and thus the scenario which achieves the best performance might not be the same for the different EV penetration values. This means that the "best" settings for the TOU DR, based on the price-change time and the DR participation, are not the same for 50% EV penetration as with 100% EV penetration.

To explore the performance of the TOU DR strategy, an overview of scenarios based on a range of input parameters were calculated. For the price changing hours, a range between 18:00 in the evening and 03:00 in the morning were explored. The TOU profiles of these different price-change hours were previously explored in figure 7.7. As stated in section 7.1.2, the DR participation input parameter will be explored in increments of 10% for both of the DR strategies. To find the best performing strategy for a given EV penetration value, these parameters are visualised in a heatmap. The values in this heatmap visualisation are the system peak load reduction compared to the uncoordinated charging based on the same EV penetration as put forth in table 7.3. The coloring of this visualisation goes from dark blue to dark red. Blue numbers are an actual reduction, and thus negative values, whereas red are where the peak of the specific TOU strategy has a higher system peak than the uncoordinated load and thus is an addition to the peak and a positive value. This particular overview of scenarios as seen in figure 7.11 is based on a 50% EV penetration.

This essentially shows how the TOU DR strategy can lower the system peak when compared to the system peak if there was no coordination of the charging load. From this overview of scenarios, a number of trends can be observed. Firstly, if the price change is too soon, i.e. before the primary load profile lowers during the late evening, the TOU does not alleviate the system peak load but actually increases it. This can be seen in the upper left corner of the heatmap, where the values are mostly red. For these price changing hours, 18:00 - 21:00 a lower participation will have result in a lower peak. These are the hours where if the TOU participation is too high, the secondary peak will actually be higher than the peak based on the uncoordinated charging load. So if not all of the sessions are shifted, the uncoordinated peak will be reduced without creating another bigger peak with the shifted charging based on TOU. An example of this can be seen in the two figures below.

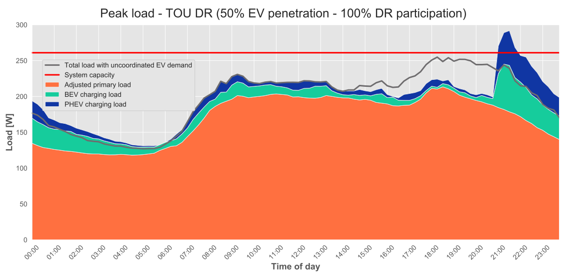


Figure 7.12: Peak load of TOU DR at 21:00 with 100% DR participation

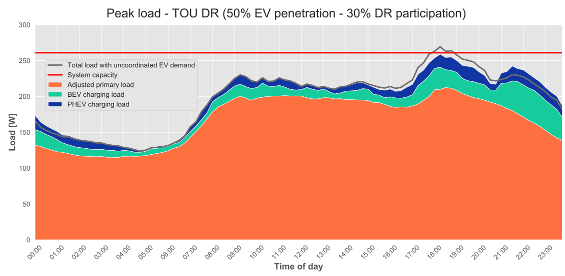


Figure 7.13: Peak load of TOU DR at 21:00 with 30% DR participation

Both of these figures are based on a price changing time of 21:00. In figure 7.12 on the left, the consumer participation is 100%. The worst day of the year, the peak load, is plotted. It can be seen that the secondary peak based on the TOU shifted profile is much larger than the uncoordinated one on that worst day. This is because at that time of day the primary load is still very high and because the shifting range is quite small, i.e. from 14:00 to 21:00 and thus many sessions that begin later than that will still be unshifted. In figure 7.13 on the right, this same TOU strategy can be seen, but with a 30% consumer participation. This exhibits the behaviour as explained earlier, the TOU shaves off the uncoordinated charging peak but the secondary peak does not become bigger. This is the problem with TOU DR at these times of the day, high consumer participation will not be favourable for the system.

However, on the right side of the heatmap, figure 7.11 the trend seems to be opposite. With a higher DR participation, the higher is the peak reduction. The upper right corner, very blue, presents the best performance of the TOU DR strategy based on 50% EV penetration. However, there is a portion in the middle of the graph, with adequate DR participation around 22:00 to midnight. These can be seen as anomalies as all of the other scenarios follow the two identified trends as explained before. These middle values might however be the most promising ones as a 100 % EV participation seems to be quite optimistic. The best performing scenario for the TOU DR strategy with this specific EV fleet size is when the price change hour is 01:00 at night and the participation is either 90% or 100%. The scenarios later in the night offer very similar peak reductions, but not as high. It was also explored if other scenarios in between these hours, i.e. from 00:15 and 01:45 would offer better results, but they had the same results as 01:00.

As explained earlier, the performance of the TOU DR strategy is different based on varying EV fleet size, based on the EV penetration. In the three figures below, heatmap visualisations of the same metric as before, the peak reduction based on the uncoordinated load for the corresponding EV penetration, can be seen for 25%, 75% and 100% EV penetration values.

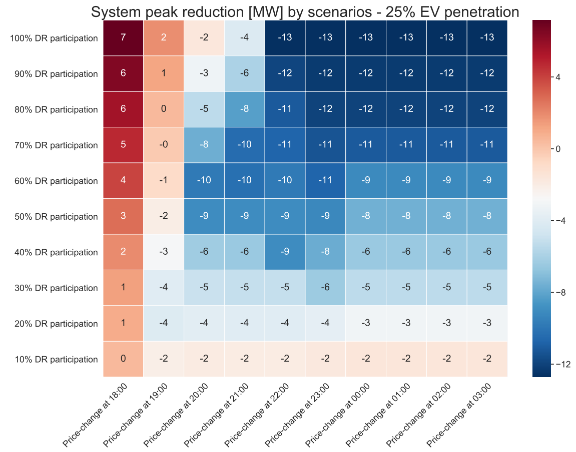


Figure 7.14: Heat map illustration of TOU scenarios for 25% EV penetration

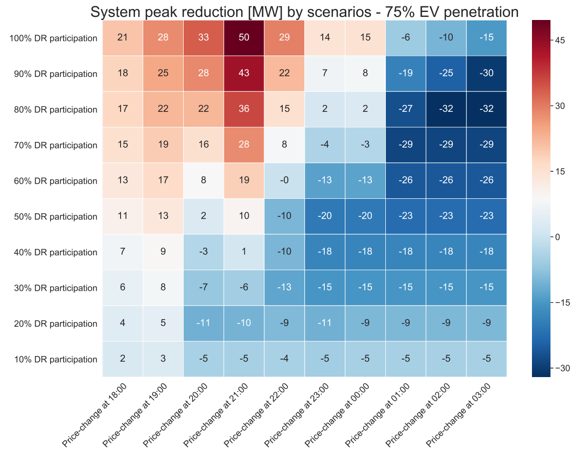


Figure 7.15: Heat map illustration of TOU scenarios for 75% EV penetration

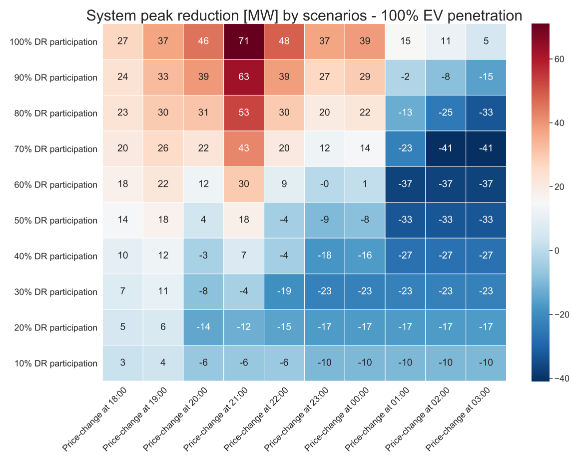


Figure 7.16: Heat map illustration of TOU scenarios for 100% EV penetration

In these scenario overviews, it can be seen that the best performing strategy is similar for all of the values, i.e. based on relatively high consumer participation levels and late in the evening and night, but the exact scenarios are still different. A trend can be observed when looking at these three heatmaps as well as the one for 50% EV penetration in figure 7.11. The dark blue area, which achieves the most peak reduction moves down to the right of the heatmap with increasing EV penetration. For 25% EV penetration, the best scenario as based on the 50% EV penetration, 100% DR participation and 1:00 is still the best performing one, but so are many others which achieve the same results. Moving over to the 75% EV penetration, the most reductions are later in the night and with a lower participation from consumers. For a 100% EV penetration, where every single passenger car in the system of interest is electric, this trend is shifted to lower participation levels. This trend of moving later into the night and lower the participation is due to the fact that in these scenarios, where

EV penetration is higher, the secondary peaks with full participation can be higher than the uncoordinated peak, as explained before and shown in figures 7.13 and 7.12.

This effect in action, can be seen for the best performing strategy for 75% EV penetration in figure 7.17. This scenario, based on 80% DR participation and a price-change time of 3:00 shifts most of the charging load that was previously during the peak hours of the day, as seen with the uncoordinated line plotted, into the valley of the night. This lowers the peak load significantly, compared to the uncoordinated load as seen in the figure.

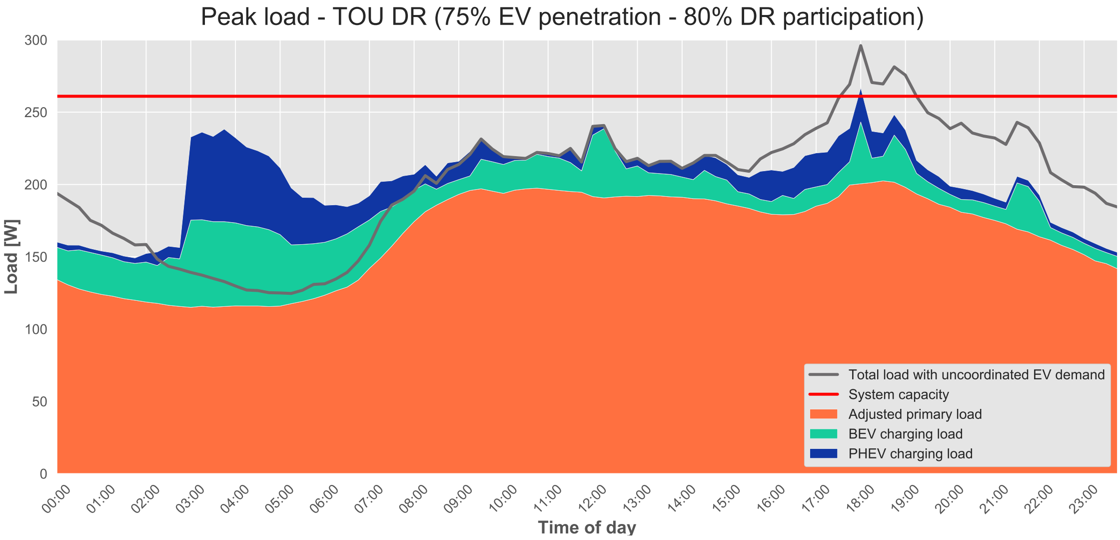


Figure 7.17: The combined load of the primary and the TOU charging load for the worst day based on 75% EV penetration and 80% DR participation

Analysing the heatmaps and the different scenarios it can be seen that the most likely DR participation for TOU, 25% which was estimated in section 7.1.2, can generate some peak reduction, as can be seen in the rows with the 20% and 30% DR user participation, but not nearly as much as the best performing scenarios though. However, to fully understand the performance of the scenarios with this 25% participation level, all of the scenarios between the time period of 18:00 - 03:00 were calculated. Therefore all of the time intervals, i.e. every 15 minutes between those times were evaluated. The results of this, based on 50% EV penetration, can be seen in figure 7.18. Almost all of the scenarios, based on the different price-change time do reduce the overall system load, but by using 20:15 or 20:30 the best results are attained, or a reduction of 9.6 MW. This is far less than best performing scenario for the 50% EV penetration, which was a reduction of 27 MW, but still better than the uncoordinated charging.

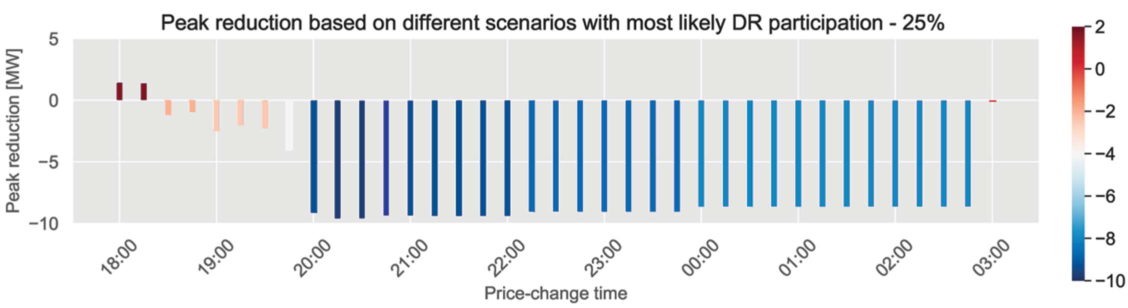


Figure 7.18: Peak reduction of most likely scenario for TOU scenario

To summarise the results of the TOU DR modelling on this overall system level, the relevant KPIs can be calculated. First, the maximum number of EVs that can be allowed onto the grid without exceeding the system capacity can be found. This was done by maximising the number of EVs over all of the different scenarios. This resulted in 91,124 EVs, and was based on 80% DR participation and a price-change time of 2:45. This is a massive increase in EV numbers over the uncoordinated charging, which was roughly 55,000 EVs. However, when the best scenario based on the most likely DR participation level, this number of EVS is 67,558 and was based on a price-change hour of 20:15. That is still considerably better than the uncoordinated charging.

To summarise the load impact on the overall system level, the load peaks for the four EV penetration values, as earlier calculated for the uncoordinated charging, can be determined. This can be done both for the best performing scenario and the most likely one. The results for the former can be seen in the table 7.5 below. To find the absolute best performing scenario, the price-change times between the hours, i.e. 15, 30 and 45 minutes past the hour were also explored. This was done for the best performing scenarios from the heatmaps, i.e. the intervals between the hours that had the most peak reductions were explored. If there were more than one price-change time that achieved the best result, those range of times are presented. In the graph the peak reduction as a percentage decrease is stated. It is also important to note how that peak reduction percentage is calculated. This can be seen in the formula below.

$$\text{peak reduction} = \frac{peak_U - peak_S}{peak_U} \tag{7.1}$$

Essentially the load peak of the scenario, $peak_S$, is subtracted from the load peak of the uncoordinated scenario, $peak_U$, for the same EV penetration value and that reduction is divided by the uncoordinated load peak, $peak_U$. This thus derives the reduction of the peak as a percentage.

	25 % EV penetration	**50 % EV penetration**	**75 % EV penetration**	**100 % EV penetration**
Best performing scenario peak load	226.9	242.4	266.6	293.2
Reduction based on uncoordinated load	5.3 %	9.9 %	10.8 %	12.2 %
Best performing scenario overall	Price-change at 22:00 - 3:00, 100% DR participation	Price-change at 1:00, 90% & 100% DR participation	Price-change at 1:15 - 1:45 & 2:15 - 2:45, 80% DR participation	Price-change at 2:00 & 3:00, 70% DR participation

Table 7.5: Overview of peak loads and best performing scenarios for TOU

For most of the EV penetration scenarios, the best performing strategy are the ones that were identified in the heatmaps earlier. However, for the 75% EV penetration, there were slightly better results by using a price change time just around the best performing scenarios as identified in the heatmap, which were 2:00 and 3:00. These same calculations were then also done for the most best performing scenarios based on the most likely DR participation value, as explained earlier. For most of the EV penetration levels, there is a range of price-change times that achieves the most reduction of the peak load based on the most likely participation. These results can be seen in table 7.6 below. These scenarios do not generate as favourable results as the best performing scenarios overall, but still offer some reductions.

	25 % EV penetration	**50 % EV penetration**	**75 % EV penetration**	**100 % EV penetration**
Most likely scenario peak load	234.8	259.7	289.2	318.7
Reduction based on uncoordinated load	2.0 %	3.6 %	3.2 %	4.6 %
Best performing scenario based on most likely scenario	Price-change at 19:30	Price-change at 20:15-20:30	Price-change at 21:30 - 02:45	Price-change at 22:00 - 02:45

Table 7.6: Overview of peak loads and most likely scenarios for TOU

Subgrid load impact

To fully understand the performance of the TOU DR strategies, the impact on the lower levels of the distribution grid must also be assessed. In the same way as was done in the previous section for the uncoordinated charging, the time-series output of the TOU DR model can be used to allocate charging profiles to the buildings in the subgrid and analyse the load impact on the subgrid. For KPI 3, the building individual peaks, the uncoordinated charging did not have a very big effect on the individual buildings, as no building went over its cable capacity based on its peak load. To see the effects of TOU on the subgrid, the best performing scenario of the overall system level for 100% EV penetration can be used, which is at 3:00 with 70% DR participation. The comparison of that scenario and the uncoordinated one can be seen in figure 7.19.

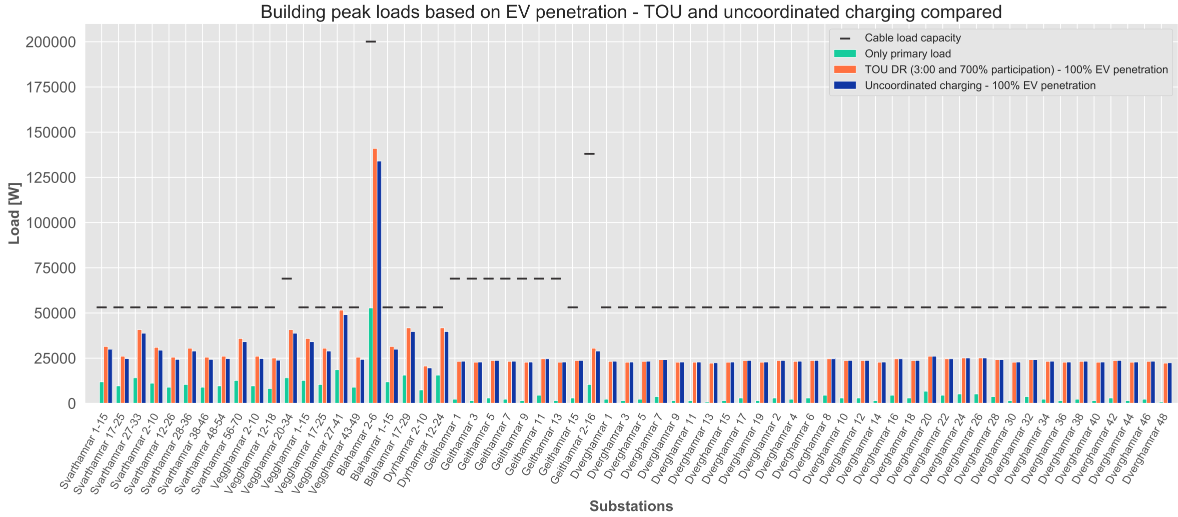


Figure 7.19: The individual building loads for the TOU and the uncoordinated charging

It can be seen that with the TOU DR strategy, the buildings' peaks are actually often higher than the uncoordinated load. This is because this scenario, the one that performed the best on the overall system level for this EV penetration, i.e. 100%, shifts sessions of the cars of each building to 03:00 every night. As the primary load is a much smaller contribution to the overall load, as can be seen in the graph, compared to the overall system level - where the charging load is a relatively small addition to the overall load - the TOU DR strategy generates a higher peak. When looking at the subgrid itself, i.e. the electricity streetboxes and the load on the station itself, the load impact of the TOU DR strategy is very similar to the uncoordinated load, but has a much lower maximum EV penetration for the buildings. This can be seen in table 7.7.

