Facilitating large-scale EV penetration in Iceland

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Abstract: With increased awareness of anthropogenic emissions, industries and sectors worldwide are changing rapidly. One of those sectors 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, especially on the residential distribution grids. Case studies and research on demand response with EVs has been increasing over the last years to try and reduce this load impact. This thesis aims to explore how the charging load of a large EV fleet impacts the distribution grid in Iceland and how it can be minimised with demand response strategies. A load model was created for the distribution grid in the capital region of Iceland and the results indicate that large-scale EV penetration can have a huge impact. Furthermore, the results showed that demand response strategies can greatly reduce that impact and offer significant peak reductions. However, based on a bottom-up approach, the lower levels of the distribution grid seem to be worst affected. Future research should be focused on mapping these local grid effects and conducting more in-depth analyses on that level.

Keywords: Demand response, electric vehicles, time-series modelling, grid impact

1. Introduction

With rising levels of anthropogenic emissions and their effects on the warming of the planet and subsequent change of climate, industries and sectors are in a transition towards more sustainable use of energy. There is a global push for renewable energy sources (RES), especially for electricity production, with wind and solar being implemented on a large scale. Worldwide, countries are working hard towards their environmental goals, decarbonising their energy production and decreasing greenhouse gas emissions (GHG).

One of the sectors that has seen immense change is road transport, with the increase of electric vehicles (EV). They can effectively reduce emissions, but do also largely increase residential electricity demand. Additionally, electrification is happening in other sectors as well as households, with heating and cooking being replaced with electricity on a large scale, instead of relying on gas. To react to this heightened electricity demand there are two options, 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) [1]. The latter is namely something that can be done with EVs, by shifting the charging of EVs to more favourable hours for the grid. This both increases grid utilisation and the utilisation of the energy produced. Increasing the share of the passenger fleet that is electric is one of the biggest things countries can do to take a major step towards reducing their carbon footprint. However, that EV fleet can increase the residential electrical demand significantly and congest the distribution grid. Therefore, coordinating the charging of a large EV fleet is vital to increase EVs without compromising grid integrity.

In this paper, Iceland is chosen as a case study, as it has very high EV penetration levels and because of its unique energy market characteristics, electrifying road transport is vital for the country to achieve its environmental targets and international agreements, most prominently its GHG emission reductions for the Paris Agreement. The goal of the research is to explore the load impact of EVs and research different DR strategies to minimise that load impact and ultimately facilitate large-scale EV penetration in Iceland.

Iceland is one of the fastest growing EV markets in the world. In 2019, 27.5% of new car sales were EVs [2]. Worldwide, only Norway has a higher share of EVs sold [3]. Iceland is a member of the European Union Emissions Trading System (EU ETS), which applies mostly to the aviation and the heavy industry sector [4]. Road transport is responsible for about 20% of the country's total GHG emissions [4] that fall outside of the ETS system and its energy transition is thus very important for the country's commitments towards climate change. The energy market and circumstances in Iceland also heighten the EV load impact, as there is only one city, where roughly 65% of the country's population lives [5]. That is where the research is focused on, as the distribution grid in this capital region is where EV charging has the most impact and where the large majority of the EVs are situated. However, the distribution grid is already congested in terms of additional power delivery to it [6] and with the increase of EVs this will be an even bigger problem. This leads to the research question: *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?*

2. Background

Much has been written on this topic in recent years; the load impact of EV charging on distribution grids and DR strategies with EVs. 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 [7, 8, 9], increased system losses [10, 11] and decreased power quality [12], often resulting in the need for costly reinforcements of the network [10, 8]. 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 [13] and in some scenarios be reduced to a level where it has no contribution to the peak demand [14].

A structured literature review was conducted in order to gather the required background knowledge for the research and to compare different types of demand response. The results of this review made it possible to select different DR strategies to research. An overview of the selected literature can be seen in table 1. One of these papers was the highly cited paper of [15], where 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 1, an overview of these two programs and the different strategies within them can be seen.

For each of these programs, the circumstances of the energy market can affect their performance and even limit their implementation. For some programs, specialised infrastructure is needed and for others, certain market characteristics are needed. Therefore it was desired to summarise these programs in order to select the ones that are most viable and realistically implemented for the case study of this research project.

