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Charge into the Future Grid

Optimizing Batteries to Support the Future Low-Voltage Electrical Grid

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LINKÖPING UNIVERSITY

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Sammanfattning

Ökningen av elbilar och elproduktion från solceller kan ge problem i lågspänningsnätet. Med ett ökat antal elbilar kan den sammanlagrade effekten vid laddning underskrida den minsta tillåtna spänningsnivån i nätet. Solpaneler kan däremot leda till att den högsta tillåtna spänningsnivån överskrids, genom att producera en hög sammanlagrad effekt när solstrålningen är som högst. Vanligtvis förstärker elnätsbolag i Sverige det befintliga nätet med motståndskraftigare infrastruktur, såsom kraftigare och större kablar eller transformatorstationer. Detta är dock en kostsam och tidskrävande lösning, som skulle kunna lösas med alternativa medel, till exempel redan existerande resurser.

Detta examensarbete undersöker hur smart laddning av batterier kan ge stöd till lågspänningsnätet, med en ökning av elbilar samt solcellsproduktion. För att undersöka detta har ett optimeringsverktyg utvecklats i MATLAB. En befintlig modell av ett lågspänningsnät har kombinerats med det utvecklade optimeringsverktyget, där styrbara batterier samt solcellsproduktion kan placeras vid specifika hushåll i elnätet. De styrbara batterierna är antingen elbilar eller stationära batterisystem, och är ämnade till att stödja lågspänningsnätet genom att antingen reducera effekttoppar, spänningsvariationer eller en kompromiss av båda. Vidare undersöker detta examensarbete det maximala antalet elbilar som ett specifikt lågspänningsnät i Sverige kan hantera.

Resultaten visar att smart laddning av batterier kan reducera effekttoppar samt spänningsvariationer. Reduceringen av spänningsvariationerna för hela lågspänningsnätet visar sig vara högst under sommaren, vilket är då solcellsproduktionen generellt är som högst. Resultaten visar även att stationära batterisystem kan reducera spänningsvariationer ytterligare, jämfört med en elbil. Att introducera flera styrbara batterier tillåter ett ännu större stöd till lågspänningsnätet. Angående det maximala antalet av elbilar som ett lågspänningsnät kan hantera visade resultaten att placeringen av elbilarna samt laddningseffekten har en stor påverkan.

Abstract

The increase in electric vehicles and photovoltaic power production may introduce problems to the low-voltage distribution grid. With a higher number of electric vehicles, their accumulated charging power might breach the lowest allowed voltage level of the grid. Photovoltaic-modules can on the other hand exceed the highest allowed voltage level, by producing high accumulated power when the solar irradiance is high. Normally, electric distribution companies in Sweden reinforce the existing grid with more resilient infrastructure, such as stronger and larger cables or transformer stations. This is however a costly and time-consuming solution, which could be solved by using alternative means such as already existing resources.

This Master's Thesis investigates how smart charging of batteries can support the low-voltage electrical grid with the increase in electric vehicles and photovoltaic power production. To do this, an optimization tool has been developed in MATLAB. An existing model of a low-voltage grid is combined with the developed tool, where controllable batteries and photovoltaic-modules can be placed at specific households in the grid. The controllable batteries belong to either electric vehicles or stationary battery systems, and are intended to support the grid by the means of either reducing peak load powers, voltage variations, or a trade-off between them. Furthermore, this thesis investigates the maximum electric vehicle capability for a specific low-voltage electrical grid in Sweden.

From the results, it can be concluded that smart charging of batteries can reduce the peak loads as well as voltage variations. The reduction of voltage variations for the entire low-voltage grid is greatest during the summer, when photovoltaic production generally is at its highest. The results also show that a stationary battery system can reduce the voltage variations to a greater extent, compared to an electric vehicle. Also, the introduction of multiple controllable batteries allows further support of the low-voltage grid. Regarding the maximum electric vehicle capability, the results show that the placement of the vehicles and the charging power strongly affect the maximum number of electric vehicles the low-voltage grid can manage.