	Distribution substation	Electricity streetboxes	Individual buildings' cables
Maximum EV penetration	43 %	18 %	108 %

Table 7.7: The maximum EV penetration threshold of the different subgrid components for best performing TOU scenario

The individual buildings' cables max load comes very close to the limit and thus there are only 8% additional EVs allowed to enter the system of the subgrid. The substation also has a slightly higher peak of 1.37 MW. For the map illustration, as shown before for the uncoordinated charging load, the results are exactly the same. The TOU DR strategy thus does not alleviate any load in these lower levels of the system and actually has a worse performance than the uncoordinated charging load. This shows that the scenario which is best for the overall distribution grid is not necessary the best for its lower levels. This disparity is quite concerning and means that designing scenarios for the system will be more challenging. However, if a more conservative approach is taken, like the scenario where the price-change time is 23:00 and the DR participation 50%, which still has a significant peak reduction as seen in figure 7.16, the impact on the subgrid is slightly different. That TOU scenario, which has a much lower DR participation and is sooner in the evening, does generate slightly better results for the subgrid, but only for the individual buildings. This can be seen in table 7.8 below. This scenario also generates a lower peak load on the substation, or 1.29 MW. It can thus be seen that by using other parameters for the TOU DR strategy, the effects on some of the components of the subgrid can be lowered.

	Distribution substation	Electricity streetboxes	Individual buildings' cables
Maximum EV penetration	43 %	18 %	119 %

Table 7.8: The maximum EV penetration threshold of the different subgrid components for more a more moderate TOU scenario

7.4. Scenario 3 - Direct load control

The second DR strategy, DLC, has much fewer scenarios than the TOU DR strategy. This is because this DR strategy does not have any specific settings. However, contrary to the TOU DR strategy, in the methodology of the DLC strategy, the EV penetration value is used. Therefore, there are different charging profiles generated based on varying EV penetration values inputted. This is because this DR strategy takes into account the primary load as well as the charging load of uncoordinated EVs to optimise the distribution of the load. As a result, there will be a slight difference between the performance of the strategy for different EV numbers. In this section, the results of the DLC modelling will be explained and guided by the same steps as before, first revealing the results of the charging behaviour itself, then assessing the impact on the top level of the distribution grid and then on its lower levels.

DLC load profiles

The simulations for the DLC DR strategy were based on the four EV penetration values. They were also explored with varying DR participation values. These two parameters are thus the only that affect the DR strategy. In figure 7.20 an overview of the different charging profiles can be seen with an incremental DR participation increase as visualised before with the TOU DR strategy. These scenarios are based on 50% EV penetration.

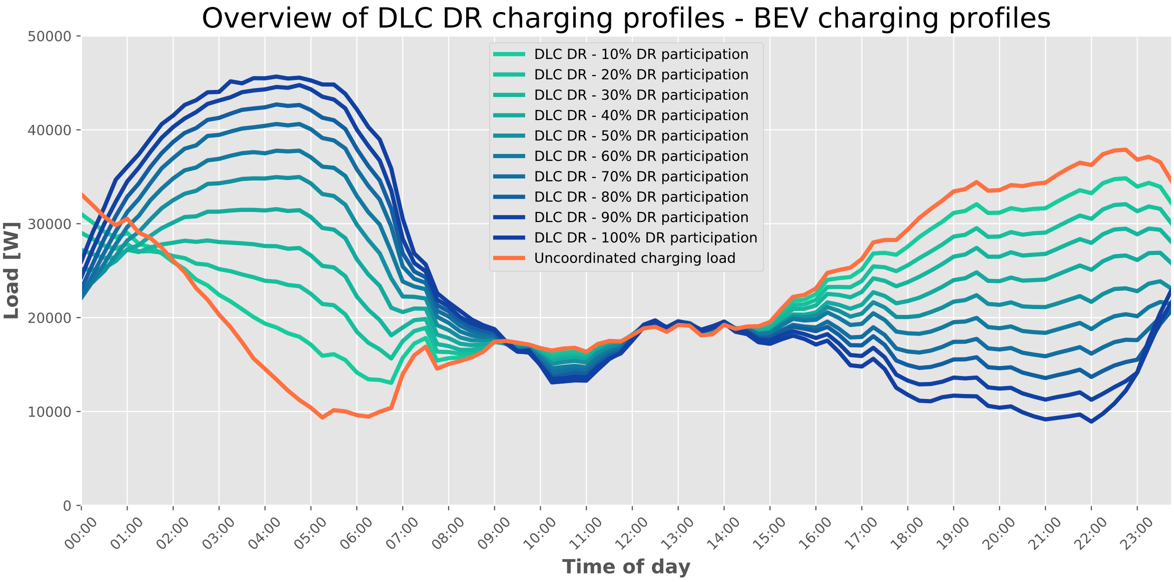


Figure 7.20: An overview of DLC charging profiles based on different participation levels

It can be seen that this strategy does not shift the charging profile in time but rather distributes them over the available time period. For participating EVs, certain sessions can be rearranged like this and the goal is to allocate the intervals of sessions to the time intervals where the primary load is the lowest. This minimises the overall impact on the distribution grid. What can also be seen in the figure is that the charging is mainly shifted to the nighttime, where the uncoordinated charging load is the lowest. This is also the time period when the primary load is the lowest, i.e. the valley of the night. Like the TOU DR strategy, which sessions can be allocated like this and the rules that applies to the methodology is mainly based on the assumptions behind this DR strategy, as discussed in section 4.5 and laid out in detail in the *Technical model implementation*, section 6.2.2.

Analysing the different charging profiles in figure 7.20, a few trends can be observed. First, it can be seen that the reduction of the load begins at 14:00. This is due to the methodology of the DR strategy, which as for the TOU DR strategy, only rearranges sessions after 14:00. From this time onwards, the load as distributed from the starting moment of the particular session until a certain time limit. This time limit is determined by the nearest charging session, trip or if both of those elements are later than 9:00 in the morning, that time, i.e. 9:00 is used as a limit. This is the reason for the sudden ramp-down of the profiles at 9:00. However, some sessions that begin after midnight can be arranged over a longer time period, if there are no conflicts with other sessions or trips as described before. This causes a small reduction in the charging profiles as can be seen from 9:00 to 12:00.

It can also be seen that the peak of these charging profiles happen during the night, which is where the lowest primary load is. This can be seen in figure 7.21. In the figure a DLC scenario based on 50% EV penetration and 50% DR participation is plotted. The former peak, based on the uncoordinated load is shaved off and spread evenly over the valley in the night, making a straight line. This is the strength of DLC, as it can distribute the load in an optimal way for the system.

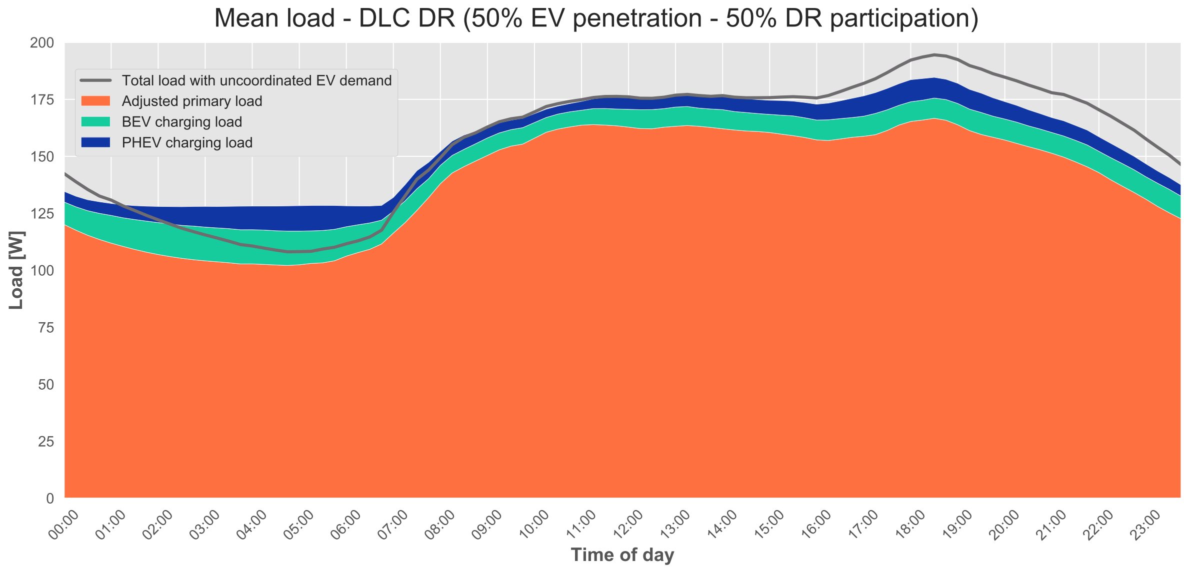


Figure 7.21: The combined load of the primary and the DLC charging load for the mean day based on 50% EV penetration and 50% DR participation

With varying EV penetration values, the arranging of the charging profiles differs slightly. A comparison of the DLC charging profiles with a 50% DR participation can be seen in figure 7.22. The overall trend is that with a higher EV penetration, the charging profile peak is lowered. This is because then there is more pre-existing charging load in the night, based on uncoordinated EVs, and the lowest system load intervals are therefore in slightly different places. With the 75% and 100% EV penetration the profile is smoother over the night, i.e. its peak is lower and more spread across the entire night.

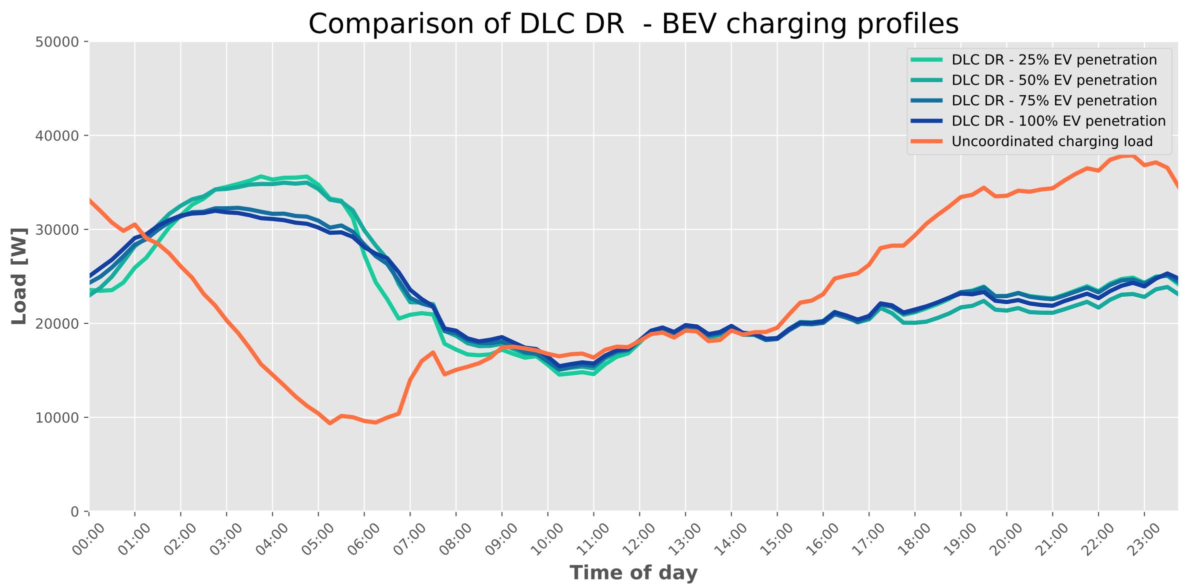


Figure 7.22: An overview of DLC charging profiles based on different EV penetration numbers

Overall system load impact

Based on the incremental DR participation and the four EV penetration values, there exist a number of scenarios for the DLC DR strategy. To see the performance of all of these scenarios, the peak reduction as presented earlier in the heatmaps, are visualised in a bar chart. This can be seen in figure 7.23 below. There are essentially four groups of scenarios, based on the four EV penetration values. For most of the scenario groups, the best performing one is the one with a 100% DR participation. This comes as no surprise, as this DR strategy is in a way more controlled than TOU and with a higher participation, the better is the minimisation of the overall system load. However, for the 100% EV penetration a 90% DR participation achieves the most peak reduction. This is probably due to the fact that the charging sessions can only be rearranged over a certain time period and with such a high EV penetration, the charging load during the night might become higher than the former peak during the evening if all EVs participate. This visualisation uses the same principle as the heatmaps, the colder the color, more peak reduction is achieved.

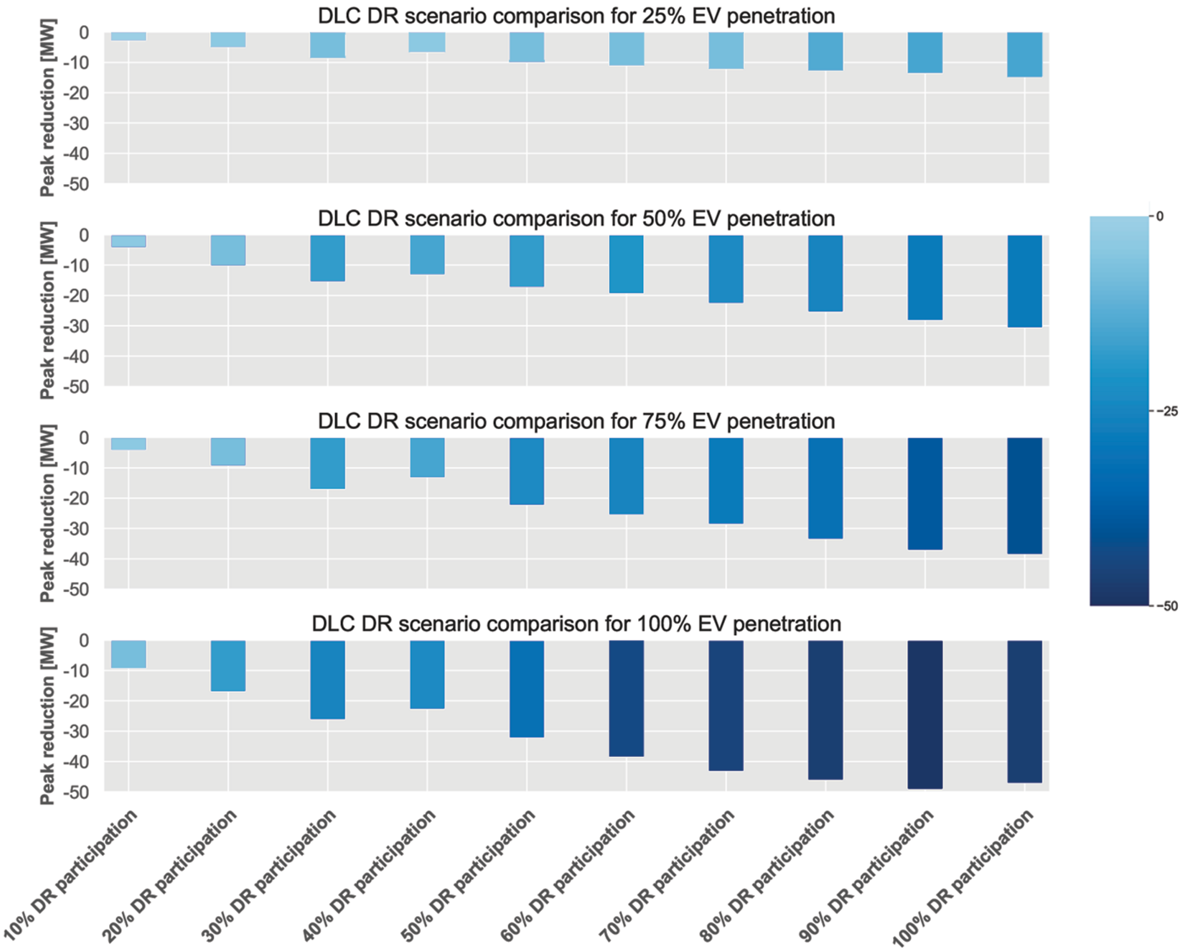


Figure 7.23: An overview of DLC peak reduction by scenarios for different EV penetration numbers

From these results, it can be seen that the peak reduction increases with increasing EV penetration. This was also the case for the TOU DR strategy. With more EVs the greater the reduction is. In the same way as was calculated for the TOU strategy, the system peaks can be calculated based on the best performing DLC scenarios for the four EV penetration values. These results can be seen in table 7.9. It is interesting to see that with an increasing EV penetration value the peak reduction increases. This resonates with the results presented earlier, that the benefit of this strategy increases with an increasing EV fleeet size.

	25 % EV penetration	50 % EV penetration	75 % EV penetration	100 % EV penetration
Best performing scenario peak load	224.8	238.7	260.5	285.0
Reduction based on uncoordinated load	6.2 %	11.4 %	12.8 %	14.7 %

Table 7.9: Overview of peak loads and best performing scenarios for DLC

To see how these favourable results are achieved, the peak load of the best performing scenario for the 50% EV penetration, based on 100% DR participation, can be visualised with KPI 2, the worst day of the year. This can be seen in figure 7.24. The former peak of the uncoordinated load is almost completely shaven off and only two small spikes remain. The rest of the charging load has been shifted into the valley during nighttime. It can also be observed that the charging load between 19:00 and 21:00 has almost completely gone. This is due to the minimisation effect of the strategy, as it allocates the charging so the overall load is minimised. The two remaining spikes are most likely built on charging sessions that do not fulfill shifting, i.e. charging sessions that are not the last ones of the day or sessions that have a trip or another session close to it. Compared to the uncoordinated charging, DLC DR really alleviates the charging load when it is needed. As can be seen in the figure, the uncoordinated charging load exceeded the system capacity, whereas the DLC distributes this peak load over the night and in return lowers the peak significantly.