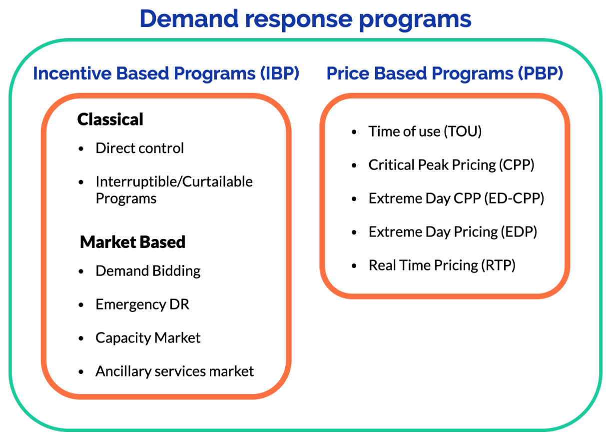

Figure 1: The two demand response programs and their classifications. Original diagram from [15] p.1990.

In table 1, the main features of the reviewed literature are presented. For the two classifications of the programs, PBP were much more prevalent. A large share of the articles focus on real time pricing (RTP). This strategy revolves around changing prices hourly or more frequently, based on the wholesale price of electricity [32]. This strategy is found to incentivise consumers to more efficient electricity consumption [11] and make demand and supply more connected [23]. However, [10] find that RTP is too dynamic for EVs and [7] finds that RTP can contribute to the creation of a second peak. The bottom line is however, that for RTP to work efficiently there needs to be specialised infrastructure; a smart metering communication system [11].

Based on the shortcomings of RTP, a number of articles suggested TOU as a feasible alternative. Articles [22] and [16] implemented TOU in a game-theoretical based way. The latter article found that the game is solved when both the retailer's profits and the customer's utility function is maximised [16], whereas paper [22] finds that increased competition with multiple utility companies can accompany higher penetration of EVs. From this it seems that with more retail energy players (REP) in the market TOU can indeed be beneficial. As a DR strategy, TOU 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 [30]. 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 [10].

However, TOU can also be made more complicated and its weaknesses possibly mitigated. Article [31] proposes a TOU strategy with multiple tariffs, where customers are grouped and each group gets a differ-

Paper	DRP	DR strategy	Main features
[16]	PB, IB	Time of use (TOU), Direct control	- Stackelberg game-model - Maximisation of both REP and consumer
[15]	-	-	- DR overview paper
[13]	IB	Curtailment	- Residential decentralised DR - EVs considered as shiftable load
[17]	IB	Curtailment	- Modelling under network uncertainties - Whether to perform DR or expand the grid
[18]	IB	Direct control	- Effects of DR programs on chargeability of EVs based on SOC - EVs modelled as interruptible load
[9]	IB	Direct control, Curtailable load	- Consumers set load priority or convenience preference
[19]	IB	Direct control, Curtailable load	- User identification for DR
[7]	PB	Dynamic tariffs (DT), Daily power based network tariffs (DPT)	- Consumption and EVs based on a HEMS - DR coordinated by REP
[20]	IB	Limit order bids (Demand bidding)	- REP as an EV aggregator - Both a centralised and a decentralised approach
[21]	IB	Multiple	- Congestion management optimisation - Aggregator's behaviour based on price signals
[22]	PB	Multiple	- Stackelberg game-model - Both multiple and a single utility company - Consumer behaviour implemented
[23]	PB	Multiple	- Multi agent system modelling with HEMS as an agent - Loads organised based on shiftability
[24]	PB, IB	Multiple	- HEMS which reacts to DR programs, both PBDR and IBDR
[25]	PB, IB	Multiple	- EV travel behaviour - Both single EV and an EVA - Multiple DR strategies modelled
[26]	-	Multiple	- Assesses charging behaviour and the potential for DR
[27]	-	Multiple	- Focus on DR customers and integrating EV into DR
[11]	PB	Real time pricing (RTP)	- Willingness to charge and participation in DR researched
[28]	PB	Real time pricing (RTP)	- Particle swarm optimisation algorithm
[29]	PB	Real time pricing (RTP)	- Loading algorithm used to determine EV load
[25]	PB	Real time pricing (RTP)	- Peak load shaving and valley filling with RTP - SOC used as demand level indication
[12]	PB	Real time pricing (RTP)	- Automated decentralised DR
[8]	PB, IB	Real time pricing (RTP)	- Decentralised EVA approach to DR - Combination of RTP and in
[14]	PB	Real time pricing (RTP)	- Optimally scheduled charging can reduce peak contribution to zero
[10]	PB	Time of use (TOU)	- EV aggregator facilitating DR
[30]	PB	Time of use (TOU)	- Explores necessary financial incentives for DR participation
[31]	PB	Time of use (TOU)	- Multiple TOU tariffs for different customer groups
[32]	PB	Time of use (TOU)	- Different levels of EV penetration are considered
[33]	PB	Time of use (TOU), Real time pricing (RTP)	- Decentralised DR based on HEMS system

Table 1: An overview of the review literature findings

ent 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 [32]. Extreme day CPP and extreme day pricing both use time-dependant pricing scheme, but seem to be less popular than CPP, which is still quite absent from the literature.