Acknowledgments

We would like to express our gratitude to our examiner Christofer Sundström (Ph.D., Assistant Professor) at Linköping University, for helping us realizing our ideas of a Master's Thesis. Also, we would like to thank him for enlightening us of the electrical grid perspective in the transition to cleaner technology, and highly valuable input in discussions.

We would also like to thank our supervisor at Linköping University, Daniel Jung (Ph.D., Assistant Professor), who has been a valuable resource for us throughout the thesis. We truly appreciate our discussions, your interesting ideas and guidance in the fields of optimization, programming, data presentation as well as structuring of the thesis report.

This thesis has been a collaboration with Tekniska verken Linköping Nät AB. Andreas Åkerman (Power Grid Development Engineer) has assisted us with data and understanding of the low-voltage electrical grid, as well as giving important input to the work and guiding us towards the company's desires. We would like to thank you for your help, and would also like to thank Christian Cleber (Head of Network Development) for allowing Andreas to use his worktime to assist us and letting us collaborate with Tekniska verken.

Two fellow people we would like to thank are Johan Häggblom and Jonathan Jerner. Thank you for allowing us to continue the solid foundation work you made, and explaining concepts and assumptions in your written code and thesis.

The received responses from our future grid survey were truly appreciated, and we would once again like to thank the persons who took their time to answer our questions.

Finally, we would like to thank our friends and families for giving us support throughout our studies, and always being there for us.

Linköping, June 2019
M.D. och J.K.E.

Contents

Nomenclature

Abbreviations

Abbreviation	Meaning
DST	Dynamic Stress Test
EDC	Electric Distribution Company
EV	Electric Vehicle
FBSM	Forward Backward Sweep Method
PV	PhotoVoltaic
RES	Renewable Energy Sources
SoC	State of Charge
SBS	Stationary Battery System
TSO	Transmission System Operator

1 Introduction

In Sweden, self-produced electricity from renewable energy sources (RES) for self-consumption is becoming more common, where individual households produce electricity by installing photovoltaic (PV) modules on roofs or by the use of a wind turbine. The electric distribution company (EDC) Tekniska verken Linköping Nät AB in Östergötland county, Sweden, has noted an increase in the amount of connected PV-modules. For instance, the number of installed PV-modules increased by nearly 74 % between 2016 and 2017, and by 56 % between 2017 and 2018[1]. Table 1.1 shows data related to the increase in connected PV-modules to Tekniska verken.

Table 1.1: *PV-module statistics from Tekniska verken*[1].

Year	Connected PV-modules per Year [-]	Power [MW]	Customer Self-consumption (estimated) [GWh]
2016	76	1.9	2.4
2017	132	2.7	3.4
2018	206	4.9	5.1

These types of households are often referred to as prosumers, as they are both consumers and producers of electricity. An increasing number of prosumers may lead to problems in the low voltage grid, as the grid is not used as destined. For instance, if the prosumers produce an amount of electricity that is higher than the usage, the current in the electric grid may change direction. A problem that prosumers may encounter is high voltage transients in the electric grid during rapid changes in the weather, e.g. sudden cloud formation that covers the sun.

[1] E-mail correspondence with Andreas Åkerman, Power Grid Development Engineer at Tekniska verken Linköping Nät AB.

For instance, PV-modules that are concentrated on small areas can during cloudy days give up to an increase of 20 % in voltage transients on a minute basis [1].

Using different types of energy storage becomes highly relevant as the production of electricity from RES increases. Since RES are highly dependent on weather, a stationary battery system (SBS) could be used to store the excessive energy when the RES are producing more electricity than the consumers are using, and use the energy at another occasion when the production from the RES is low [2]. This type of energy storage could also be used to support the rest of the electric grid by shifting the peak load, and eliminating voltage transients and variations. SBSs can also be considered as substitute investments to support the existing electric grid, rather than upgrade it with larger cables and new infrastructure, which is a costly and demanding process.