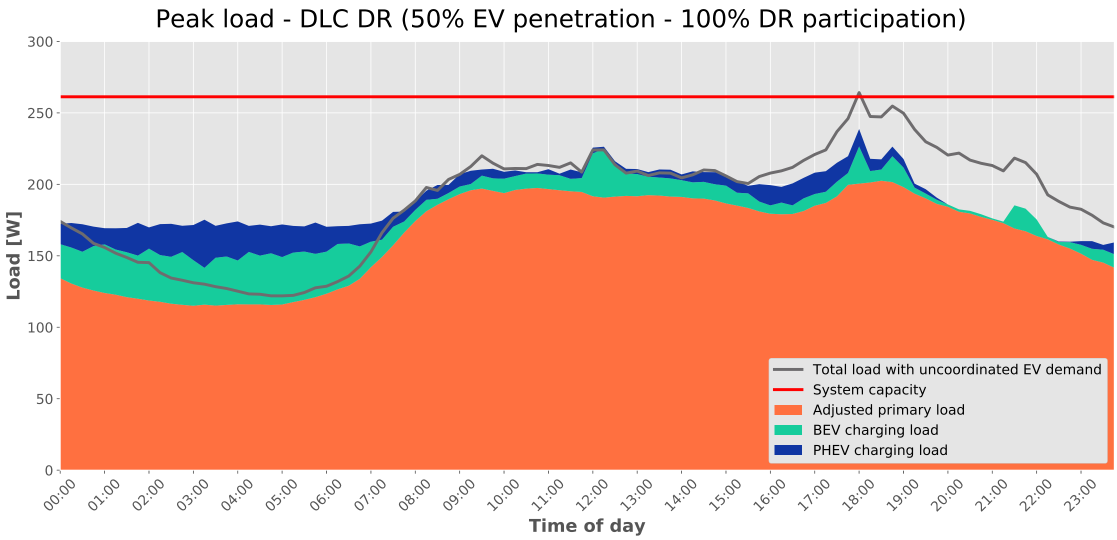


Figure 7.24: The combined load of the primary and the DLC charging load for the worst day based on 50% EV penetration and 100% DR participation

This can also be exemplified by finding the worst day of the uncoordinated load and seeing how the DLC DR srategy performs on that day. This is essentially KPI 2, but based on the worst day of the uncoordinated load instead of the DLC DR strategy. In figure 7.25 this can be seen, based on 75% EV penetration. It can be observed that on this worst day that the uncoordinated peak is nearly 300 MW. However, with the DLC DR strategy, this peak is completely gone and shifted over to the night. The two peaks of the uncoordinated load are completely gone and the highest system peak based on the DLC DR strategy is well under the system capacity. This shows how much DLC can actually increase the system utilisation, as on this day there is a difference of more than 60 MW difference between the uncoordinated and the DLC DR strategy.

The performance of the DLC strategy based on the most likely DR participation can also offer some insights. That participation level is 30% as explained in section 7.1.2 before. As seen in the overview of the scenarios in figure 7.20, this participation level achieves quite high peak reduction, compared to participation levels close to it. As was done for the TOU DR strategy, the maximum number of EVs that can be allowed into the system without exceeding its capacity can be determined for the DLC DR strategy. Based on the best performing scenario, this number is 99,276 EVs. This is a massive number and is just above 75% EV penetration. For the most likely scenario, based on 30% EV penetration, this number is 73,362 EVs.

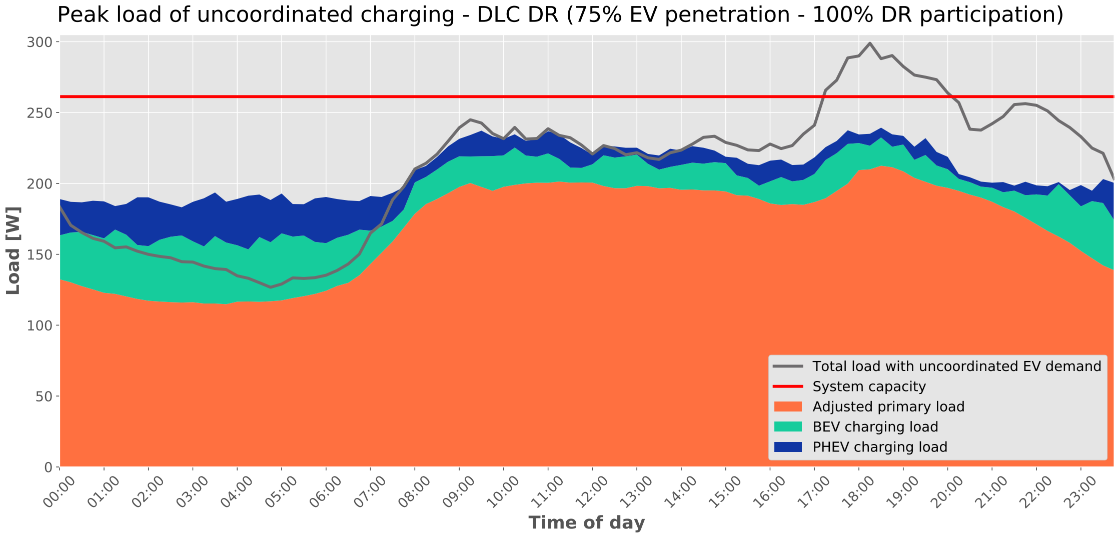


Figure 7.25: The combined load of the primary and the DLC charging load, based on 75% EV penetration and 100% DR participation, plotted for the worst day of the uncoordinated charging load

Subgrid load impact

To really see the effects of the DLC strategy, it must also be measured on the two lower levels of the distribution grid. It is desired to know how the performance of the DLC scenarios on the top level of the grid translate to the lower levels. This can also be compared to the performance of the TOU DR strategy and uncoordinated charging load on this subgrid level. To do this, the best performing strategy of DLC can be compared to the uncoordinated charging, the same way as was done for the TOU DR strategy. The results of using these charging profiles at a 100% EV penetration can be seen in figure 7.26, where the load peaks of the individual buildings in the subgrid can be seen.

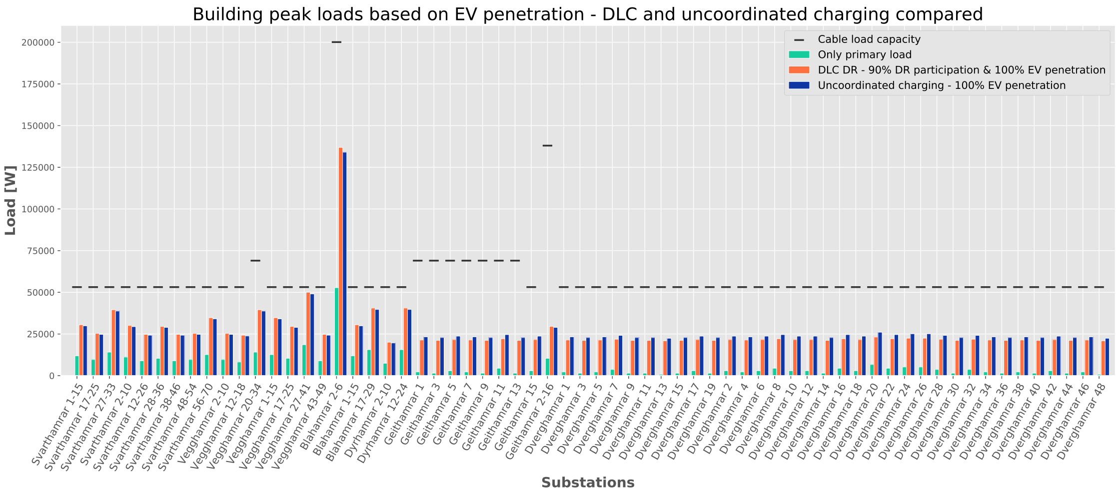


Figure 7.26: The individual building loads for the DLC and the uncoordinated charging

The DLC DR strategy achieves similar results when compared to the uncoordinated load. For the apartment buildings, the max building load is either the same or a bit higher. However, for the houses, the peak load is lower for all of them. Compared to the best performing TOU DR strategy, this thus has less effects on the subgrid. When this scenario of the DLC DR strategy is applied to the subgrid and its map is illustrated it again has the same results as the uncoordinated load based on a 100% EV penetration. That map illustration can be seen in figure 7.6. However, the load impact on the different components in the subgrid is different to the

TOU and the uncoordinated load. Again, the maximum EV penetration for the individual building cables is lower than for the uncoordinated peak and is actually the same value as for the TOU DR strategy. However, the distribution substation has a much higher maximum penetration value of 60%, which is considerably higher than the TOU and uncoordinated load scenarios. The substation peak is also much lower, at 1.07 MW. The maximum EV penetration levels of the components, as calculated before, can be found in table 7.10.

	Distribution substation	Electricity streetboxes	Individual buildings' cables
Maximum EV penetration	60 %	18 %	108 %

Table 7.10: The maximum EV penetration threshold of the different subgrid components for best performing DLC scenarios

Similar to the TOU DR strategy, another scenario of the DLC can also be explored in terms of the effects on the subgrid. Actually, it is relatively easy to explore the effects of all the DLC scenarios on these three components of the grid to further explore how different scenarios perform. This is because the DLC strategy has much fewer possible scenarios. A comparison of the DLC scenarios based on 100% EV penetration can be seen in the figures below.

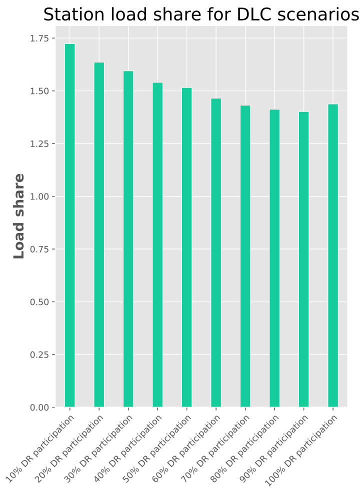


Figure 7.27: Overview of station load share by DLC scenarios

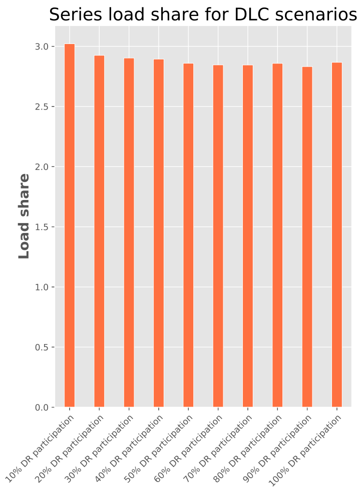


Figure 7.28: Overview of series load share by DLC scenarios

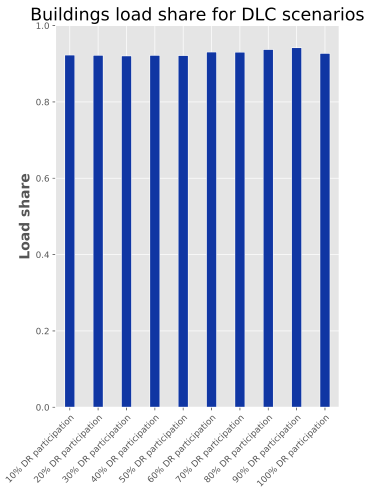


Figure 7.29: Overview of buildings load share by DLC scenarios

In these figures the effect is measured a load share on the components. For the station, this is simply done by finding the peak load of each scenario on the station and dividing it by the station's capacity. For the series and the buildings load, the maximum loading on each electricity streetbox or building is found per scenario. It can be seen that for the best performing DLC scenario based on the overall system level, which is 90% DR participation, the station load and the series load, i.e. the electricity streetboxes, are the lowest of all of the scenarios. However, for the building load, the load share of this best performing scenario is actually the highest. If another scenario is chosen, same as was done in the TOU section, the effects on the subgrid are somewhat different. Based on the scenario which achieves the lowest buildings load share, as seen in figure 7.29, which is based on 100% DR participation. The load impact of that scenario on the subgrid components can be seen in table 7.11.

	Distribution substation	Electricity streetboxes	Individual buildings' cables
Maximum EV penetration	51 %	18 %	119 %

Table 7.11: The maximum EV penetration threshold of the different subgrid components for best performing DLC scenario

This DLC scenario also minimises the system load just as the best performing DLC scenario, but now allows the same EV penetration based on the individual buildings' cables, but does that at a cost, as the substation peak is heightened to 1.1 MW and thus the maximum EV penetration of the station lowered. Based on these results it can be observed that choosing the best performing scenario for the subgrid level is challenging, as the impact on the different components varies between scenarios. It is also worthy to not that the impact on the electricity streetboxes however still remain the same for both these DLC scenarios and thus it is clear that there is a big bottleneck in the system there.

7.5. Scenario comparison

In this section the results of these three main load scenarios are summarised. Although there are different results based on the scenarios, some results can easily be compared. For the main assessment for the grid's overall system level, the peak loads based on the uncoordinated charging load as well as the two DR strategies can be seen in table 7.12.

		25 % EV penetration	50 % EV penetration	75 % EV penetration	100 % EV penetration
Uncoordinated load	**System peak load**	239.6	269.3	298.9	334.1
TOU DR peak reduction	**Best performing scenario**	5.3 %	9.9 %	10.8 %	12.2%
	Most likely scenario	2.0 %	3.6 %	3.2 %	4.6 %
DLC DR peak reduction	**Best performing scenario**	6.2 %	11.4 %	12.8 %	14.7%
	Most likely scenario	3.6 %	5.7 %	5.7 %	7.8 %

Table 7.12: Overview of peak reduction for DLC and TOU

The load peaks set by the uncoordinated charging are used as a benchmark, to which the TOU and DLC DR strategies can be compared. In the table, the reduction in percentage form is presented for both the best performing scenario and the most likely scenario, based on the estimated DR participation. That participation is 25% and 30% for TOU and DLC, respectively. For the best performing scenarios of the two DR strategies, DLC outperforms TOU for every EV penetration value. This is also the case for the most likely scenarios. Both of the DR strategies have an increasing proportional peak reduction with increasing EVs, based on the best performing scenarios. This essentially means that with more EVs, the strategies can reduce the overall system load more.

However, what is interesting to see for both the strategies is that this trend does not seem to apply to the most likely scenarios. For the TOU DR strategy, 75% EV penetration achieves lower proportional peak reduction than 50% EV penetration. For DLC, those scenarios achieve the same reduction, but the 100% EV penetration increases the reduction significantly. This is best explained by the fact that because these most likely scenarios have relatively low participation levels, they might not be able to reduce the main evening peak. As the size of the EV fleet dictates how big the main evening peak is, it can indeed happen that increasing the EV fleet size will worsen the performance as is the case for the most likely scenarios.

Another result from these load scenarios which can be used to compare them is KPI 7, the maximum number of EVs that can be allowed onto the grid without exceeding its capacity. This can be seen in figure 7.30.

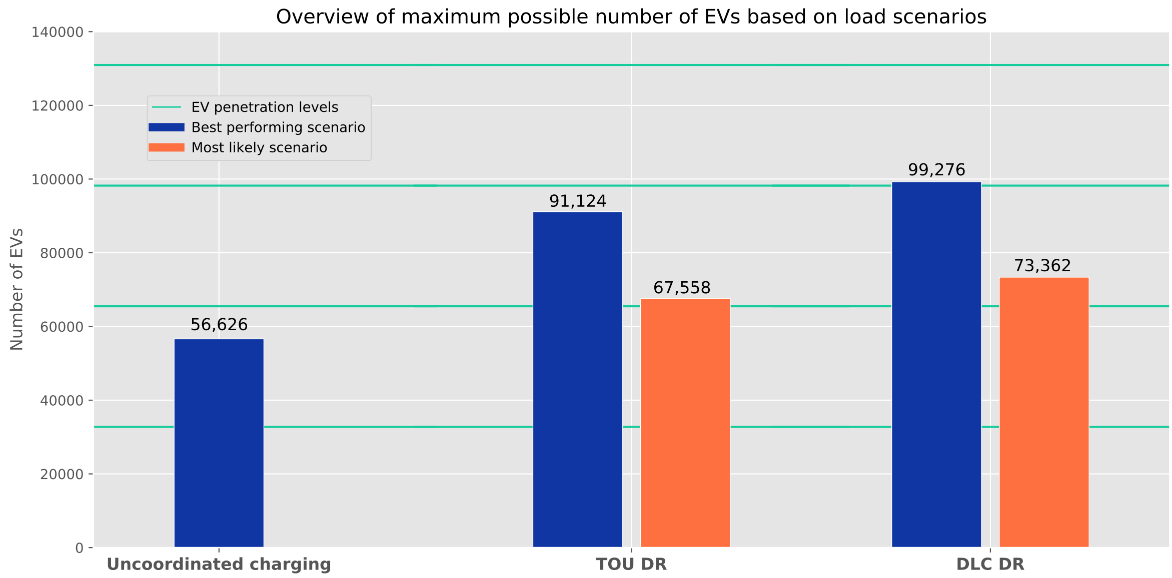


Figure 7.30: A comparison between maximum EV numbers based on the three main load scenarios

In the graph, the results for the best performing scenario as well as the likeliest scenario can be seen. The EV numbers of the four main EV penetration levels, 25%, 50%, 75% and 100% are also plotted to see how the performance of these scenarios compares with them. The maximum EV fleet size essentially indicates how many EVs can be allowed to enter the grid without having to upgrade the infrastructure at the highest level. The current system capacity is based on the capacity of the transformers in the high voltage substations, as was visualised in figure 5.6 on page 43.

For the uncoordinated charging load, where there is only one scenario, the maximum fleet size is significantly lower than the other scenarios based on the two DR strategies. That is the only scenario which has a maximum EV penetration value that is lower than 50% EV penetration as can be seen in the figure. For the TOU, the best performing strategy exceeds the estimated number of EVs in system of interest in 2030, as explained in section 7.1.1, which is 86,000. The TOU DR strategy thus allows almost 35 thousand more EVs to enter the distribution grid without exceeding its capacity with its best performing scenario. However, the DLC strategy can allow even more EVs to enter the system or 99,276, which is actually more than 75% EV penetration. For the most likely scenarios, based on the more moderate DR participation values, there are still improvements over the uncoordinated charging load. The TOU DR strategy allows just over 50% EV penetration and DLC around 5000 EVs more than TOU. From this it can thus be seen that the utilisation of the distribution grid can be heightened significantly by using the two DR strategies.

However, these EV numbers are based on the top level of the grid and do only offer measurements of the impact on that level. The load impact on the lower grid levels was also analysed by using a subgrid based on a distribution substation. There is an apparent bottleneck in this part of the system, as none of the scenarios were able to allow very high EV penetration in this part of the system. That is because the electricity streetboxes are a bottleneck as they are severely overloaded. The maximum EV penetration for each of three components in the subgrid can be seen in table 7.13. This is based on the best performing scenario on the overall system level for the two DR strategies and the uncoordinated load.

	Distribution substation	**Electricity streetboxes**	**Buildings' cables**	**Substation peak**
Uncoordinated charging	43 %	18 %	119 %	1.36 MW
TOU DR	43 %	18 %	108 %	1.37 MW
DLC DR	60 %	18 %	108 %	1.07 MW

Table 7.13: The maximum EV penetration threshold of the different subgrid components for the three main load scenarios

It can be seen that the effect of the load based on the TOU DR strategy is overall actually worse than the uncoordinated load with its best performing scenario based on the overall system level. However, when another TOU scenario is used, which relies on less DR participation and with a price-change time closer to midnight, similar results to the uncoordinated can be generated. However, for the DLC, the impact on the subgrid based on the best performing scenario offer significant improvements based on the substation load, but still performs worse than the uncoordinated load on the individual buildings' cables level. However, as that load share is over 100% in all scenarios, and thus does not pose a real problem to the grid integrity, the improved performance of the DLC strategy indeed makes it the best performing load scenario on this subgrid level.

In itself, the very low threshold of the most important connections in the subgrids, the station itself and the series connected streetboxes, is an interesting and concerning result. In the next chapter, these results will be explained and discussed. In that chapter the parts of the modelling process that need additional verification or reflection are discussed.

8 Discussion

In this chapter the findings of this research project will be summarised and discussed. They are both based on the overall research project as well as the modelling part of this project. Following those findings, the limitations of the research, mainly based on methodology and the use of data, will be discussed.