Going over to the other group of DR programs, it is evident that incentive-based DR (IB DR) is often carried out with an autonomous system. According to [32], a home energy management system (HEMS) can control EV charging to minimise the electricity cost. In [24], a load priority method is used to determine how the consumption changes under a DR event. Article [18] examines similar things and finds 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 [8]. This type of IB DR are quite different to the PBPs.

In price based DR (PB DR), the distribution system operator (DSO) changes the price hoping that the consumers will react and change their consumption. However, with IB DR, consumers enter an agreement with the DSO, EV aggregator (EVA) or another operator, to allow the change of their consumption under certain circumstances. Direct load control has been offered to consumers before as [30] 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. Article [24] states that direct load is the most frequently used DR program since the 1960s, to quickly react to system load changes. According to [7], 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 evolves around reducing or stopping charging when the system is overloaded. As EV charging is viewed as a shiftable load, as stated before, curtailment with EVs is a good option. The paper [18] studies 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 other types of IBPs, the market-based strategies, their footprint was smaller in the literature findings as seen in the overview in table 1. Demand bidding was one of those strategies. It functions very much like the spot electricity market. Bidding is usually day-ahead and has both a demand and a price component [20]. Another popular strategy in this category is the ancillary services market, where EVs participate in maintaining the power grid's reliability [20].

3. Methodology

The chosen methodology of the research project is based on the type of research problem. From the conducted literature review, a knowledge gap emerged, which is grounded both in academics and practicality. 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. Furthermore, how the effect of different DR strategies are modelled and evaluated matters immensely to properly measure the impact on the distribution grid. As [13] states, such analyses must be done over a full year of data.

This knowledge gap comes from the missing knowledge on which DR strategies should be implemented and how. As stated earlier, the evaluation of the performance of different strategies is very important and has up to this point been very challenging due to limited data and information on charging behaviour of Icelandic EV users. However, this research project, uses a novel EV study dataset and is the first academic project to do so. The research question as put forth earlier, is based on this knowledge gap. If this 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. Secondly, it is to analyse the effects of different demand response programs based on EV charging and distribution grid properties.

The methodology of the research 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 research approach is chosen to be a modelling approach, and more specifically; modelling and simulation. This can both be considered a method and a tool [34]. The energy system and distribution grid will be modelled and demand response programs will then be simulated in that model.

The modelling process is essentially a three part process, centered around the first part, which is a conceptual model. In that model, the problem situation as mentioned before is described and constrained, and the intended outputs of the model specified. This conceptualisation process is vital as it reveals all of the necessary steps that have to be taken to answer the research question. Assumptions and simplifications shape this process and have to be reflected upon to fully quantify the results of the modelling. This conceptual model is then implemented technically, using the programming language Python. The middle step, between the conceptualisation and the technical implementation is based on the data and inputs that are available for the modelling. In the following subsections, these parts will be explained.

3.1. Conceptual model

The process of formulating what is to be modelled is done with a conceptual model. 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*" [35, p. vii]. In the book, Robinson proposes a framework for developing a conceptual model, which will be used to guide the formulation process for this research project. This framework is essentially a sequence of activities to be carried out and together formulate a conceptual model.

However, these activities can be carried out non-sequentially as this process is an iterative one. These activities are identifying the scope and problem situation, determining the modelling objectives, identifying the model outputs and inputs and determining the model content and identifying assumptions and simplifications [35, p.75]. An overview of these activities, formulated for this research project, can be seen in figure 3. They will be further explained in this section.

Problem situation

The problem situation starts with identifying and scoping the system of interest, which is the system to be modelled. This system is the capital region distribution grid in Reykjavik, Iceland's capital and only city. More specifically, the system of interest, is the part of the distribution grid that is operated by the DSO Veitur. The physical boundary of this system are five municipalities where Veitur is active in. Over these municipalities, the combined population is 196,120 (2020 Q2), or 53% of the country's population [5]. 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 [36]. Apart from this physical boundary, the building blocks of the system can be seen in figure 2, where the infrastructure of Veitur is clearly specified.