8.1. Findings

For this research project, numerous research activities were carried out. At the center of that process was a modelling and simulation methodology, to explore and evaluate the effects of large-scale EV charging on the distribution grid in the capital region in Iceland. Additional to that a literature review was conducted and background knowledge was gathered on the energy system and state of EVs in Iceland. In the two parts of this section, the general research findings will first be explained and then the findings based on the model use.

8.1.1. General research findings

The problem that this thesis tries to solve is one that is currently ongoing in many energy systems around the world. This was explained in the introduction; countries are in an effort to decarbonise their energy systems and other sectors, such as the transport sector. The general findings from this part were that EVs are increasing at an incredible rate and are slowly taking over as mainstream passenger cars in many regions. Iceland is a prime example of this, with very high EV sales numbers. Furthermore, due to increasing focus on international environmental agreements, conventional energy sources are being phased out. This makes the operation of power grids more challenging with intermittent sources and more variability. Electrification also impacts the grid and increases residential demand significantly. With the surge in EVs, this demand is further heightened which puts the distribution grids at risk.

Choosing Iceland as a case study was no coincidence as the circumstances there are somewhat unique. The small population of this big country is highly concentrated in the capital region, where two thirds of the population live (Statistics Iceland, 2020). Additionally, car ownership is incredibly high or 0.75 passenger vehicles per inhabitant (Statistics Iceland, n.d.) and most commuters travel by car as was illustrated in figure 5.2. These circumstances exaggerate the problem of EV charging load and the impact it can have on the distribution grid. In the *Energy system overview* section, the current congestion of power delivery to the distribution grid was shown. It is thus apparent that additional power demand, which increases load peaks in the system, will cause major problems for the distribution grid.

In section 2.2, the status of EVs and their development in Iceland was explained. Main findings were that in recent months the share of EVs of new car registrations has been higher than conventional cars and over the last three years or so there has been a surge in EV sales. This was visualised in figure 2.4. The Icelandic government has supported this increase with different types of incentives. These are mostly financial incentives, that make EVs more appealing to the public and more competitive in price compared to conventional cars. Furthermore, future plans have been announced that will inevitably support this growth even further. Undeniably the biggest one is that all new registrations of diesel and gasoline cars will be banned after 2030.

This regulation confirms the direction Iceland has taken in the energy transition in the road transport sector. This is why the prediction of the power-industry working group, as described before, is 145,440 EVs in 2030, which is more than 50% EV penetration.

Apart from these findings from the background research, the findings of the literature are important to note, as they also shaped the modelling methodology and thus the model findings. In the section on the *Literature findings*, they were explained in detail. The most important ones will be summarised. Not all DR strategies are relevant or applicable in Iceland. Some require specialised infrastructure while others require well functioning and complex spot energy markets with intra-day prices and even others use EVs to participate in the ancillary services market. Based on this, many of the strategies are not viable to implement in Iceland. That being said, the price-based programs could almost all be implemented, the exception being RTP, which often needs specialised infrastructure and is often times too dynamic for the residential consumer. Most of the incentive-based DR strategies however would be challenging, especially the market-based ones, while the two classical ones; curtailment and DLC, are a little bit less complicated. Those too need some infrastructure, smart metering and 2-way communication between consumer and DSO, but were deemed to be the most applicable and practical after TOU and the other price-based ones, which is the reason that DLC and TOU were chosen in the end.

8.1.2. Model findings

The findings of the modelling part of this thesis project are based on the results of the model simulations, as displayed and explained in Chapter 7. The results were split up into three main parts, based on the three main load scenarios that were modelled and simulated; uncoordinated charging, TOU DR and DLC DR. Furthermore, numerous simulations were done for each of these main scenarios, which generated many different charging scenarios. The best performing scenario as well as the most likely one were then analysed for two different levels of the distribution grid; the overall system level and on a subgrid level.

First, the state of the distribution grid without any EV charging can be discussed. Based on the system's capacity, there is only 44MW in additional slack on top of the current peak load without any EV charging load. Although the distribution grid in the capital region is quite small by international and European standards, this slack is concerning with the rate of increasing EVs. The result was that for an uncoordinated EV fleet, where no control is over the charging of consumers, the peak load of the system would be significantly increased by relatively few EVs. This is because the current charging profile has a high correlation with the primary load profile and thus exaggerates the system peak.

For the two DR strategies, the utilisation of the electrical infrastructure on the top system level can be greatly improved, as they reduce the peaks significantly compared to the uncoordinated load. The DLC strategy outperformed the TOU, which was expected, as it gives the DSO greater control over the load. A calculation of the maximum number of EVs that could be allowed into the system based on these load scenarios was done for both the overall system level and the subgrid level. For the overall system level, the uncoordinated load had only roughly 55,000 EVs, while the best performing scenario for the DLC load had nearly 100,000, which is more than 75% EV penetration. The TOU DR strategy allowed roughly 90,000 EVs. This means that by using DR strategies, more EVs can be allowed to enter the system without reinforcing the infrastructure on the top level. For the most likely scenarios, based on 25% and 30% DR participation for TOU and DLC respectively, the improvements were less but still offered a significant increase in EV numbers as was shown in figure 7.30.

However, the most important finding were the effects on the subgrid. First, for all of three different load scenarios, the effect was similar, in the way that the series connected electricity streetboxes could only handle 18% EV penetration without exceeding their capacity. Additionally, the maximum allowed EV penetration on the distribution substation itself was also relatively low and allowed 43% - 60% EV penetration. This is concerning as it is very different to the numbers that were measured on the top level of the grid. Secondly, the best performing DR scenarios on the top levels of the grid were not the best ones for the lower levels and sometimes actually had worse performance than uncoordinated charging. By exploring more scenarios of the two DR strategies better performance on the subgrid level could be achieved, but finding the scenario with the best performance for every component of the subgrid is challenging. This makes it challenging to implement both the DR strategies in reality as the approach has to be taken with all of the grid levels in mind. Determining the best overall scenario must be done both with a bottom-up and top-down approach. It is also concerning that there is a clear bottleneck on the subgrid level which is the electricity streetboxes.

Lastly, the viability of the results and the comparative nature of the two DR strategies can be discussed. The findings of the model results is very much based on a comparison between the three main load scenarios. The DR strategies are both compared to the uncoordinated charging load and to each other. Therefore, analysing the fairness of that comparison can also impact the model findings. In this thesis project, these two DR strategies were conceptualised in a certain way, based on available inputs, assumptions and the modellers understanding of the system. This was done in the *Conceptual model* chapter. In this conceptualisation process, the fairness of the performance between the two DR strategies was kept in mind. This was mainly done with the modelling constraints, which ensure that the charging behaviour of users is respected and that the performance of the two DR strategies is presented as realistically as possible. Based on this, it can be said that the representation of the two DR strategies is as accurate as they can be based on the available data and also that their performance can be compared on an even ground, as they are both based on exactly the same objectives and constraints.

However, it should also be noted that the the two DR strategies are formulated in a certain way. As discussed before in this thesis, there exist many different implementations of these strategies, which might perform better or worse. The implementation of the strategies in this project were done to have them be as realistic as possible and in a way that they would be implemented in real life. That being said, the TOU strategy was done in a very simplistic matter, using only one price-change time. The strategy could be improved by using multiple price-change times which would reduce secondary peaks and distribute the load shifting better. As the results of the TOU strategy are very close to the DLC results, with this improved version of TOU it might possibly be better than the DLC strategy. That version however is one that is much harder to implement realistically, both in technical terms and in terms of energy equality between consumers and thus the other simplified version was chosen.

8.1.3. Comparison to other case studies

The results of the model can also be compared to other similar cases to gather some insights into the soundness of the model. That is done by comparing the model results with cases that use either the two chosen DR strategies or measure the load impact of EVs. Beginning with the load impact of EV charging, the buildup of peaks of EV charging when combined with the primary load, i.e. high correlation and a high additive effect was also observed by (Hoog et al., 2015; Z. Wang & Paranjape, 2014; Zhang et al., 2012) as can be seen in the figures of the respective papers. According to those cases, the peak load of EV charging lands at nearly the exactly same time as the peak of the primary load, which is the same result as was obtained from this thesis project. For the comparison of results for the two DR strategies, the articles and papers explored in the literature review conducted in this thesis project were mainly looked at. That is because they are based on more similar circumstances and settings as the case study of the thesis.

For the use of TOU DR, there exist many variations and possible implementations. To compare the results of other cases, studies which use settings which are as close as possible to the ones that were explored in this project were desired. Furthermore, when comparing the results, it is hard to compare exact numeric results. Instead, the main findings and shape of charging profiles can be used. In the article of (Zhang et al., 2012), a single TOU tariff was used, where the price-change time was set to midnight. The results showed that the charging load over the day is shifted until that time and results in a profile that has a secondary peak at midnight and then gradually decreases until the morning, almost flattening out at 7 in the morning, which results in a decrease in the overall system peak. This is very similar to the results of the thesis project. (Z. Wang & Paranjape, 2014) used a similar TOU price structure, where the price from 23:00 - 6:00 was lower then the rest of day, with a peak pricing from 17:00 - 22:00 also. With that, the system peak was lowered substantially when the majority of the charging load was shifted to the night. However, the profile shape was a bit different as it was not as a gradual decrease from the lower price period, but a more stable profile over the nighttime which then lowered into the morning. But again, very comparable results.

(Hoog et al., 2015) researched TOU based on off-peak pricing between 23:00 - 7:00. With the use of that strategy, there was a significant reduction of the system peak and the main peak was shaved off and the charging load spread throughout the night. The results were that EV penetration levels could be significantly increased with TOU DR and the impact on the distribution grid greatly minimised. For the uncoordinated charging scenario in that study, network failures were observed around EV penetration levels of 10-15% (Hoog et al., 2015, p. 263). This is very close to the 18% maximum EV penetration of the electricity streetboxes in the case study of this thesis. However, for the TOU strategy, this seemed to not be the case in the study whereas this 18% penetration value was consistent with all DR strategy scenarios explored in the thesis project. This underlines the significance of the bottleneck of this part of the distribution grid in the capital region of Iceland.

For the DLC strategy, there are less case studies that could be found. Direct load control also has arguably more variations and thus harder to find a similar case to compare to. Many studies also depend on specialised management systems like HEMS or day-ahead forecasting which was not the case in this thesis project. In the article of (Shao et al., 2011), direct load control was implemented based on the priorities and preferences of consumers. This was done on a fairly small scale with only a couple of EVs. The results were that the DR strategy decrease the charging peak load but oddly enough the shifting of the load profile was not to the nighttime or to the most optimal times for the distribution grid but inside the peak hours. The reductions were not very significant but still offered better performance than uncoordinated charging. Another DLC example is (Afzalan & Jazizadeh, 2019), where shifting and curtailment of consumer loads were explored. They found that with only a 20% DR participation, significant demand reduction and reduced peaks.

(Dupont et al., 2014) researched scheduling of appliances and BEVs, by optimising the consumption patterns with a holistic model approach which also takes generation into account. For the scheduling of EV load, mobility patterns were taken into account, just as was done in this thesis project. The results from that study were that EV charging load was mainly distributed over the nighttime and the charging load peaks were reduced, mainly at noon and during peak time in the evenings, and during those times, the EV charging load could be reduced completely to zero. This is also very similar to the DLC results, where at some peak times the charging load was almost completely reduced, as showcased in figure 7.24 between 19:00 and 22:00 for example.

Overall, the results of this thesis project align well with results from similar cases or research projects where DR with EVs is carried out. Finding the exact same setup of the two DR strategies is very challenging, but finding similar outcome directions and findings is sufficient to compare the results on the fundamental levels. Based on these comparisons as described before, the strengths and uniqueness of the thesis project can also be identified. First, it is the fact that two different strategies were modelled for the same case study and under very similar circumstances. Most of the reviewed literature research either one type of DR strategy or very similar ones. Secondly, the range of scenarios that was explored seems to be more extensive than many other cases, as multiple participation levels were explored, as well as different EV penetrations and price-change times for TOU. This makes the analysis very strong and able to give more insights into the performance of these two strategies with different settings. Thirdly, the coherence and holistic approach towards the performance of the scenarios on all levels of the distribution grid, as well as comparing most likely scenarios of them both makes the research outcomes more meaningful for real life applications.

8.2. Limitations

In this section the various limitations of this research project are explained and discussed. These limitations affect the results and findings and mainly come from the main methodology of the research, the conceptual model that was created and its technical implementation. In order to generate the model results, numerous assumptions and simplifications had to be made as well as choices on how to implement certain elements.

8.2.1. Reflection on modelling assumptions

In the formulation process for the conceptual model, a number of simplifications and assumptions were identified. In sections 4.5 & 4.6, they were motivated and explained in detail and their predicted impacts on the modelling process as well as the results were discussed. In this section, the simplifications and the main assumptions will be reflected on.

The two main simplifications, which are based on how the distribution grid is represented in the model and then how the DR strategies are implemented, can be seen as the two biggest implementation choices, which many of the fifteen subsequently identified assumptions build on. The first one is that the grid is presented in a two-step process. First on the upper level, where the data is quite sufficient and then on the lower levels, where the data is extremely limited and thus these lower levels are based on only one substation out of roughly 900. This simplification was made to be able to measure the impact on these lower levels in some way, and this was seen as the best way to do so. However, this means that the results on this subgrid level are very limited and must be taken caution. The sensitivity of this factor in the modelling the results is thus very high, as if any other subgrid had been taken, the results would be completely different. That being said, this limitation can be reduced if the results are used only to compare the three main load scenarios, as was done in the summary of the results in section 7.5.

For the second main simplification, which states that the characteristics of charging sessions that were affected by the two modelled DR strategies cannot be changed or manipulated, there are also some consequences for the results. In reality, these two DR strategies would exhibit different charging sessions than uncoordinated charging, probably with higher charging power and longer duration when the price is more favourable for the consumer and shorter sessions when it is not. The predicted impact that this has on the modelling outputs is thus that it might make the DR strategies undervalued when it comes to their performance in shifting the load. However, this simplification was also made in order to minimise the number of assumptions that had to be made for the two distinct DR strategies. In a way this restricted both of them but also meant that they are modelled with the same starting conditions and rules and minimises the specialised, detailed assumptions that would have been inevitable if sessions could have been manipulated more. For the sensitivity of this and how it would affect the results is hard to analyse, but most likely this worsens the performance of the DR strategies slightly.

For the modelling assumptions, presented in section 4.6 in the conceptualisation chapter, both main and minor assumptions were identified. In this section, only the main ones will be reflected on as the minor do not have a very big effect on the model of project outcomes. They are most often a result of other assumptions or made to deal with input inconsistencies and minor elements in the technical model implementation.

For the base modelling assumptions, the impact is mostly how the EV fleet itself is represented. The composition of EV subgroups are assumed to be the same as in the study, as there is no other information on that available. The same for the BEV and PHEV composition, which is assumed to be equal in all simulated scenarios. This affects the results and presents them based on these assumptions. For the latter element, its sensitivity on the results is significant as BEVs and PHEVs have slightly different charging profiles. This was explained shortly in section 5.1.2. This might also be motivation for future work, to explore the composition of the fleet. The effects of Assumption # 2 on the results - which reduces the primary load based on EV numbers - was already explained, as it lowered the primary load peak by roughly 5 MW. This affects the results, but was thoroughly explained. The last assumption that applies to the base is the validity of the results which was carried out in a separate subsection in 6.1.1. The results of that will be discussed separately later in this chapter in section 8.2.2.

For both the TOU and DLC based assumptions, #5 - #10, the impacts and sensitivity already discussed for simplification two apply. These assumptions were made to make these strategies more comparable in terms of performance and subsequently the results of the modelling of them should be evaluated with these strategy-specific settings in mind. The sensitivity of this element in the modelling is incredibly high, as if any of these assumptions would be different, the generated results would undoubtedly be very different. However, as there is no correct way to implement those strategies, the results still have great value and can generate insights for the audience of this thesis project, as long as the implementation of the DR strategies is clear.

Lastly, the assumptions for the grid impact modelling, are probably the ones that have the most sensitivity to the results. The overall system assumption, that the grid capacity is defined by the N-1 rule is based on the recommendation from the DSO. On this assumption, and this capacity limit of roughly 261 MW many of the results are based, e.g. the number of EVs that can be allowed onto the grid without exceeding its capacity. A simple check of this sensitivity for the this result can be done based on a more aggressive approach to this capacity limit as explained on page 43, where only two of the biggest stations have to use the N-1 rule, meaning a capacity limit of 395 MW. Based on that number, all of the EV numbers determined in the results would be entirely different, and the load for the uncoordinated charging with 100% EV penetration would be well under the capacity, compared to exceeding it by a lot when using the chosen approach. However, energy market players or researchers that have different opinions can essentially determine their own capacity and interpret the results based on that, and this might also be motivation for some future research. For the last assumptions, which all apply to the subgrid formulation and impact determination, the assumptions based on simplification one mostly cover it. This is the part of the modelling which utilises the most assumptions and is the least robust, as the sample of only one station is a tiny part of the total of 900. However, as mentioned before, using that station on a comparative basis for the scenarios will take some of that inaccuracy away.

8.2.2. Model validity

Based on the modelling assumptions and methodology, some validation of the steps and techniques is desired. However, as mentioned before in the technical model chapter, only a small part of the technical modelling can be validated. This validation process for the base modelling was reflected in modelling constraint number three; **the variability and heterogeneity of charging behaviour of EV consumers must be taken into account and validated**. Setting this constraint on the validity of this part of the modelling process was done in order to make sure that this step had some accuracy, as most of the subsequent modelling steps build on it.

The validation method that was used was both supported by industry experts and literature and relies on coincidence factor. It should showcase how well the relatively small EV fleet that was used, 121 EVs, captures variability in charging and thus, how well it can represent a much larger fleet, like was done in the modelling steps. The validation steps are laid out in section 6.1.1. The main approach was to observe this coincidence factor and how it develops with an increasing sample size. This development of the factor almost follows an exponential curve, as it very quickly drops from 1.0 to around 0.1 and then seems to flatten out and almost stagnate. For the 100th EV, when 100 EVs are used to represent the EV fleet, the factor value is 0.0584 and for all of the EVS, 121, the factor value is 0.0547. That is thus less than 0,02% change for each additional EV added to the sample size. However, it could be expected that this factor approaches the limit zero with increasing cars. This is though not entirely correct. As this factor is based on actual EV values, there is in theory a minimum factor value which would never be 0, and probably significantly higher than that. With a bigger sample size used in this project, a 1,000 EVs or 10,000, the accuracy would of course be improved but it is unlikely that a dataset like the one that was used will ever have such a big sample size, especially in Iceland.

Although the performance of the validation method cannot be validated in itself, it is deemed sufficient as the desired performance of the factor development was shown. The change for the last EVs added was very minimal. By using a EV-specific dataset from Iceland, the results are far more accurate than using trip data and international datasets to approach the charging power based on that, which has been the case in many research project and case studies. Based on that and the favourable result from the validation steps, this limitation of the modelling project can still generate accurate and insightful results.

As said before, the base modelling steps were the only ones that were properly validated, as methods to validate other steps are scarce. However, much like the validation for the base modelling, one of the modelling constraints puts a requirement on the accuracy of the two DR strategy modelling steps. This is constraint four; **The annual total charging load of a given EV-fleet must be equal under any charging scenario**. Although not a validation method in itself, this ensures that the shifting of the sessions is done correctly and that the charging load profiles are not manipulated. This was calculated for both the TOU and DLC DR methodologies and presented in the technical model chapter. Here it will shortly be reflected upon. For the TOU, when comparing the annual total charging load of all of the EVs between the uncoordinated base model and any TOU model based on different price changing hours, the difference in total charging load was about 0.4 %.

For the DLC however, it was much less and almost non-existent (2e-14 %) which can be considered to be zero as such a small difference comes from calculation methods in the programming language. For the DLC, the difference is thus truly negligible. The TOU however has a more moderate difference. To reflect on this, the modelling steps were considered and examined in terms of a slight error that might cause such a difference. That was nowhere to be found and so this difference is unexplained. Although this is an important constraint, the other constraints and modelling objectives were also kept in mind for both of the strategies and based on those, the methodology of shifting sessions for TOU was also checked and they are carried out with high accuracy. However, somewhere in the over four million cells of each time-series output, there seems to be a calculation error, most likely due to faulty or missing data, which produces this difference. But as the methodology of the TOU DR strategy is correctly done, which is the main goal of the DR modelling, this difference does not make a very big difference to the results, especially when over 100 scenarios are explored like was done in the results chapter. Therefore, this was considered negligible.

Lastly, there is another approach which can be used to approach a verification or validation of the model. That is by reflecting on how adaptive the model is in terms of applying it to other cases. By using the model with other datasets for other countries, cities or cases, the results could be compared and some insights into its validity be observed. To reflect on the ease of adapting the model, the whole modelling process must be looked at. As has been explained before, the main model formulation is centered around a conceptual model, which is then used to implement a technical model. The conceptual model can thus be viewed as a guide towards the technical, more detailed model which is based on specific data and properties of each case. That is why the conceptual model does translate over to other cases and countries but the technical model does not necessary do so. Adapting the model to other cases would thus require a new technical implementation every time, but could be based on the conceptual model steps and properties. This modelling process is a big strength of the project and makes it possible to validate the model if used for other cases.

8.2.3. DR modelling iterations

The methodology of the modelling for both the DR strategies uses randomly selected EVs when DR participation is lower than 100%. Randomness always requires iterations, but determining how many will be sufficient can be challenging. In the technical modelling chapter, the setup of the used iterations was explained but 10 iterations are used for both the DLC and the TOU DR strategies. Over these 10 iterations, the mean was calculated and used for the results. There is no need for iterations in any other part of the modelling process, as no randomness is used. In this section, two things will be discussed; first why 10 iterations were chosen and subsequently determined to be sufficient and second, how using the mean based on those iterations affects the results.

For both of the DR strategy modelling parts, which were implemented as functions in Python, it required numerous runs to generate the results. For a single run for the DLC DR strategy, based on 100% DR participation, the run time was close to four minutes to run. For the TOU DR strategy, again with full DR participation, the run time was about two and half minutes. Additional to that, the data outputted in each run is a full time-series load model with over four million cells of data. Based on this, 10 iterations were chosen as a moderate approach towards introducing variability but still maintaining ease of analysis in terms of runtime and processing of the model. This was also reflected by the number of EVs that can actually be selected, which is 121 in total.

For an "average scenario", with 50% DR participation, this means there are 60 cars that can be selected. This was also taken into account when choosing the number of iterations to use. If a much higher number is chosen, 100 for example, the outputs of the modelling would be much larger and the runtime increased. This would also mean that the number of iterations are higher than the actual pool of EVs that can be selected and thus might be too extensive. Based on the performance of the 10 iterations compared to the example of a 100 iterations, which will be shown and analysed later in this section, it was deemed that 10 iterations would suffice which drastically reduced the required runtime and improved ease of analysis. To put this into perspective, using a 100 iterations to produce all scenarios for only the TOU DR strategy, the total runtime would be more than 200 hours.

To determine how well the chosen number of iterations would capture the variability of the random EV selection, a few comparative measurements were calculated for these two iteration values. First, an average scenario was chosen for both the DLC and TOU DR strategy. This was based on 50% DR participation and a price-change time of 23:00 for TOU DR. Then this scenario was run with both 10 and 100 iterations and the results compared. In the same way that was done in the results using KPI 1, the average day was calculated. This is done by finding the mean value of a certain interval over the entire year. This both produces the profile which is used in many of the modelling KPIs and offers a visual representation of the iteration comparison. This mean profile can thus easily be compared based on 10 or 100 iterations. The standard deviation of the iteration runs can also be calculated, on an interval level. Additionally, the spread, which is the highest and lowest value of any iteration for a certain interval calculation can also be observed. Together, these three metrics, mean, standard deviation and spread can be used to compare the two iteration numbers. Starting with the visual representation of the iteration runs, the individual runs as well as the mean for DLC can be seen in figures 8.2 & 8.2 below. As the BEV and PHEV are aggregated separately in the modelling methodology, as described before, those profiles are calculated separately. In these figures, the BEV profile is used, which is the aggregate charging profile of all of the BEVs, both shifted and non-shifted.

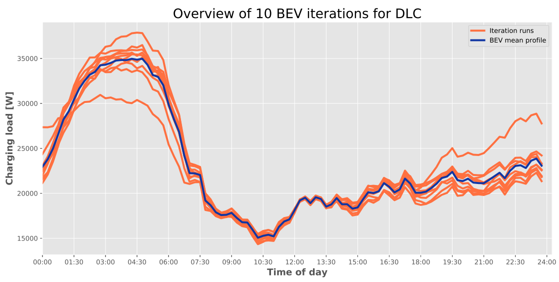


Figure 8.1: A visual representation of 10 iterations for DLC BEV

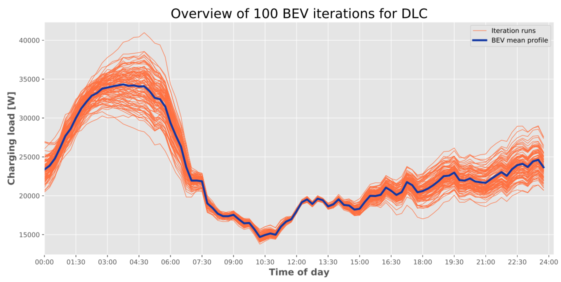


Figure 8.2: A visual representation of 100 iterations for DLC BEV

What can be seen is that the mean profiles are very similar and seem to be situated well in the middle of the iteration results. However, for the 10 iterations, there is one iteration that produces results that are quite far from the rest, which can also be seen in the 100 iterations, with some iterations values quite far from the dense area around the mean. To dive deeper and explore the three metrics as described before, visualising the results is best. This can be seen in figures 8.3 & 8.4. The mean values are plotted as a line and the standard deviation is represented as a shaded area around the mean as well as the spread which is a darker color. These graphs thus show the three metrics together. It is however important to note that the distribution of the charging profile is assumed to be symmetrical around the mean. This means that the standard deviation range would also be symmetrical around the mean, i.e. $(-\sigma, +\sigma)$ as seen in the figure. However, this might not always be case which could skew the standard deviation range in either way.

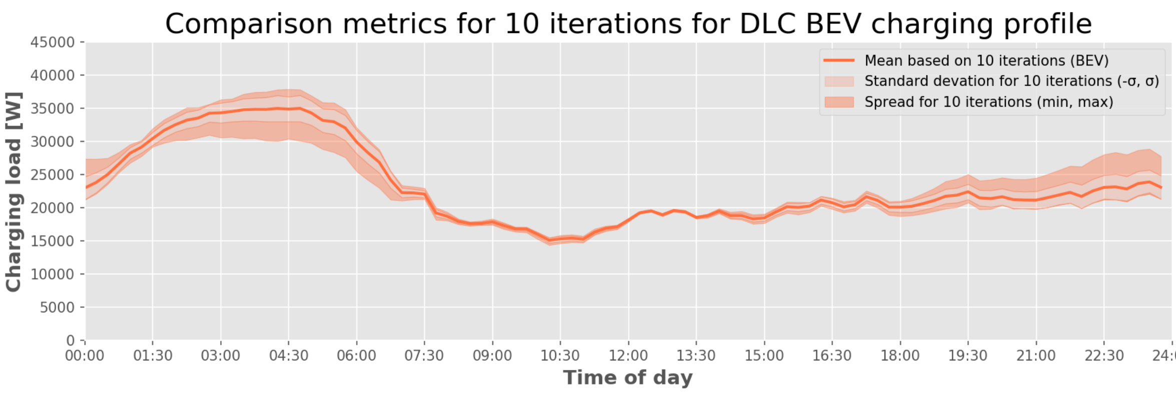


Figure 8.3: The mean, standard deviation and spread of the DLC BEV profile based on 10 iterations

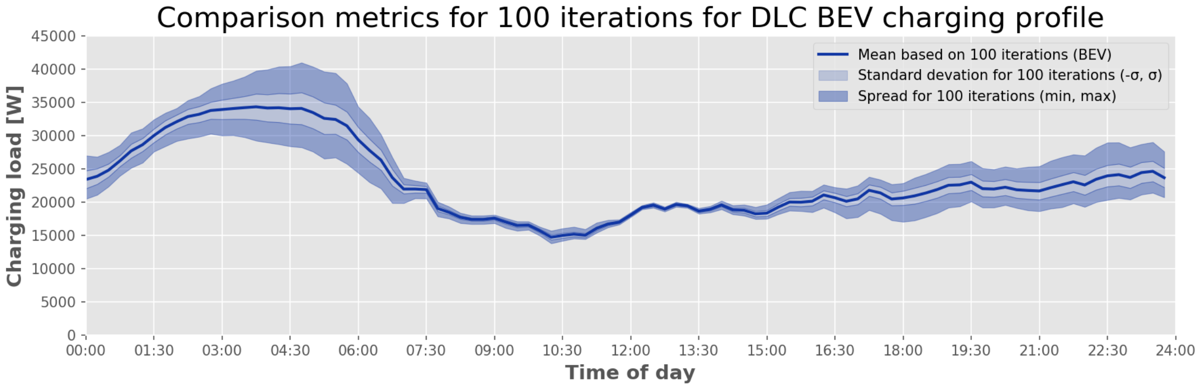


Figure 8.4: The mean, standard deviation and spread of the DLC BEV profile based on 100 iterations

It can be seen that for the daily charging profile, the standard deviation and the spread is the smallest when the least of the rearranging occurs, during the day and the evenings, and the highest over the night when the most shifting and rearranging occurs. It can also be seen that the standard deviation is very similar for the two profiles and does not change very much between 10 and 100 iterations. However, the spread does increase substantially, which is based on the absolute minimum and maximum values over the different iterations. The standard deviation gives a better indication of the actual values as it represents how much all of the different iterations differ from the mean value. The spread is solely determined by the extreme values which happen very rarely. To properly compare the two profiles, the mean with the standard deviation range can be visualised together to see the differences. This can be seen in figure 8.5.

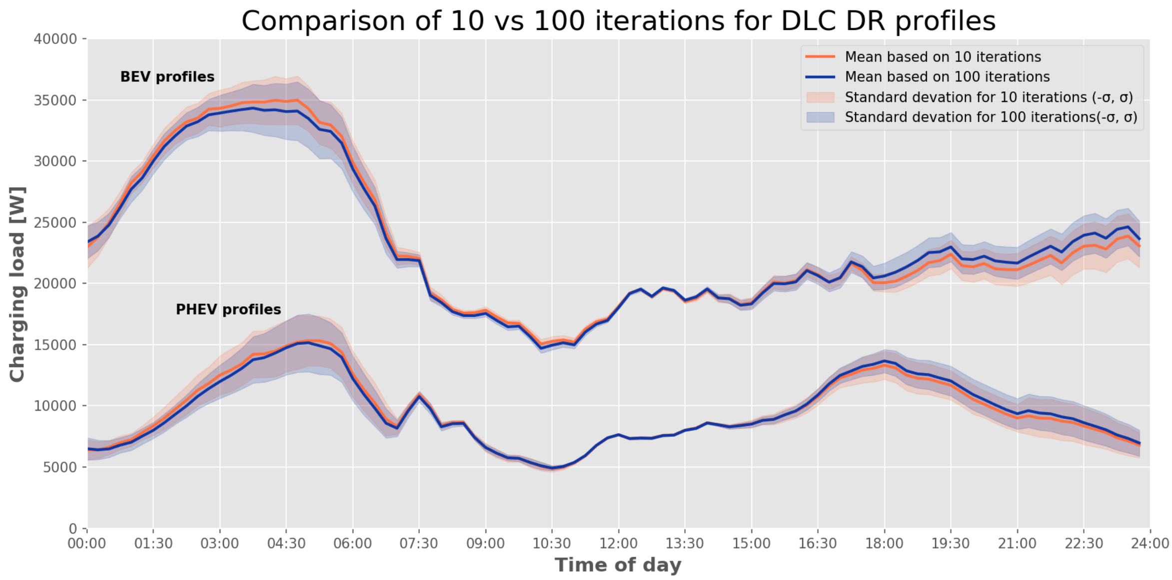


Figure 8.5: A comparison of iteration performance for DLC

In this graph the mean profiles for both the BEV and the PHEV aggregates can be seen. The PHEV profiles are the lower lines as indicated in the figure. It can be seen for both the BEV and the PHEV profiles that the mean values based on 10 and 100 iterations are quite close. The standard deviation ranges can also be seen and are very similar. For the PHEV profiles the difference is smaller than the BEV ones, which is probably due to the fact that the BEVs are actually fewer overall and thus the aggregate load is lower. The full graphs of the three metrics for the PHEV profiles as shown before for the BEV profiles can be found in Appendix A.3.

This visual representation shows how well the 10 iterations manage to capture the variability of the random selection as it achieves very similar results when compared to the 100 iterations. For this mean daily charging profile, there is a 1.9% difference in the peak load for the BEV profile and 1.1% difference for the PHEV.

Considering that most of the modelling process is highly sensitive due to numerous assumptions and simplifications, this approach of using 10 iterations is deemed accurate enough. However, this skews the results in some way, as the peak charging loads will be slightly higher than if more iterations would be used.

The same was done for the TOU DR strategy, but that showed even smaller differences than DLC for all of the three metrics. The full graphs of the metrics for both iteration setups, 10 and 100, for BEV and PHEV separately, can be found in Appendix A.3. To see the differences for the TOU DR strategy the BEV and PHEV profiles were visualised as was done earlier for the DLC DR strategy. This can be seen in figure 8.6.

It can be seen that the mean profiles are extremely close and the standard deviation ranges also are even more similar than for the DLC strategy. That is most likely due to the fact that DLC can have more variability in terms of its profiles, as it can rearrange charging intervals over a large period, whereas TOU is more structured and focused. For this mean daily charging profile, the differences are even smaller and come out to about a 0.2% difference in the peak load for the BEV profile and 0.8% difference for the PHEV.

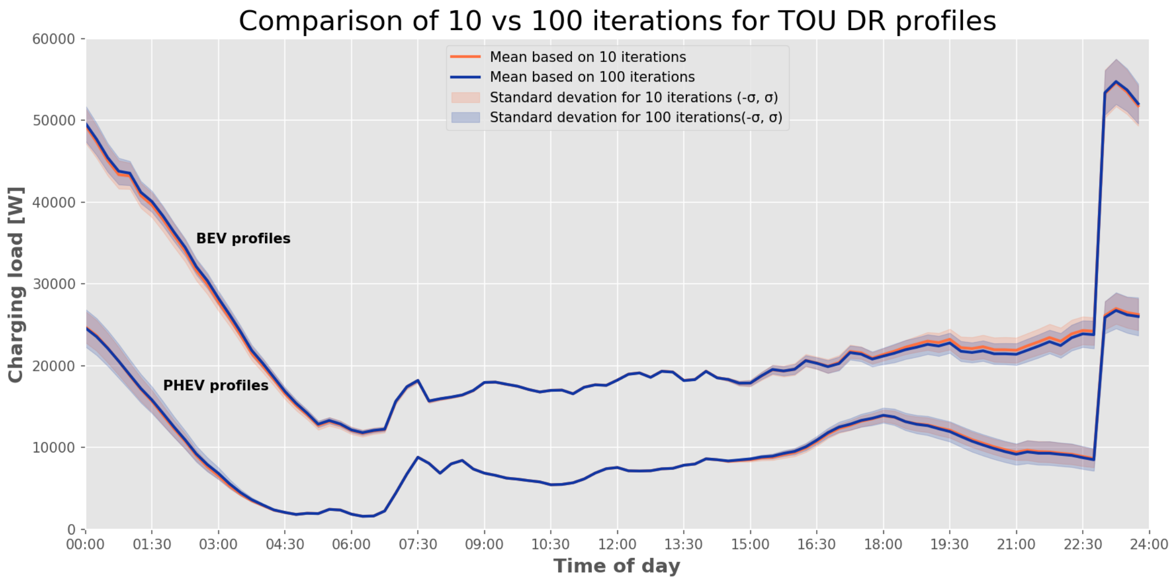


Figure 8.6: A comparison of iteration performance for TOU

Lastly, how the use of these mean values as presented above affects the results will now be discussed. As most of the results are based on KPIs, which were defined in 6.1.2, the outputs of the modelling scenarios based on these iterations can indeed have an effect on those results. Since many of these KPIs are visual, using graphs to illustrate the effects of charging load on the distribution grid, using the mean value alone was deemed to be the best way. This is because these visual KPIs are stacked demand plots and using shaded areas with the profiles as was done in this section, with the standard deviation and the spread, would have made those graphs hard to read and analyse. This would have made those modelling KPIs much less effective. Therefore, only the mean values are presented in the results chapter. However, in Appendix A.2, additional values of most of the displayed results from the results chapter can be seen.

Additionally for the numeric KPIs, this was also the approach, i.e. showing only one mean value, but not all of the outputs from the different iterations. This was for example done in in the heatmaps visualising the 100 different scenarios for the TOU DR strategy. Showing the range of the iteration results would have been very hard for those KPIs and made the results and subsequent analyses less effective. However, using the mean is in itself a simplification, but one that is necessary to make in order to conclude on the results.

9
Conclusion

In this chapter the outcomes of the thesis project will be concluded on. First the research questions will be answered and then a reflection on the project and its relevance will be presented.

9.1. Main research question

In the beginning of this thesis, multiple research questions were formulated, which motivate the research. The main research question comes from the identified knowledge gap as explained before, grounded both in practicality and academics. From this question, several sub-research questions are derived. In this section, this main research question is first answered and then the sub-research questions one by one. This main research question is:

How can demand response strategies be used to coordinate the charging of a large EV-fleet to reduce the load impact on Iceland's capital distribution grid?

In the question itself, the goal of the research can be seen; to reduce the load impact. That is what was done in this thesis project, i.e. show that DR strategies can indeed lower the grid impact on the distribution grid. By using those strategies the charging load profile of a large EV fleet can be shifted from the times where it adds the most to the peak and shift or spread it across hours where the load is minimised. This coordination can be done with various DR strategies but two were selected based on their applicability. Both offer significant reductions in peak load and thus lowered grid impact in its optimal implementation. Participation of consumers is a big factor in the performance of these strategies and for likely participation levels the benefit is still considerable, but much less than the best versions of these strategies. Reducing the load impact on the lower levels of the distribution grid is more challenging than at the top level and where DLC DR is the preferred option. The other strategy that can be used to coordinate this load is TOU, which has certain drawbacks as it often produces large secondary peaks. This is the case on the lower levels. Additionally, DLC offered more peak reduction on all levels of the grid. Therefore, DLC can best coordinate and reduce the load impact of a large EV-fleet.