The problem situation is positioned within this system of interest and is based on the identified knowledge gap as established earlier. 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.

Modelling objectives and constraints

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

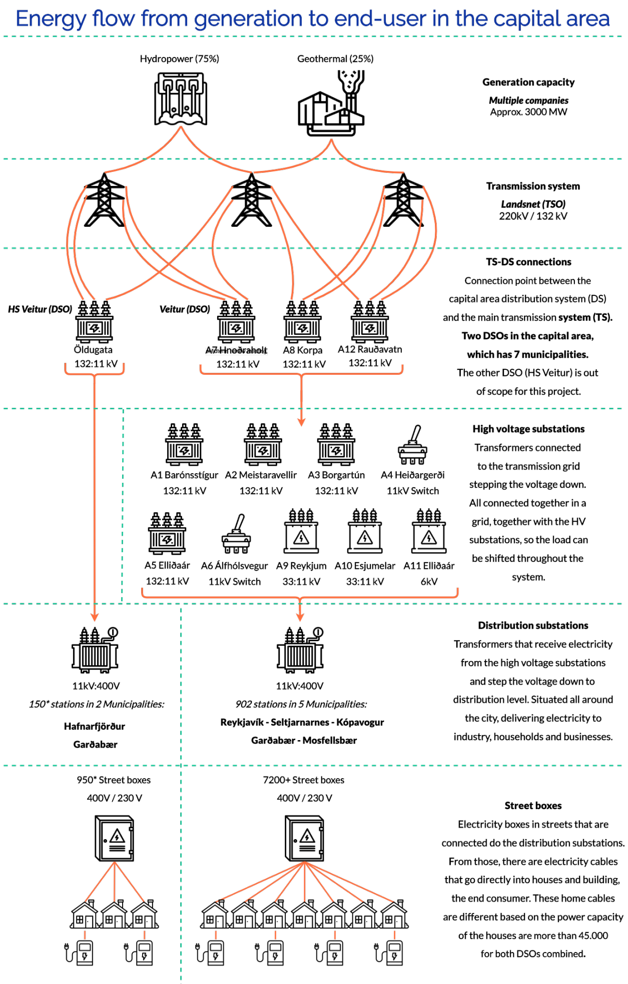

Figure 2: An overview of the distribution grid and its different voltage levels. The infrastructure of the DSO Veitur is clearly specified.

grid infrastructure, but also a market, where supply and demand must match at all 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. The delivery of this power supply through different levels of the system, mainly three levels, as illustrated in figure 2.

These levels are based on voltage, where with each level the voltage decreases, starting at 132 KV at the very top level where the TSO delivers the power from power stations to the TSO, and going all the way down to the household voltage level of 230 V, where the majority of the EV charging takes place. 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. Based on this explanation of the system of interest, the main modelling objectives can be elicited. They are listed below.

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 system capacity is exceeded under different charging scenarios**
5. **To determine how system load can be minimised under different charging scenarios**
6. **To determine the required consumer participation in different DR strategies**

These objectives reflect the problem situation and guide the modelling process towards solving it. The first two include the scope of the modelling, which is to be done over a full year on a 15-minute basis. This is to truly see the effects of the load in the most realistic way. As was mentioned earlier, a full year of data is deemed necessary to accurately evaluate modelled DR strategies. It is desired to have the primary load - which is the base electricity demand of the capital region without any EV charging - and the charging load separate in the model. This is why these load elements have two objectives. The next two state that the power capacity of the distribution grid must be found and then used to evaluate the maximum EVs that can be allowed onto the grid under different charging scenarios, based on different DR strategies. The last two guide the exploration of the settings of the DR strategies that are to be modelled, by finding how to minimise the load with their use and how much participation is required of consumers.

The modelling process is also guided by constraints, that limit how the objectives can be achieved. The objectives guide the formulation and functioning of the model and define what it should do, whereas the constraints create boundaries for it. In the list below, these constraints can be found.

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 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. They ensure that the modelling will be accurate, based on actual historical values and over a full year. The third constraint puts a necessary validation process on the charging behavioural dataset, to ensure that it can represent the large EV fleet that it is supposed to represent. The two last constraints apply to the DR strategies that are to be modelled and creates a boundary to which the charging behaviour of EV users can be affected. This makes sure that the charging scenarios, based on different strategies can then be compared on an even ground.

Model content

At this point, the model content, centered around the two different DR strategy implementations, must be explained. In figure 3, the model formulation process can be seen, where the model content, as well as the objectives and the constraints are derived from the problem situation. 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 thus be described.