9.1.1. Sub-research questions

The main research question can be dissected into a few smaller questions, that together make it possible to answer it. These sub-research questions are answered in detail throughout this thesis but will be summarised here, as well as referring to the part in which the full answers can be found.

What is the current state of EVs and EV related policies in Iceland?

This question explores how big of a problem the EV increase in Iceland is and gathers some insight into the possible future state of the problem. That was answered in a dedicated section of this thesis; section 2.2. The current state of EVs in Iceland is that they are increasing rapidly. Iceland is second only to Norway in share of EVs sold and major incentives and regulations put in place by the government will only increase this growth further. Additionally, charging stations and infrastructural developments for the public charging grid are ongoing. Iceland's characteristics, i.e. the high car ownership share and commuting habits, also heightens the impact of large-scale charging on the distribution grid. Additionally, the characteristics of the capital region make the impact on the lowest level of the distribution grid greater. The public charging grid is quite limited, most people have access to private parking and so the majority of users charge their EVs at home, which is illustrated by the relatively lower mean charging power as seen in table 5.3. This means prolonged charging sessions which exaggerates the problem at the lowest levels of the grid as the results have shown.

What kind of DR strategies are applicable to utilise a large EV-fleet as a DR resource in Iceland?
This question is part of the information and data gathering stage of this research project, along with the first sub-research question. A literature review was conducted for this thesis, partly to elicit and confirm the knowledge gap but mostly to explore DR strategies that can be applied to the EV fleet in Iceland. From this literature review it became clear that ten strategies are most commonly used. They are presented in figure 3.2 on page 15. Out of these strategies, most can be used to treat EVs as the load that is shifted or reduced. However, some are better than others and especially when taking the characteristics of the focus of this research project, the Icelandic capital grid, into account. Based on that it became clear that in general, price-based programs are more applicable in Iceland than incentive-based. Out of the incentive-based ones, classical are the more viable option. However, some of the price-based are also hard to implement. In the end, two were selected to be modelled in for the project, one price-based and one incentive-based. The argumentation for ultimately selecting the two - and rejecting others - was the ease of implementation based on market characteristics and specialised infrastructure. These choices were also supported by industry experts.

How can EV load effects on the distribution grid be measured?
This question is the start of the modelling process and makes up most of the model conceptualisation process. To measure the effects of EV load, information and data is needed. Grid capacity data was gathered from various sources and was explained in detail in section 5.3. However, limited data on the lowest level of the grid made this process challenging. To evaluate the load effects on the distribution grid, a combination of metrics for the overall system level as well as a snapshot of the lower levels, based on one subgrid, were used. Representing the overall system capacity were the high voltage distribution stations, seen in figure 5.6. Representing the lower levels was one distribution substation and all the connected buildings to it. By gathering information on the electrical infrastructure in this subgrid and determining cable capacity, the charging load on this subgrid could be mapped out. This was conceptualised in the conceptual model formulation and subsequently implemented in the technical model, namely section 6.3.2. With this formulation the load effects of the different scenarios of the modelling could be evaluated.

How can the effect of different demand response strategies be assessed and modelled?
This question covers the main model formulation process. To assess the effect of the two chosen DR strategies, they had to be modelled. As has been explained before, the main research approach in this thesis project is a modelling and simulation approach. However, creating the model that does the simulations is a very important step. This was done by using a conceptual model methodology, which is essentially the process of deciding what to include in the model and what to leave out. This process uses a few main elements; identifying the problem situation, determining modelling objectives and constraints, defining inputs and outputs and determining the model content and identifying the assumptions and simplifications. This formulation process is the main methodology of this thesis project and is carried out in chapter 4. Based on this conceptual model required data can be acquired and then it is implemented in a programming language. With that technical model, the different demand response strategies can be assessed and outputs and results generated. The limitations of the model however must be reflected upon and taken into account when analysing the results, as was done earlier in this thesis.

How does EV charging affect the distribution grid under different DR scenarios?
This last sub-research question is answered with the use of the created model. The *Results* chapter answers this question extensively and those results are then discussed in the *Model findings* section. Charging of a large EV fleet affects the distribution grid the most if the load is uncoordinated. With the two DR strategies, this load impact can be reduced and the peak load of that additional demand can be greatly lowered. Of the two DR strategies, DLC works better in this reduction and allows for a much better utilisation of the electricity infrastructure on the overall system level. However, EV charging does affect the lower levels of the distribution grid much more than the top levels. The threshold of the different components on this level is lower, especially cables between electricity streetboxes and the distribution substations themselves. The individual building cables, at the very lowest level, seem to have sufficient capacity.

9.2. Reflection

In this section, the thesis project as a whole will be reflected on. This is done by discussing the relevance of the research outcomes, both from an academic perspective as well as a practical and societal perspective. Recommendations for the audience of this thesis project is offered and future work and improvements are discussed. Lastly, a personal reflection is included.

9.2.1. Academic relevance

In this thesis project, modelling and simulation techniques were used to model the behaviour of a large EV-fleet and simulate different DR strategies. A literature review was conducted to develop an academic knowledge gap. The identified gap was mainly that *it is not known how large-scale EV charging affects the distribution grid and what DR strategies should be used to minimise the negative impacts.* The literature review and the identified gap can also be used to place the research within the literature. Iceland has many unique characteristics, such as very high EV penetration, high car ownership and a high share of RES. For countries and cases with similar characteristics, the research outcomes contribute to the applicability and ability of DR to reduce the load impact of EV charging. Moreover, the contribution is significant as it uses historic EV-specific charging data, but in many cases, this is not available and the charging load is thus approached in some other, less accurate way.

The strength of this project academically is also that it models two distinct DR strategies and applies it to the same case study. This makes for a very good understanding on the performance of each of those and with well documented assumptions, the results can contribute to future research of those strategies. As shown in the literature findings, most of the reviewed literature focused either on one strategy or one type of strategy, i.e. incentive-based or price-based. The comparative approach of the two strategies can be used to identify which approach works better for a certain implementation, given the context of this research project. The holistic approach towards the grid impact, on three different voltage levels is also relevant to this field of research. Comparing the peak reduction performance of strategies on the high-voltage level and the residential low-voltage level gives new insights into the disparity that can be in that performance. The strategies that work best for the overall load reduction, might not be best overall. This too contributes to the existing body of research in this field and might make future analyses more robust.

In section 8.2.2, how easy it would be to adapt the model for other cases was discussed. The capability of the conceptual model to translate over to other cases was considered quite high and seen as a possible way to validate the model. The model formulation can thus be seen as a contribution to the research field of demand response. Furthermore, by positioning the results of the model use and comparing it to other cases, the academic relevance is also illustrated. This was also carried out in section 8.2.2 and the results of the model use and thus this thesis project compare nicely to other similar works.

9.2.2. Practical & societal relevance

This thesis project was carried out in loose cooperation with Veitur, a DSO active in the capital region. Additionally, the dataset used for the behaviour of the EV fleet was acquired from Samorka, the association of the electricity industry, district heating, waterworks and sewage utilities in Iceland for research purposes. Therefore, the practical relevance of the project is also important.

First of all, modelling the EV fleet provides valuable insight into how Icelandic EV users behave and interact with the distribution grid. This gives industry experts and other stakeholders information that has not been available before and can be used to formulate approaches towards infrastructure development, reinforcements and other ways to react to increasing EV growth. Secondly, the simulations of the DR strategies give insight into how such strategies can be implemented and what the benefit might be. By simulating numerous scenarios, based on different EV numbers and participation of consumers, the results can be used to estimate performance of the strategies based on the audience's own prediction of these parameters. Never before have DR strategies for EVs been researched in Iceland, in this detail and with the used data. The outcomes of this research can thus be used as a guide towards future decision-making on DR strategies.

Reflecting on the societal relevance of the project, it becomes clear that the outcomes can indeed aid greatly in the reduction of emissions in Iceland and for other cases. By allowing more EVs to enter the distribution grid with the use of DR strategies, as was showcased in the results, the growth of EVs can be supported. This growth is vital for the country to achieve its goals in emissions reduction and environmental agreements. It is truly a social welfare maximising solution, as it can increase EV numbers and increase the utilisation of the distribution grid. The cost of implementing these DR strategies is hard to estimate, but the cost of inaction might be even greater.

9.2.3. Recommendations

Based on the research findings and their relevance to the DSO and the practical implementation of the two DR strategies, some recommendations can be given. First, what the model results and the research findings really mean can be explained and then based on that, what should be done can be recommended. First of all, the findings of the model have shown that large-scale EV charging is truly a problem that cannot be ignored as it has a large impact on the distribution grid. Secondly, it tells the DSO and other industry experts that there is a disparity between the threshold of EV penetration on the top level of the system and the lower levels of the system. The lower levels are much more constrained. To put this into perspective, based on the model results on the subgrid level, a total of five major cables were severely overloaded, as illustrated in figure 7.6. These five cables are dug into the ground and have a total combined length of 430 meters (Reykjavik City, n.d.). The number of distribution substations like the one that forms this subgrid are over 900 and thus nearly 5000 cables would have to be replaced meaning nearly 400 kilometres of cables would have to be dug up and replaced, based on the length from this specific subgrid. It is thus evident that this is a real problem. Third, the research findings showed that DR strategies can significantly lower the load impact on the distribution grid, especially on the top level.

To act on the findings of the research several recommendations can be provided. The first would be to look at the possibility of implementing either one of the DR strategies explored in this project or other ones. Even though the lower levels of the grid are very constrained, with and without DR, the benefit on the top level and for other components of the subgrid are undeniable. It is easier to implement TOU as it only requires smart metering infrastructure, which is being rolled out in Iceland in coming years. Even for lower participation levels, like the most likely participation, significant benefits are present that allow for much more EVs to enter the system. So for the recommendations on implementing the DR strategies, it would be best to start with TOU as it is easier, and then when the technical level of the infrastructure catches on, when all of the distribution grid is based on smart metering and two-way communication between consumer charging stations and the DSO, DLC could be implemented. As the best performing scenarios for TOU do not depend on complete participation levels, starting with that strategy would also be optimal as it would most likely take some time to get a high participation from consumers.

Moving forward, there are essentially two pathways that can be taken. The first is to just reinforce the infrastructure as problems arise and have no active coordination over charging load. The other option is to implement either one of the strategies and taking an active approach to dealing with increasing charging load. This could be done as said before first with TOU in a cost-efficient and simple manner which could offer significant improvements over uncoordinated charging. The best way to implement would be to start a few pilot projects based on different subgrids and learn from their differences. This way, the best performing scenarios for either of the two DR strategies could be found and also be based on variations of TOU as described before. Many factors affect how well the subgrids can be expected to handle EV load, such as their topology, type of buildings and construction date. The subgrid that was explored in this project was mainly built in the late 80s and can thus be viewed as an average representation of a subgrid in the capital region. Implementing DR in any form will always lower the load impact and increase the utilisation of the distribution grid. According to the result findings the possible benefits are more on the top level, but will also provide improvements on the lower levels, especially when looking at other subgrids. To conclude, DR will require less reinforcement of the grid and later and most likely be a less costly option long term.

9.2.4. Future work

Based on these contributions and the positioning of the thesis project within academics and in practicality, future work and research can be identified. It is mainly focused on improvements of different elements of the research project but also on the practical implementation of the DR strategies.

The modelling of the two strategies could be improved with more time and additional data. For the TOU DR strategy it would especially be interesting to have multiple price-change times for the EV fleet which is being coordinated. This could be based on zip-codes, house numbers or any other way, but it would most likely greatly reduce the secondary peaking effect of TOU, which is its biggest drawback. This could for example be done by assigning one share of the participating cars in one area to one 15-minute interval, and the next one to the next interval and so-forth in a step-wise approach, or it could randomise it for every single car. Based on the effects that TOU had on the lower grid levels, it would be advised to have different price-change times in the same household or street, so multiple cars would not generate a peak. It could also be done randomly for all of the participating EVs every single day to approach even load shifting. However, in this process, the energy equality of consumers must be taken into account. By improving the TOU in this way, it could most likely improve its results significantly. For the DLC DR strategy, there was only shifting and rearranging of the sessions in time, but not curtailment of the charging power. Including curtailment could also generate different results and would be interesting to simulate and analyse.

How the EV fleet is represented in the model could also be motivation for future work. As explained earlier, the composition of the EV fleet, i.e. how many PHEVs and BEVs from family homes, businesses or apartment buildings were assumed to be the same as the EV study dataset for the aggregation profiles for BEV and PHEV. Data on this could not be found, but would greatly improve the accuracy of the modelled EV-fleet. Additionally, predictions into how the future EV fleet will be composed of in terms of share of BEVs and PHEVs could also make the simulation outputs more accurate.

For the distribution grid impact determination, the lower levels of the grid were quite limited. Gathering data for more stations and carrying out the same steps would be very beneficial as it could give a much better indication of the actual effects on these levels. As the impact on the lower levels of the grid is only based on the one distribution substation, it is hard to know if the effects are exaggerated or conservative. Additionally, mapping out the system in a better way, connecting the three levels together more holistically, could deepen the grid analysis. This could be done by finding out how many distribution substations belong to each of the high voltage substations and thus analysing each high voltage substations individually. To do this, additional information and data would be needed.

Lastly, as future recommendations of improving the project itself have been summarised, some guidance on how to act on the results and implement the DR strategies in real life can be discussed. To better predict the DR participation, an Icelandic study could be conducted aimed at EV users. This is fairly simple but can improve the estimation on the most likely scenario. To test out the validity of the results of the research, pilot projects could be deployed in parts of the grid where the infrastructure allows it, i.e. the technical capability. Pilot projects for both DLC and TOU could provide real load data and could then be compared to the simulated profiles. This could indicate how well the strategies would work realistically for a larger EV-fleet.

9.2.5. Personal reflection

The last part of this thesis project is the reflection of the researcher. This thesis is the final step in obtaining a Master of Science in Complex Systems Engineering & Management (CoSEM) from the TPM faculty at Delft University of Technology. The research process has been both challenging and rewarding. It has taught me so much about energy systems, in Iceland and in general and how to model and simulate them. It was also a process that improved my modelling skills in Python, writing thousands of lines of code and simulating hundreds of different scenarios. The courses in CoSEM provided a strong background for a project like this, where modelling and energy systems came together. I think approaching the problem of this thesis with a CoSEM methodology greatly improved the analyses and the results. The energy field is so fascinating to me and this project was a fantastic opportunity to really dive into a subject that is important to me.

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A

Appendices

In this section, the various appendices that contain additional or complementary information to the main content can be found.

A.1. Literature review

In the table below, the full search string for the structured literature search that was conducted by using the online database Scopus can be seen:

Outer Operator	Inner Operator	Keyword
TITLE:	-	("demand response")
AND TITLE-ABS:	-	(("EV" OR "electric vehicle")
AND NOT	-	(microgrid*
	OR	"micro-grid"
	OR	"V2G"
	OR	"V2H"
	OR	"V2N"))

Table A.1: Search string for the structured part of the literature search

A.2. Extended results

In this section some of the results that were displayed and discussed in the *Results* chapter are extended by showing the standard deviation and spread of those results. As explained earlier in the results for the uncoordinated charging, section 7.2, there are no iterations for that load scenario and thus no need for extended results. Therefore, the extended results presented in this appendix are only for the results of the two DR strategies. The results that were displayed and laid out in the results sections for those strategies will be extended here and lastly summarised and compared.

A.2.1. TOU DR extended results

For the first result that is displayed in the TOU results section, there is no need for an extension, as that is based on a 100% DR participation. This means that there are no iterations needed. This is always the case for both of the DR strategies, if there is full participation there is only one possibility of selecting the EVs, as they are all selected.

However in the second graph, figure 7.8, the participation levels are explored and thus the results are based on iterations. In figure A.1 below, that same graph can be seen but with the standard deviation and the spread, i.e. the minimum and maximum values over the 10 iterations. This was done by finding the mean daily profile over the year for all of the iterations as was done in the main results section and then finding the standard deviation and spread. For the different profiles, the light shaded area around the plotted lines represents the standard deviation and the dark shaded area represents the spread.

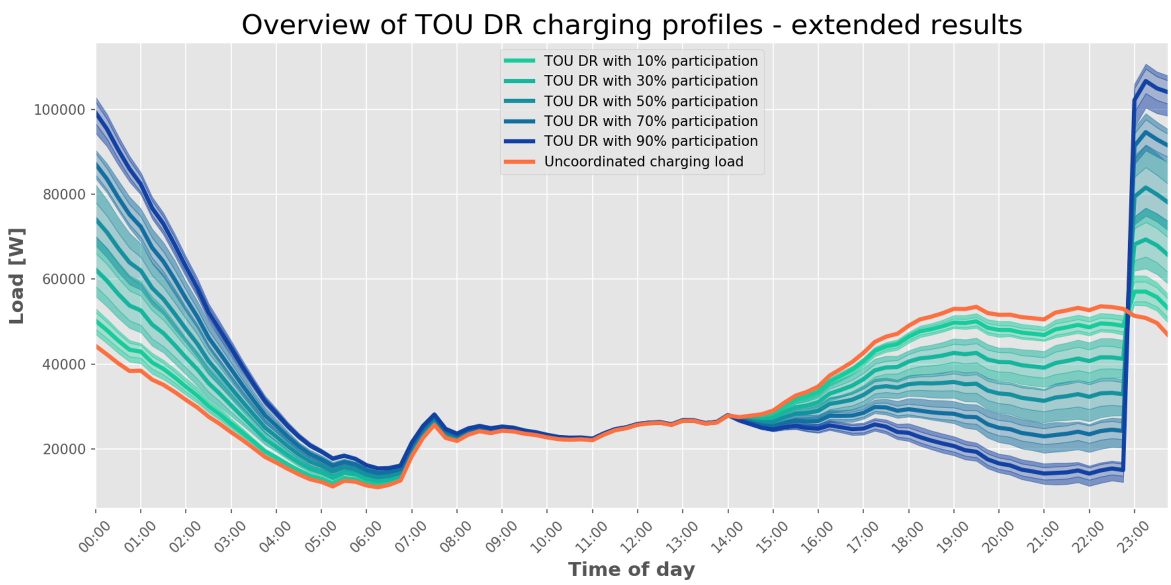

Figure A.1: An overview of a few TOU charging profiles based on different participation levels with extended results

A few chosen participation levels are displayed as with all of them the visualisation would become hard to read and analyse. The shaded areas around each mean profile essentially shows the range of the results and where they land. The standard deviation gives the best indication of the overall iterations as it takes into account the values of all of the iterations. The spread shows the extreme values of the iterations. What is interesting to see is that the range of results is the smallest when the DR participation is either very low or very high. For the 10% DR participation, the range is very small, as there are so few EVs selected. The same goes for the 90% DR participation, where most of the EVs are selected, the range is also quite small as the differences are small because almost all of the EVs are selected in every iteration. For the participation levels in between there are more possibilities for variance and thus the standard deviation and spread is much larger.

To see this range of results from the iterations, the stacked plots can be used as in KPIs 1 and 2. In figure A.2, the mean load of TOU DR with 50% DR participation and based on 50% EV penetration can be seen. This is essentially figure 7.9 from the results chapter. It is important to note that now the charging load is not displayed separately for the BEV and the PHEV profiles but both together as charging load. The range of iterations is also combined, so the standard deviation of the BEV and the PHEV are added to together, and so is the spread. This makes it possible to effectively see the range of iterations results for the modelling.

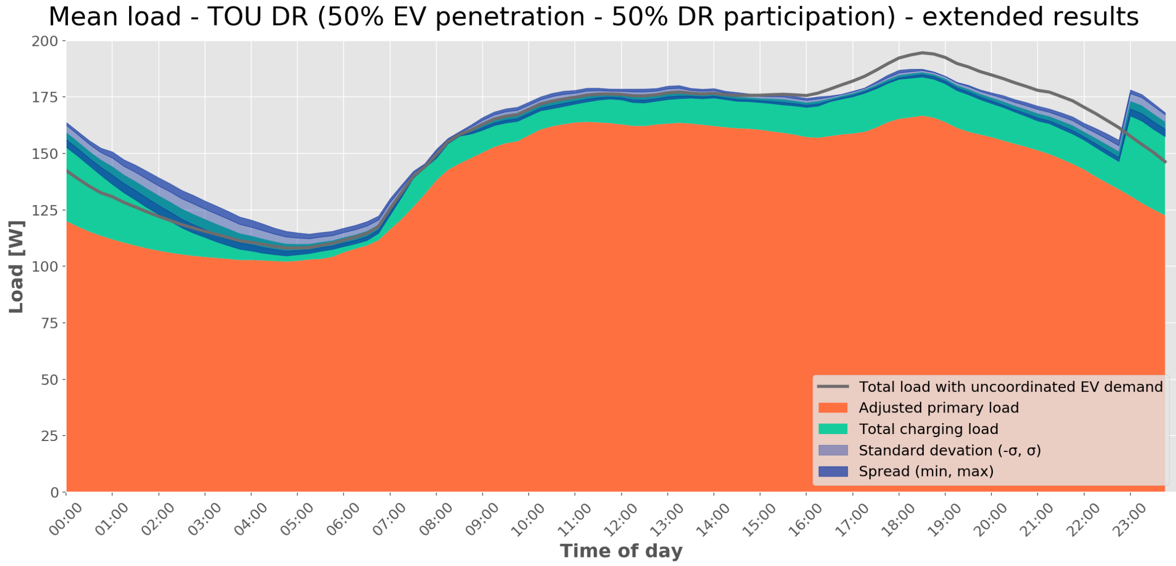

Figure A.2: The combined load of the primary and the TOU charging load for the mean day based on 50% EV penetration and 50% DR participation with extended results

This can be seen in the figure, where the charging load is now in the greener color and the range of the iterations results in the blue shades. What is interesting to see, is that the spread and standard deviation range increases when the sessions are actually shifted. Over the nighttime the range is much bigger than during the day when much less shifting occurs.

Overall system load impact

Going over to the overall system load impact, the first result that was displayed was based on the same scenario as before, i.e. 50% EV penetration and 50% DR participation. However, that figure was based on the peak of the uncoordinated load, to show the effects of TOU DR when combined with the primary load. That figure from the main results chapter with the extended results, can be seen in figure A.3.

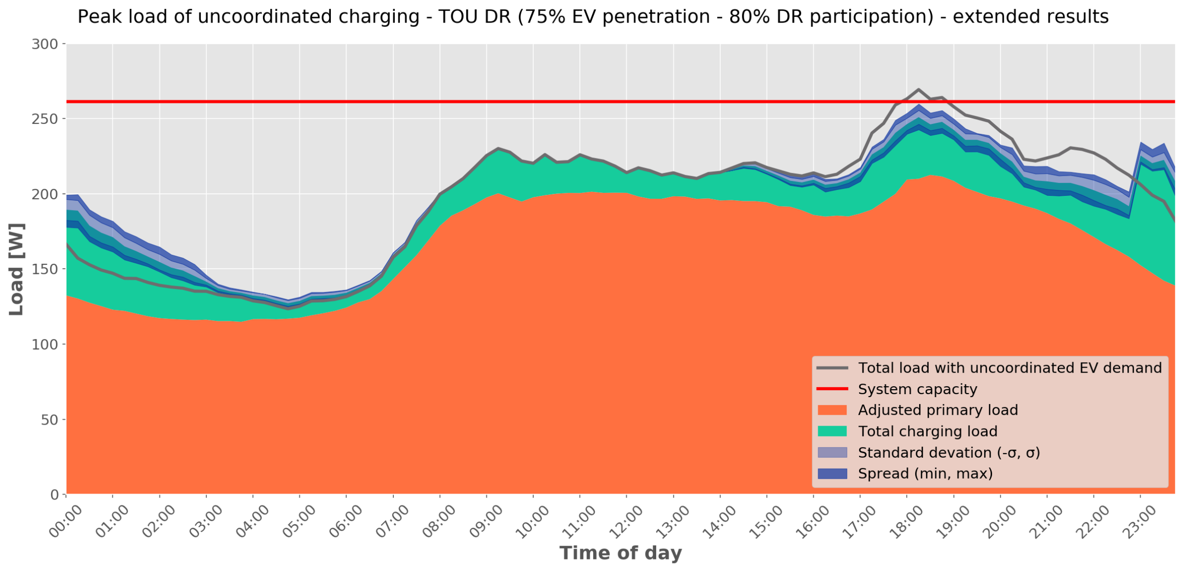

Figure A.3: The combined load of the primary and the TOU charging load, based on 75% EV penetration and 80% DR participation, plotted for the worst day of the uncoordinated charging load with extended results

It can be seen that for a long period over the day, from around 7:00 to 14:00, there is no range of results, which is caused by the fact that there are no shifted sessions over that period. It is also interesting to see that from 14:00, when the shifting begins, the range of results, i.e. the standard deviation and the spread increases slowly and then becomes the biggest around the nighttime and then lower again towards the beginning of the day, or around 7:00. It can be seen that for the TOU DR peak, which is directly below, i.e. at the same time, as the uncoordinated peak, there is some range of results.

In the main results section it was noted that the peak load for the uncoordinated load based on the parameters as visualised in the graph, 50% EV penetration and 50% DR participation was roughly 270 MW, or 269.3 to be exact. Based on the mean profile and the result displayed in the main results section, the TOU DR strategy achieved almost a 20 MW saving, with the mean profile peak reaching 250.9 MW. This result can also be extended and explored based on the range of the iterations results. The range based on the standard deviation, which is the standard deviation values of both the BEV and the PHEV profiles combined, this TOU peak load is 246.3 - 255.5 MW. For the spread, which is the minimum and maximum values of the mean peak load value of 250.9 MW, the values are 242.6 - 259.8 MW. The range of results is thus quite substantial, but as said before, the standard deviation range is more indicative of the actual results. The TOU DR strategy still offers significant peak reduction, even for the worst iteration value of nearly 260 MW.

For the next part of the results from the main results section, it is hard to analyse this range for all of the values in the heatmap. And that is also unnecessary as the range of the results for best performing scenarios are the most important to explore. This can be seen in table A.2 below.

	25% EV penetration	**50% EV penetration**	**75% EV penetration**	**100% EV penetration**
Mean value	226.9	242.4	266.6	293.2
Standard deviation range	-	-	264.1 - 269.1	286.3 - 300.2
Spread range	-	-	264.0 - 270.8	286.1 - 308.5

Table A.2: An overview of the range of results for the best performing TOU scenarios by EV penetration values

For the best performing scenarios for the 25% and 50% EV penetration, the DR participation was 100%. This means, as explained before, that no iterations are needed to produce those scenarios. However, for the 75% and 100% EV penetration values, this was not the case and thus iterations needed to produce those scenario results. In the table, the range of the standard deviation and the spread can be seen. Unsurprisingly, with the higher EV penetration value scenario, the range is bigger, both for the standard deviation and the spread. However, both of these result ranges still offer very good peak reductions. For the range of results for the most likely scenarios and the maximum EV number value, that will be presented in the comparison section of this appendix; A.2.3.

Subgrid load impact

For the results for the lower levels of the distribution grid, the subgrid load impact, some of the results can be extended. Those results, are based on the values of the different iterations, just as before. In table A.3, the extended results of the best performing scenario (based on the overall system level) of the TOU strategy can be seen.

	Distribution substation	**Electricity streetboxes**	**Buildings' cables**
Mean value	43%	18%	108%
Standard deviation range	35% - 43%	18%	98% - 108%
Spread range	35% - 43%	18%	108% - 119%

Table A.3: Range of results for the impact on the different subgrid components

What is interesting to see is that the maximum EV penetration for the electricity streetboxes is always the same, as the load impact on it is so high that even the minimum and maximum values from the iterations do not make a difference. For the standard deviation range, it is apparent that the distribution of this profile is not symmetrical, causing the spread to be completely different to the standard deviation range, which assumes a symmetrical distribution. This is explained in the DLC section later in more detail. From these results, it can be seen that there is quite the range of results based on these subgrids.

A.2.2. DLC DR extended results

Similar to the extended results for the TOU DR strategy, first the charging profiles will be explored. The first result in the DLC DR results section is the overview of the charging profiles based on the different participation levels. This was displayed in figure 7.20. As was done for the TOU DR extended results, the standard deviation and spread of these charging profiles can be explored. This can be seen in figure A.4.

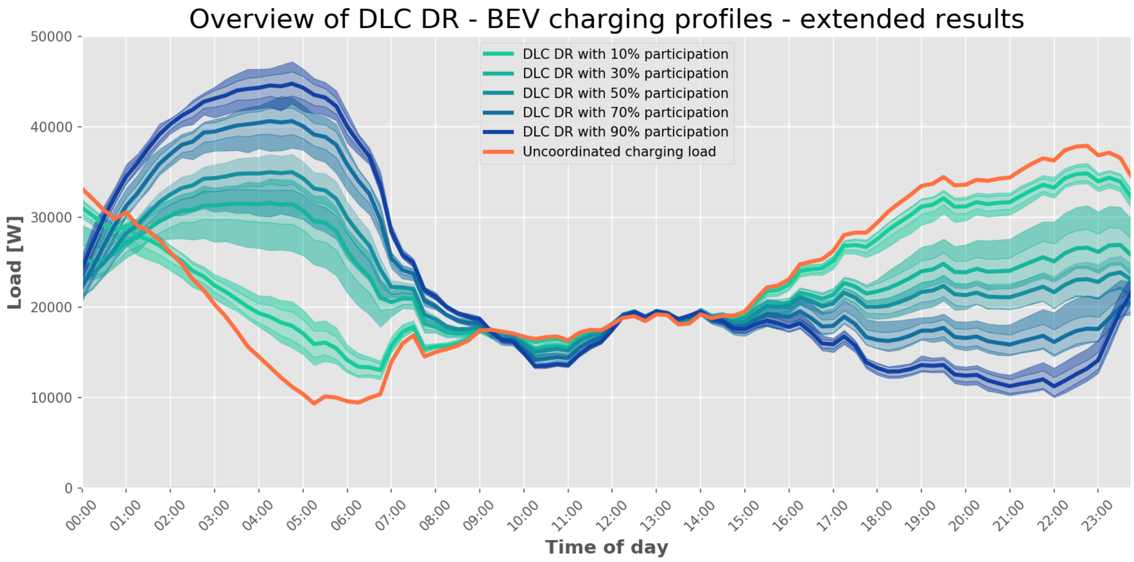

Figure A.4: An overview of a few DLC charging profiles based on different participation levels with extended results

Similar to the TOU charging profiles, the range of results is the smallest for the least and the most participation. It can also be noted that the range of results is quite bigger than the TOU DR strategy. This is due to the nature of the DLC strategy, as it has more possibilities as it can rearrange the charging sessions more freely than TOU. Selecting different EVs will thus have a bigger change, as the charging sessions of different cars can indeed be very different. It can be seen that for charging profile based on 30% DR participation, that the difference between the mean value and the spread, i.e. the max, is around 5000 W at 22:30 or so. This is a quite substantial range of results.

To see the range of the results when scaled up and combined with the primary load, the mean load can be visualised. This is essentially the extended version of figure 7.21, based on KPI 1. This can be seen in figure A.6. It can be seen that the range of the results is the biggest over the night, where the most rearranging occurs. This is very similar to the extended results of the TOU DR strategy.

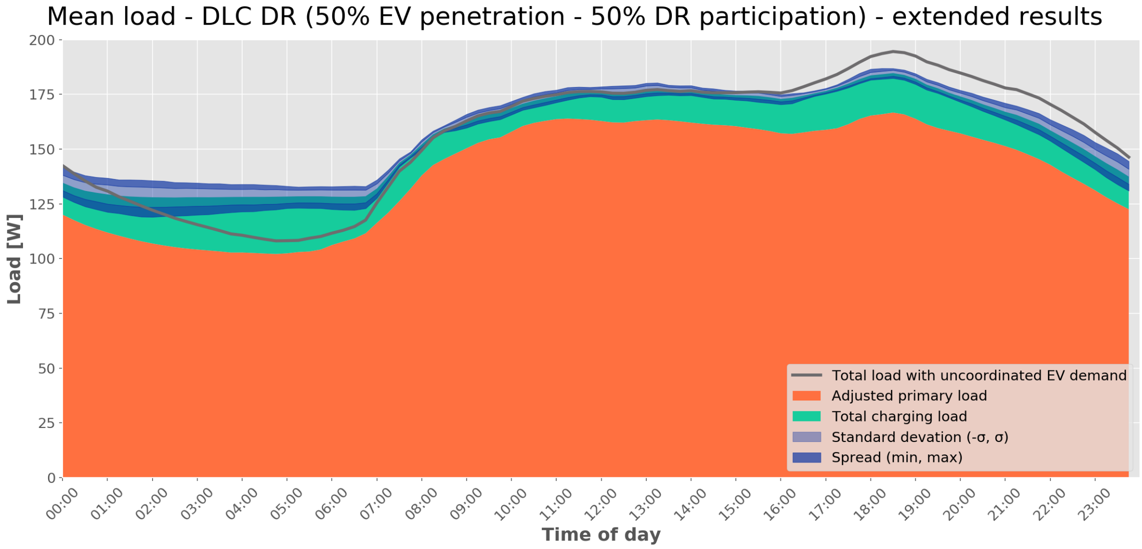

Figure A.5: The combined load of the primary and the DLC charging load for the mean day based on 50% EV penetration and 50% DR participation with extended results

Additional to these results from the main results section, the different profiles based on different EV penetrations were also explored. The same scenario, based on 50% DR participation was plotted for the four EV penetration values and can be seen in figure 7.22. As these profiles are very close to each other, it would be really hard to see the results range of each profile visually. Therefore, for this extended version of this graph only the 25% and the 100% EV penetration profiles will be explored. This can be seen in figure A.6 below. Interestingly, the standard deviation range and the spread is larger for the 25% EV penetration scenario than the 100% one. This is based on the exactly same strategy settings and the same DR participation of 50%.

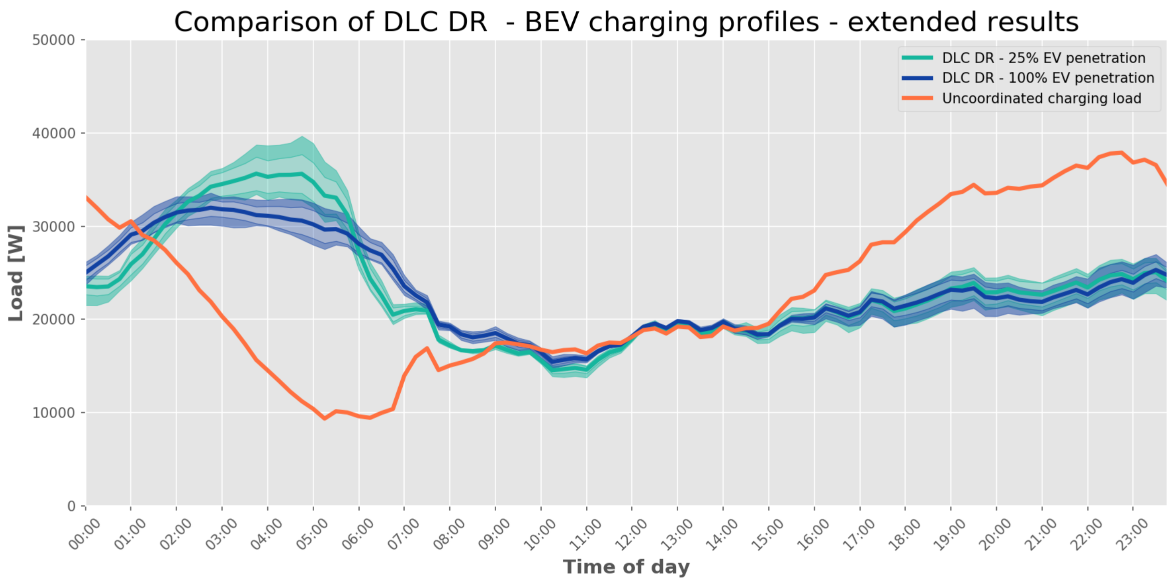

Figure A.6: An overview of DLC charging profiles based on different EV penetration numbers with extended results

Overall system load impact

Going over to the results that determine the impact on the overall system grid, the main results are the peak reductions of different scenarios, as seen in figure 7.23. Similar to what was done previously for the TOU DR strategy, the range of the results for the best performing scenarios can be found. However, as was stated in the main results section, most of the best performing strategies for the DLC strategy are based on 100%

DR participation and thus need no iterations. Only the best performing scenario for 100% EV penetration is based on iterations as it is based on 90% DR participation.

For that scenario, the range of the results can be explored. The highest peak of that strategy was 285.0 MW. The standard deviation range is 283.2 - 286.9 MW and the spread is 283.4 - 288.8 MW. This might seem strange, that the standard deviation range reaches lower than the spread but is explained by the fact that it is assumed that the distribution of the charging profile is symmetrical around the mean. If that were true, it would be correct to assume that the standard deviation is also symmetrical around the mean, or $\mu-\sigma, \mu+\sigma$, as shown in the figure legend. However, this is not always the case for the distributions of the charging profiles, which means for some profiles the standard deviation might fall more on the other side of the mean, causing the standard deviation range to be lower or higher than the spread in some cases.

Looking at the extended results for this best performing scenario, it can be seen that the range is not very substantial. The mean result, 285 MW, is a reduction of 14.7% compared to the uncoordinated load. For the standard deviation range, the peak reduction is 14.1% - 15.2%, which is very close to the mean value and when compared to the TOU strategy and put into context, very similar findings as based on the mean value. For the visual results in the main results section, which is the worst day of the DLC strategy based on 50% EV penetration and the worst day of the uncoordinated load compared to the the DLC strategy based on 75% EV penetration, the participation in both scenarios is complete and thus no iterations used. However, to visually show the range of results, the best performing scenario of the 100% EV penetration can be visualised. That is the scenario which was analysed previously. This visualisation can be seen in figure A.7 below.