In choosing 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. The number of DR strategies that were chosen, two, was based on the limited timeframe of the research project. Furthermore, it was desired to choose one strategy from each of the two different DRP types; price-based and incentive-based.

The first demand response strategy to be incorporated was **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.

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, as described before. 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. The other category however, classical IBP strategies, has only two types of strategies that are similar in many ways; direct load control and curtailment. Out of these two, **direct load control (DLC)** was chosen, which essentially gives the DSO control over the load of a consumer according to an agreement between the two parties.

Inputs & 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-dependent values of both charging load and primary load are used to model the effects on the distribution grid. 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 date range. 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 date range.

From this main output, a multitude of outputs can be derived which will be used to measure the effects

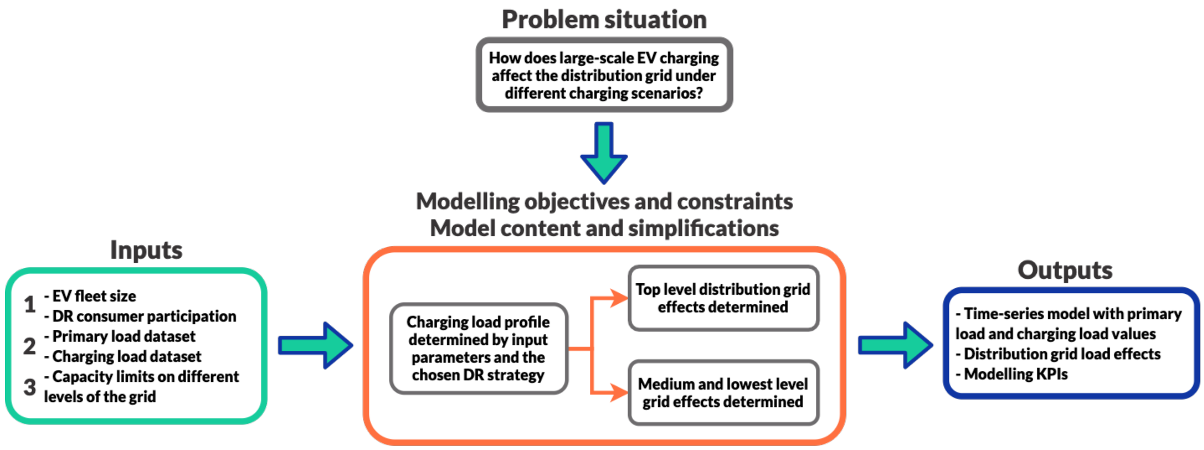

Figure 3: A visual representation of the conceptual model.

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. Additional to this main output and its derived outputs, modelling KPIs are formulated that ultimately translate the raw numerical outputs of the time-series model into results. These will be presented in the Results section itself.

For the inputs, the majority is based on datasets that were acquired for this research project. Those inputs are the primary load, charging load and capacity limits as seen in figure 3, and will be explored later on. Additional to those, there are two input parameters used for the modelling, to create the different charging scenarios. First, the EV fleet size which is the number of EVs which is modelled. The second one is the DR consumer participation, which depicts how many of the EV owners actually respond to the price changes in the TOU DR strategy or enter an agreement for the DLC DR strategy. These 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.

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. 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 and simplifications. The scope of the model has been explained shortly before, with the constraint of it having to run over a full year. The simplifications however have an even bigger impact on the conceptual model.

Model simplifications & assumptions

The system of interest is based on the modellers 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 built on assumptions and simplifications. They can also be viewed as the necessary design choices of the model; what to include and what not to. These simplifications and assumptions have an effect on all of the conceptual model components mentioned before and thus shape the conceptual model in a sense. They can be classified into two categories.

The first category is based on how the distribution grid system is represented in the model. The primary load data, as mentioned before, was not available on all the voltage level of the grid as illustrated in figure 2. Only for the top level, was the primary load fully available. On the lower levels, primary load data was only available for one distribution substation. 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 a distribution substation. Furthermore, to fully represent these lower levels of the grid, the individual buildings behind this substation were allocated primary load values based on proportional population numbers. Data on the electrical infrastructure in each building this subgrid, based on this station, as well as the inhabitants in each house were available online. Based on those numbers, EV numbers per building could be assumed and both charging load and primary load allocated to these buildings.

The other category is based on how the charging load input is used and handled to formulate the three main load scenarios. In the dataset that makes up this input, the charging load profile is made up of individual charging values from the 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 parts 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.