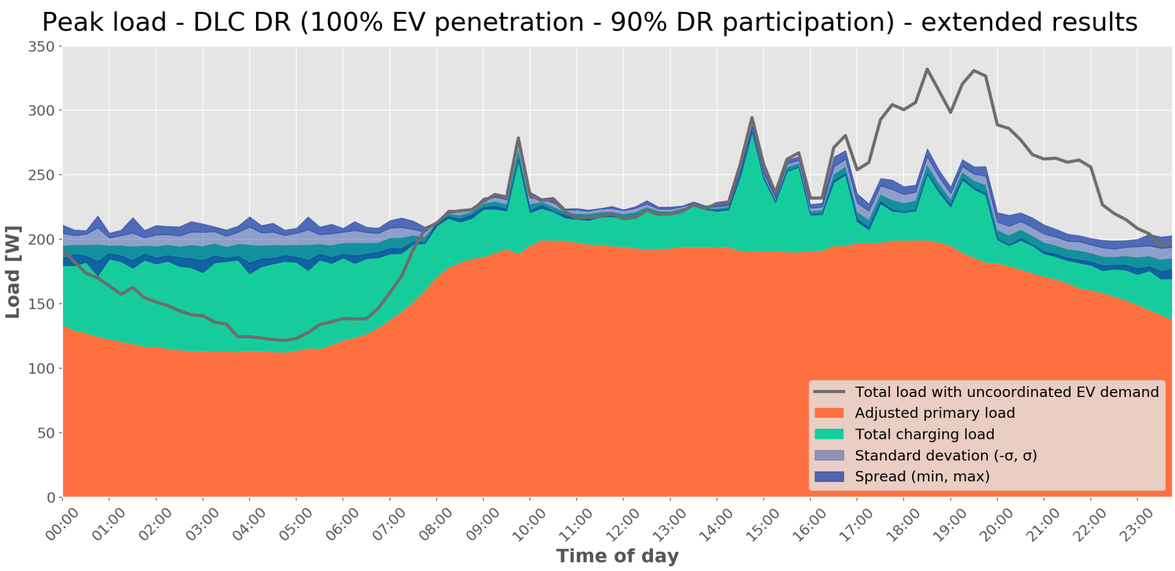

Figure A.7: The combined load of the primary and the DLC charging load for the worst day based on 100% EV penetration and 90% DR participation with extended results

It can be seen that for the time periods where the strategy is most actively shifting the load, i.e. in the late evening and the night, the standard deviation range and spread is the largest. It is also interesting to see that the peak of that day is actually based on a spike in the middle of the day which apparently the DLC strategy cannot rearrange based on the shifting rules. This makes the range of results for the nighttime and the evening less concerning, as they do not actually affect the peak load, as for the peak, there is only a very small range of results. As with the extended results of the TOU strategy, the number of EVs and the most likely scenarios will be explained in the comparison appendix section, A.2.3.

Subgrid load impact

For the load impact on the lower levels for the DLC DR strategy, the same methodology as in the earlier TOU section was used. That is to show the range of results for the best performing strategy based on the overall system level. This can be seen in table A.4. Again, the maximum EV penetration for the electricity streetboxes is the same for all the range of results. For the impact on the distribution substation and the buildings's cables, there is however a wide range of results, showing that there might be some even more appealing results based on some of the iteration results.

	Distribution substation	Electricity streetboxes	Buildings' cables
Mean value	60%	18%	108%
Standard deviation range	43% - 68%	18%	108% - 119%
Spread range	43% - 68%	18%	98% - 119%

Table A.4: Range of results for the impact on the different subgrid components

A.2.3. Comparison extended results

In this section, the extended results will be summarised and compared. First this will be done by revealing the range of the results for the best performing and the most likely scenarios for both DR strategies. This has partly been done in previous sections and those results visually displayed. These extended results are presented in table A.5 below.

		25% EV penetration	50% EV penetration	75% EV penetration	100% EV penetration
Uncoordinated load	**System peak load**	**239.6 MW**	**269.3 MW**	**298.9 MW**	**334.1 MW**
TOU DR peak reduction	Best performing scenario	5.3%	9.9%	10.8%	12.2%
	Standard deviation range	-	-	*10.0% - 11.6%*	*10.1% - 14.3%*
	Spread	-	-	*9.4% - 11.6%*	*7.7% - 14.3%*
	Most likely scenario	2.0%	3.6%	3.2%	4.6%
	Standard deviation range	*1.1% - 2.9%*	*2.2% - 4.9%*	*1.9% - 4.6%*	*3.0% - 6.2%*
	Spread	*0.5% - 3.5%*	*1.4% - 5.8%*	*1.5% - 5.8%*	*2.5% - 7.6%*
TOU DR peak reduction	Best performing scenario	6.2%	11.4%	12.8%	14.7%
	Standard deviation range	-	-	-	*14.1% - 15.2%*
	Spread	-	-	-	*13.6% - 15.2%*
	Most likely scenario	3.6%	5.7%	5.7%	7.8%
	Standard deviation range	*2.6% - 4.5%*	*4.2% - 7.3%*	*3.6% - 7.8%*	*5.3% - 10.3%*
	Spread	*2.0% - 5.4%*	*3.8% - 8.1%*	*1.6% - 9.1%*	*4.4% - 12.5%*

Table A.5: An overview of the full range of results for the three main load scenarios

It can be seen that for many of the best performing scenarios, there is no range of results, as these scenarios have a 100% DR participation and are thus not based on iterations. A few interesting trends can be observed. First it can be seen that the range of results for the best performing scenarios for the TOU is bigger than the DLC. For the highest EV penetration scenario, DLC has a very small range of results, even based on the spread. For the best performing results for the TOU, this range is much bigger and the spread for the highest EV penetration scenario for the TOU is substantially bigger than for the DLC DR strategy. The second trend is exactly the opposite of this, for the most likely scenarios, the range of results is generally bigger for the DLC than the TOU one. This has been seen before in this appendix chapter and can be explained by the fact that DLC has more freedom and thus has more variability in its methodology. As a result, the iterations exhibit more variability and thus the standard deviation and the spread is larger. The last observation for these results is that for the higher participation based results, the best performing scenarios, the range of results still does not overlap too much, i.e. the range of results for the 75% EV penetration and the 100% EV penetration for TOU, especially the standard deviation range, do not overlap too much. However, for the most likely scenarios, which all have much lower peak reductions, the range of results overlap very often and by quite a bit.

For the other overall system level result, the maximum number of EVs, the range of results can also be compared quite effectively. This can be done by using the graph that was displayed in the main results section, figure 7.30. This same graph can be seen in figure A.8, but with the extended results, which is the number of EVs based on the range of results.

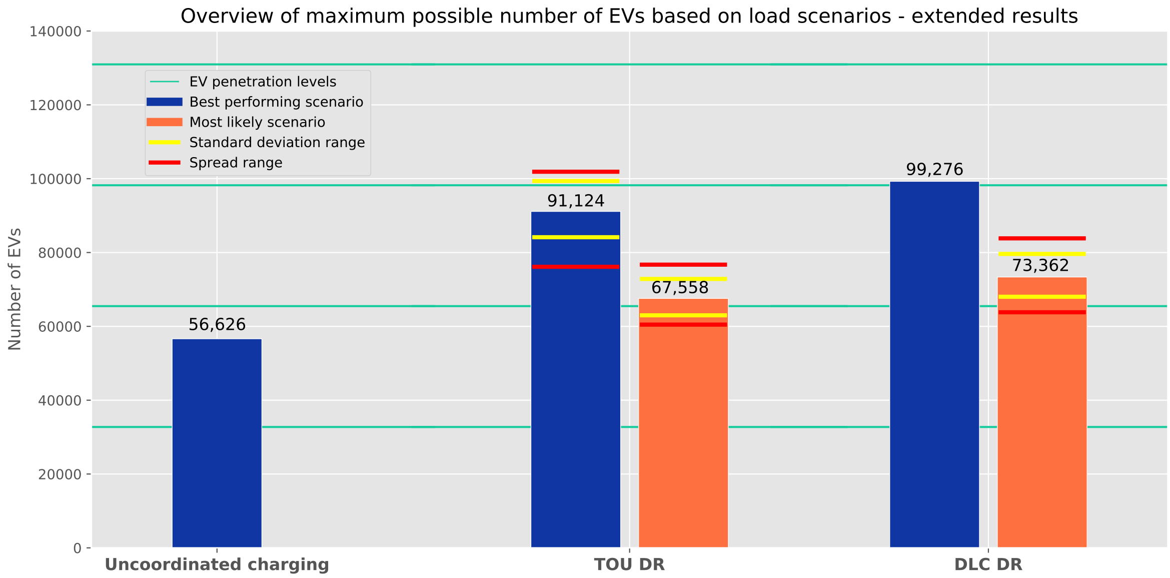

Figure A.8: A comparison between maximum EV numbers based on the three main load scenarios with the range of results

In the graph the maximum number of EVs based on the standard deviation and the spread can be seen for the scenarios which rely on iterations. These range of results show that the number of EVs actually differ quite substantially when using these values instead of the mean. For the TOU strategy, the maximum number of EVs based on the minimum value, which then allows the most EVs, is actually higher than the DLC value. For the most likely scenarios, the range of results is smaller, but still vary significantly from the mean.

For the comparison of the subgrid level, the two tables are essentially all of the extended results for that level, i.e. tables A.3 & A.4. The most interesting result is that for all of the range of results, the maximum EV penetration for the electricity streetboxes is the same, which further states the concerning finding that the subgrid is most overloaded in that area. To compare the extended results of the two, the DLC strategy had a bigger range of results which is also what was observed for the range of results on the overall system level.

A.3. Iteration comparison

In this appendix section there are additional figures that support the discussion in section *DR modelling iterations* on the number of iterations chosen for the modelling. All of these graphs show the three main metrics that were used to compare the performance between 10 iterations and a 100 iterations. Those are the mean, standard deviation and spread of the mean daily charging profiles.

First are the remaining graphs for the DLC DR strategy, which are the PHEV profiles.

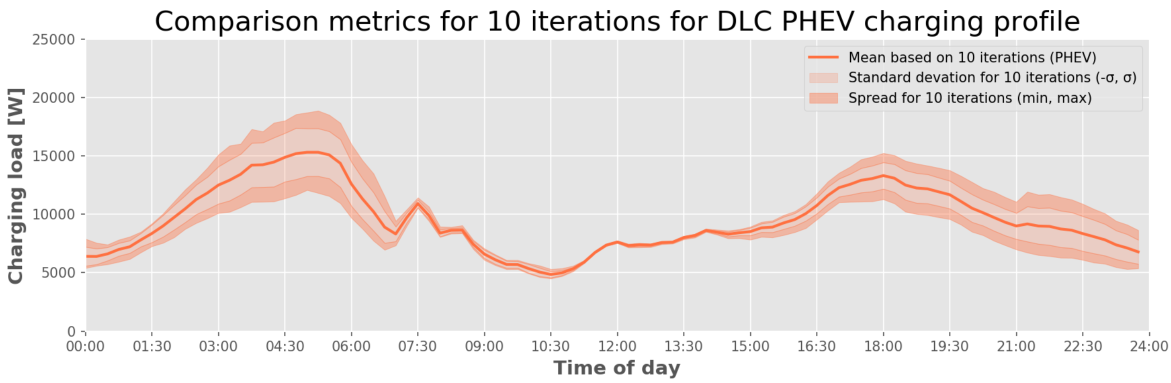

Figure A.9: The mean, standard deviation and spread of the DLC PHEV profile based on 10 iterations

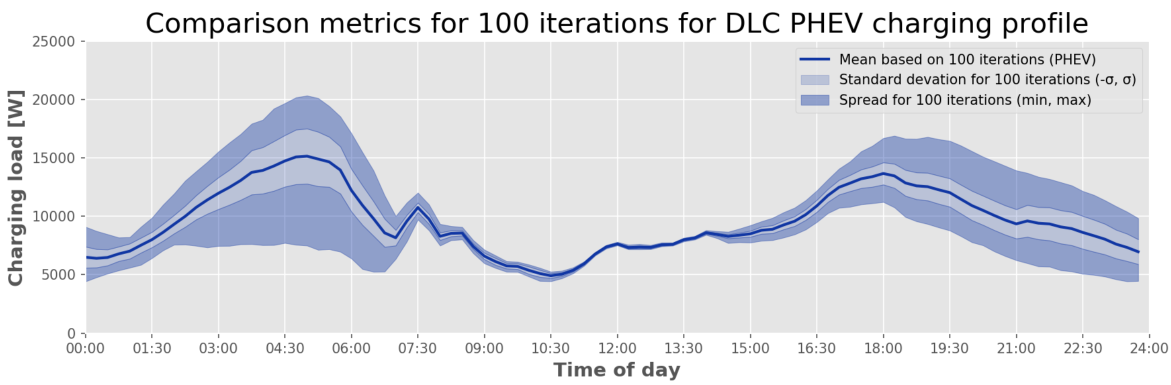

Figure A.10: The mean, standard deviation and spread of the DLC PHEV profile based on 100 iterations

Then the graphs for the TOU DR strategy, first the BEV profiles.

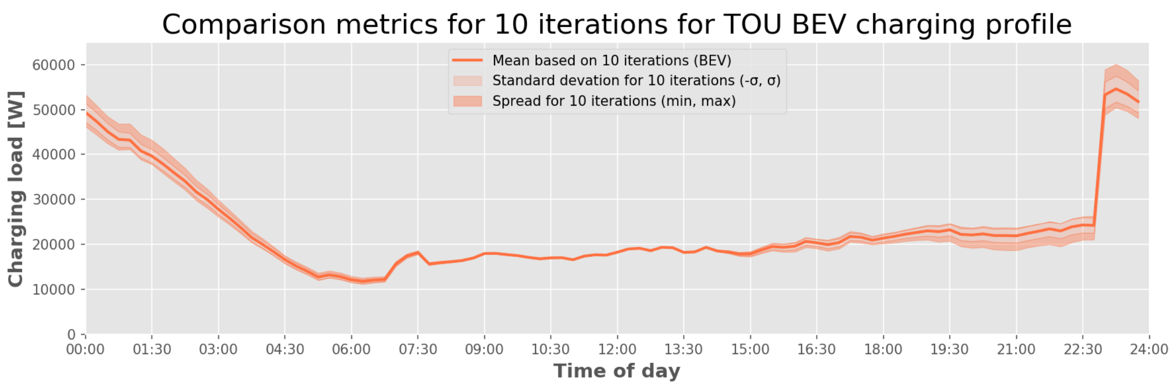

Figure A.11: The mean, standard deviation and spread of the TOU BEV profile based on 10 iterations

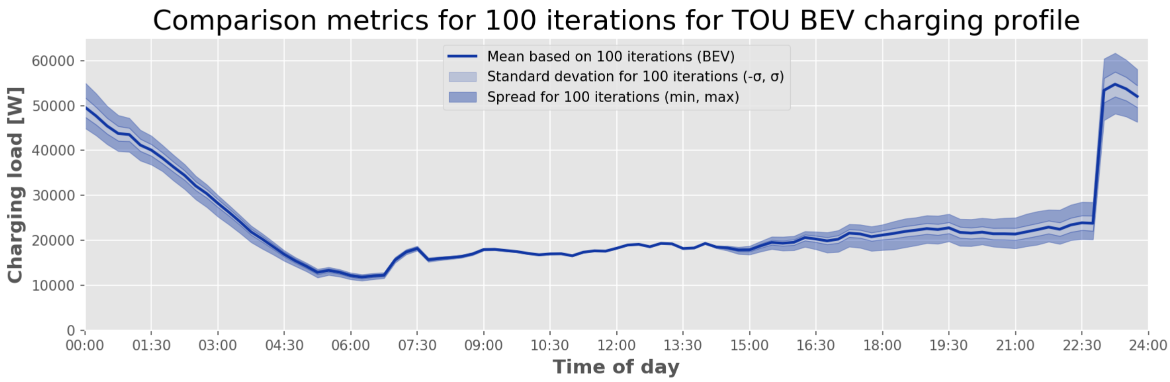

Figure A.12: The mean, standard deviation and spread of the TOU BEV profile based on 100 iterations

Then last the PHEV profiles for TOU DR.

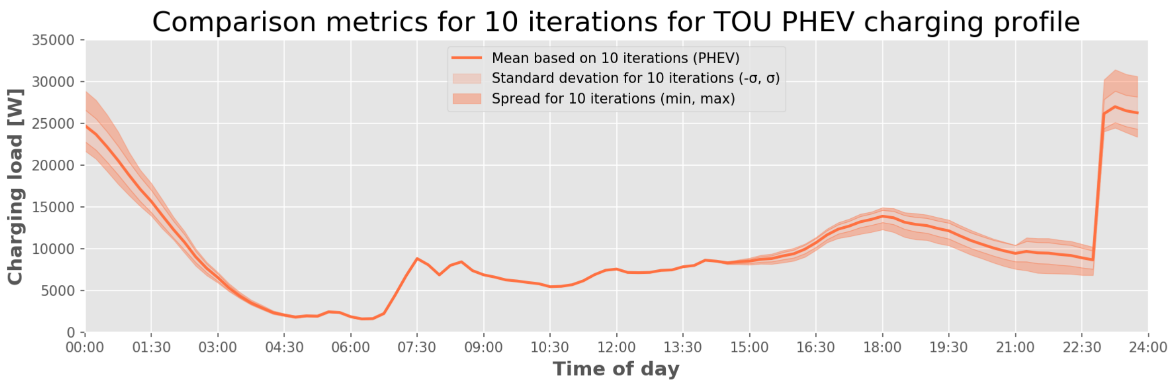

Figure A.13: The mean, standard deviation and spread of the TOU PHEV profile based on 10 iterations

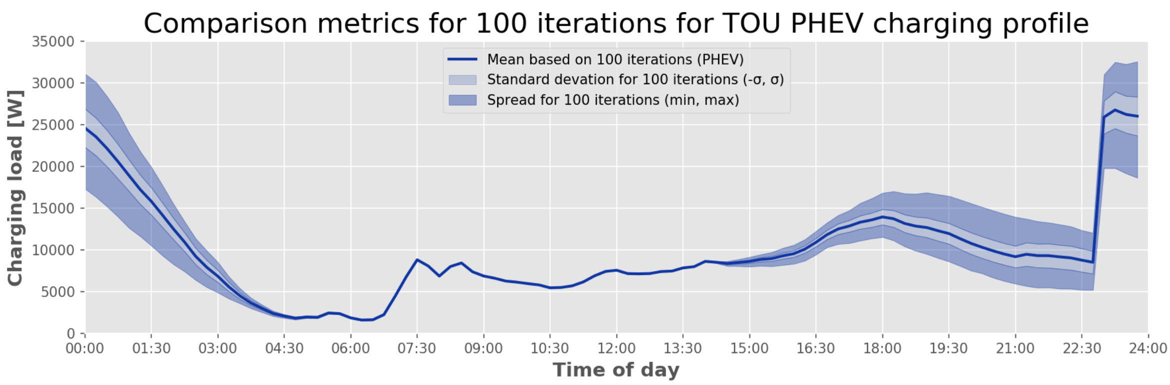

Figure A.14: The mean, standard deviation and spread of the TOU PHEV profile based on 100 iterations