3.2. Data

The acquired data for this research project plays a major role, as the data used in this project, to model the charging behaviour of consumers in Iceland, has never before been used. Additional to this dataset, data on the primary load and the capacity of the distribution grid was acquired.

The charging dataset 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 [37]. 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 grid and charging infrastructure. The study itself was conducted by using a tracking device in the vehicles which measured and collected various performance and behaviour metrics [38]. For every trip the vehicles made over the study period, various metrics were collected such as; distance, driving time and start and end state of charge (SOC). 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. 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, EV location and residency type.

For the primary load data, the main data that was used was from the highest level of the distribution grid. 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. Additional to this primary load data from the high voltage substations, load data from one distribution substation could be accessed. That data will be used together with the local grid capacity data and provides a better insight into consumption data of households at the lower voltage levels. However, as it is only available from one station, this data cannot serve as the primary load data for the whole capital region. These two load datasets 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 to measure the load impact of EV charging on those levels.

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 was acquired for all of the high voltage substations on the top level of the grid, as well as the distribution substation for the lower levels. This data is simply the size of the transformers in these stations. As said before, additional data was acquired to represent the electrical infrastructure in the subgrid behind the distribution substation. This subgrid is essentially all of the houses that are connected to this particular substation, as illustrated in figure 2. This data was available online from [39], and has cable types of all the electrical connections in the subgrid and from that the individual cable capacities can be determined. With the modelling methodology of assigning primary load and charging load to each building in the grid, the capacities of each building can thus also be used to quantify this load based on different charging scenarios.

3.3. Technical model implementation

The technical model implementation, was guided by the conceptual model. Therefore its methodology and modelling steps are based solely on the formulated part of the conceptual model. The assumptions and simplifications earlier described, shape this process as well as the constraints and objectives. The technical model consists of three main parts; the base modelling - based on the uncoordinated charging, the DR strategy implementation and the grid impact modelling. As the methodology of those parts comes directly from the conceptual model and in fact the data, which have both been explained in detail, this technical methodology will be shortly summarised.

The base methodology was mainly based on the handling of the EV study dataset. From the dataset, only the EVs situated in the capital region - the system of interest - were used, which resulted in 121 EVs. As described before, whenever charging these EVs generate 15-minute intervals of data. This data was matched to the corrent intervals over an entire year - based on the study period - and the charging values of every single car was put into a column. With this, a simple time-series load model was formulated, with each EV in its own column. Based on the type of EV, BEV or PHEV, these 121 cars were then aggregated into a yearly BEV profile and yearly PHEV profile. For the base modelling, this was simply scaled up to represent the desired amount of EVs, keeping the ratio between BEVs and PHEVs equal. This charging load of the modelled EV fleet was then combined at the correct timestamps with the primary load to get an overall load profile. Based on that, the grid impact could be determined.

For both of the DR strategies' modelling, the methodology was similar. First it was taking the output of the base modelling, which is the uncoordinated time-series load model and using it as a starting point. Next, all sessions were identified and iterated over. Based on the rules earlier described, in the objectives and constraints, the sessions were then either shifted for the TOU or distributed over a certain time period for the DLC. This was only done for participating EVs. In the end, another time-series model was outputted, with shifted sessions and thus a different overall profile. This too, could then be scaled up as the uncoordinated load.

The last step was then to to determine the grid impact on the two levels; overall system level and subgrid level. The overall level was simply to compare the combined load peaks of primary load and scaled charging profiles based on the different DR strategies or the uncoordinated load. For the lower levels however, the unscaled time-series models were used and allocated to individual buildings in the subgrid based on EV penetration in each scenario. From the acquired data on the subgrid level, population numbers in the subgrid were accessed for each house. With that information, primary load from the substation level was allocated proportionally to each building. In the same way, number of cars were estimated based inhabitants in each house and car ownership in Iceland, which is 0.75 [40] per inhabitant. Paired with the EV penetration value, the EVs in each building could be approached. The capacity data for the different cables in the grid was then used to measure the load impact in the same way as was done for the top level.

4. Results

The results of the three main load scenarios can be presented together, which makes the comparison even clearer. Starting with setting the benchmark, without any EV charging, i.e. only primary load, the peak load over the modelling period was 217.3 MW. For the overall grid level, 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 two input parameters that were used to generate these scenarios were picked in incremental values. The EV penetration values and the corresponding EVs can be seen below. These are based on the total number of EVs in the system of interest [36].

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

Table 2: Overview of the chosen EV penetration values for the simulations

For the DR participation input, incremental values from 10% to 100% were simulated, in 10% increments but another scenario was defined; the most likely scenario. Based on prices for peak and off-peak electricity use, cost savings of consumers were calculated for both DR strategies, by calculating energy used when sessions where affected and when they were not. These savings can be seen below.

These prices were based on the Icelandic energy price [41] and savings based on historical prices which utilised time of use [42, 43, 44]. The same price difference was assumed for DLC and TOU. Based on these savings, as seen in table 4, the most likely DR participation could be estimated. That was based on a Norwegian study on the topic [26, p.3]. Based on that,

		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 3: Overview of peak reduction for DLC and TOU

the most likely participation was estimated to be 25% for TOU and 30% for DLC.

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

Table 4: An overview of the savings between uncoordinated charging and DR strategy charging based on different price reductions based on varying price difference

With these input parameters, the results of the different load scenarios can be compared. This can be seen in table 3. The first row shows the load peaks for the uncoordinated load. It can be seen that with only 50% EV penetration it goes over the system capacity; 261.3 MW. The two DR strategies however can offer a a significant peak reduction compared to the uncoordinated charging. These reductions are both shown for the optimal scenario for each strategy as well as the scenario based on the most likely DR participation as defined earlier.

The benefit is reduced with the most likely scenario, but still offers improvement offer the uncoordinated charging load. The DLC strategy outperforms TOU quite substantially and also seems to increase its performance with an increase EV fleet size. This is not the case with the TOU, which achieves its best performance for 50% EV penetration but then reduces with a bigger EV fleet.

	Uncoordinated	TOU	DLC
Best performing scenario	56,626	91,124	99,276
Most likely scenario	-	67,558	73,362

Table 5: An overview of the maximum number of EVs allowed into the system without exceedin overall system capacity.

Another result which can be used to compare the performance of the scenarios efficiently is the maximum number of EVs that can be allowed into the system without exceeding the system's capacity, based on the top level of the system. This again was done based on the best performing scenario and the most likely one. This can be seen in table 5. Again the DLC strategy performs the best, almost allowing twice as many EVs to the enter the system as the uncoordinated charging does. The TOU DR strategy sits in between. For the most likely scenarios, the increase in EV numbers is fairly minimal for both strategies.

The effects of the load on the lowest level of the grid were measured in a similar way, based on the EV penetration. These results might however need some additional explanation. In this subgrid, as explained before, there are three levels; the individual buildings, the electricity streetboxes that connect them and the distribution substation itself. Based on the capacities of these components, the maximum EV penetration for each of them can be determined. This can be seen in table 6 below.

	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 6: A comparison of the maximum EV penetration values for the different components in the subgrid based on the three load scenarios

A visualisation of this subgrid can be seen in figure 4, where all of these different components are illustrated. The numbers in the table represent the maximum number of EVs that ensures that none of the components of the same type exceeds their capacity. That map illustration also acts as a result as it shows the effects of the load on this subgrid. This result did not change between the scenarios and thus shows the effects of all scenarios compared. The different colors of the cables represent different loading values and is explained in the legend in the figure.

The effect of the load based on the TOU DR strategy was actually worse than the uncoordinated load with the best performing scenario for these lower levels of the system. 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 its best scenario are much better than the uncoordinated load. The substation load is what is mostly lowered, but the performance of the other components are equal or marginally better than what is achieved with the uncoordinated load. 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. This will be discussed in the next section.

5. Discussion

The discussion is mainly focused on the findings of the literature review and the findings from the modelling results. However, this section will also reflect on the main limitations of the methodology of this research.

From the literature review it became clear that not all DR strategies are relevant or applicable in Iceland. Some require specialised infrastructure while others require well functioning and complex spot energy markets where 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 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.

For the modelling findings, the utilisation of the electrical infrastructure on the top system level can be greatly improved with the two DR strategies, as they reduce the peaks significantly compared to the uncoordinated load. The DLC strategy out- performed the TOU, which was expected, as it gives the DSO greater control over the load. 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 allowed load on the distribution sub- station itself was also relatively low and allowed 43% - 51% 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 scenario for the TOU DR strategy on the top level of the grid was not the best one for these lower levels. This finding makes it challenging to implement TOU in reality as the approach has to be taken with all of the grid levels in mind. Determining the best overall scenario must therefore be done both from a bottom-up and top-down approach. For the DLC, this was not the case, as the best performing strategy of the DLC based on the overall system level, still hade some improvements over the uncoordinated charging on the lower levels of the grid. It is therefore clear that the biggest bottleneck in the distribution grid is the subgrid level, especially the electricity streetboxes.

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. 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.

6. Conclusion

The findings of the research demonstrated that large-scale EV charging is a lurking 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.

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 challenging to quantify in this project. This is necessary as this is the part of the system where the bottleneck lies. Different variations of the modelled demand response strategies should also be explored, as that could offer improved performance and lowered peaks.

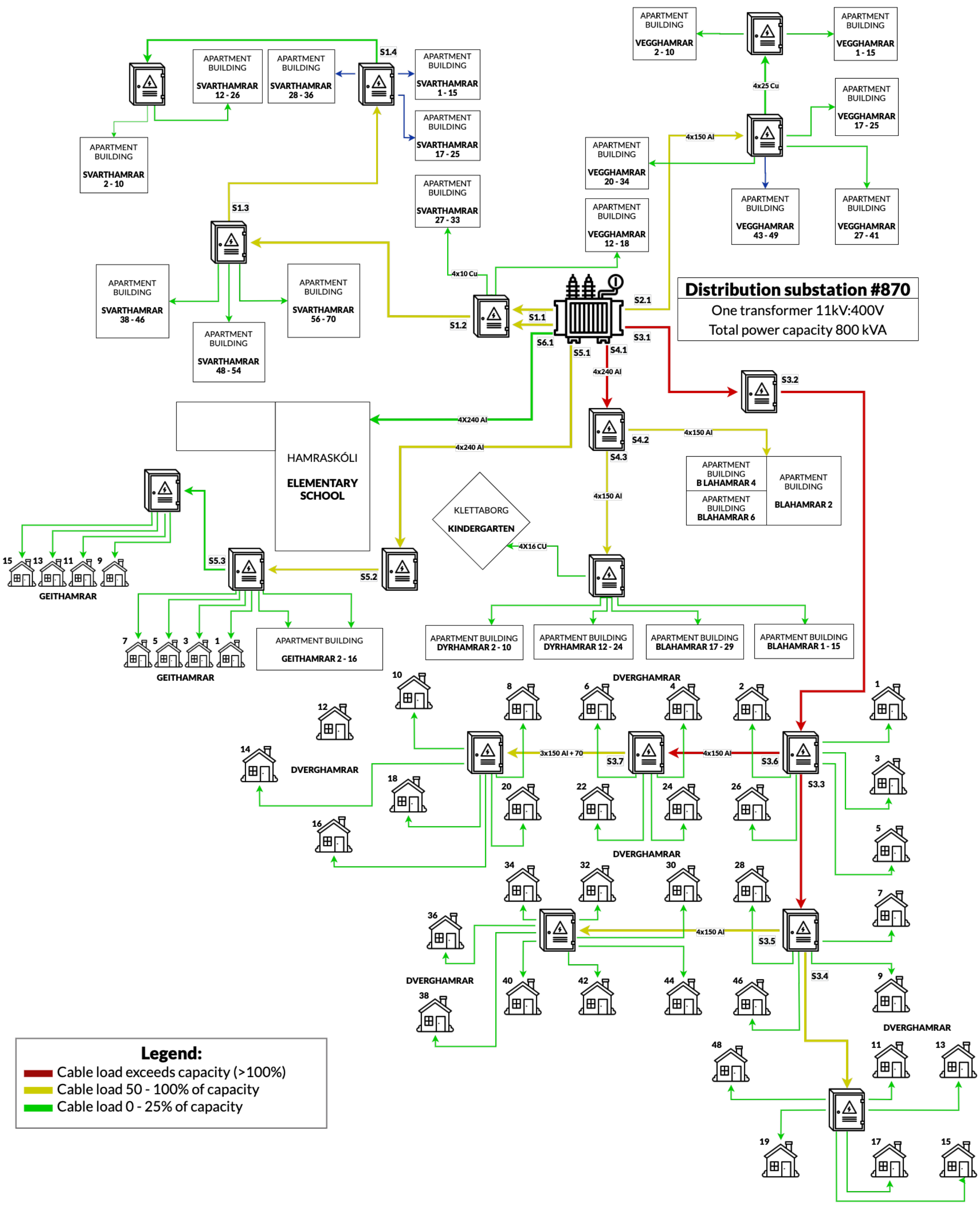

Figure 4: The map illustration of the subgrid based on a 100% EV penetration for all of the scenarios

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