According to a forecast by the interest organization Power Circle, the share of cars on the new sales market that are electrified i.e. they are chargeable, is expected to be around 50 – 80 % beyond year 2025. Also, in the year of 2017 alone, the number of electric vehicles (EVs) in traffic increased by nearly 51 % [3]. The increasing amount of EVs opens up possibilities to support the electrical grid. The battery in an EV could act as an energy storage unit that is used whenever the EV is connected to the grid [2]. EVs are in a fast development, resulting in new battery technologies, larger capacities and quicker charging. This development could affect the electrical grid in a positive manner, as the availability of EV batteries increases. A known fact and drawback with batteries is the degradation on its total capacity due to wear. However, worn batteries of EVs, that no longer meet the requirements of automotive applications due to the lower capacity, can be given a "second-life" and reused on a less demanding grid-connected energy storage application as a SBS [1, 4]. This can increase the availability of stationary batteries, as well as reducing the costs to purchase one as a customer.

EVs may also impose problems to the regional and local grid if their potential use as an energy storage is ignored, or by the lack of scheduled or smart charging. The reason behind this is that the charging of EVs can require large amounts of electric power, and there is a great possibility that the time of day when an EV is plugged in for charging coincides with the time of day the peak loads occur, which is usually during early morning and late afternoon.

1.1 Future Grid Survey

The increase in RES and EVs is a problem that EDCs in Sweden are facing. This is supported by conversations with representatives from the department of network development at Tekniska verken, as well as the answers to a survey sent out to five EDCs and the electricity transmission system operator (TSO) in Sweden. The authors of this thesis formulated the survey questions, which were open-ended. Also, they were sent out to a company working with SBSs and asked to an adjunct lecturer in electrical engineering at Linköping University. The survey questions as well as the persons that provided responds can be found in Appendix A.1.

The following bullet points summarize the collected replies:

- In general, the replies expressed concerns regarding the integration capability of EVs, and to meet the power demand when transitioning to a larger production from RES such as PV-modules. The impact of EVs will initially be seen in the local and regional grids, and electrical grids in rural areas are expected to get more problems than grids in urban areas. A problem that might arise in the future due to PV-modules are increased voltage variations.
- Many were optimistic about energy storage systems (ESS), such as SBSs and EVs, being a part of the solution to support the electrical grid in the future. However, due to the current legislation, EDCs are not allowed to own SBSs to store energy. The larger part of the EDCs follows the development of ESS, and some of the companies have started to investigate the potential of SBSs.
- An issue that many addressed was that the availability of EVs is unpredictable. Another issue was how the EV owners should be compensated whenever the battery is used. Finally, it is a risk that the electrical grid becomes more complex to control, so smart systems that aid the control are necessary.

1.2 Electrical Grid

Essentially there are two categories that electrical grids are divided into, namely transmission grids and distribution grids. Sweden uses three categories for its electrical grids: transmission grids, regional grids and local grids. This thesis uses four categories instead, where the local grid has been divided into two sets of grids, which can be seen in Figure 1.1. Figure 1.1 also outlines how electricity travels through the electrical grid from production to the end consumer. The transmission grid transfers high voltage electricity (220 – 400 kV) throughout long distances in Sweden with small energy losses. The distribution grid transfers electric energy (20 – 130 kV) to cities and companies who use a large amount of electricity. The local grid and the low-voltage grid distributes electricity (0.4 – 20 kV) to end consumers, such as households. Today's transmission network was developed in 1950 due to the expansion of the hydropower plants and in 1980 as nuclear power emerged to become one of the main sources of electricity. Hydropower plants are mainly localized in the northern parts of Sweden, whereas the nuclear power plants are found in the middle and southern parts [1].

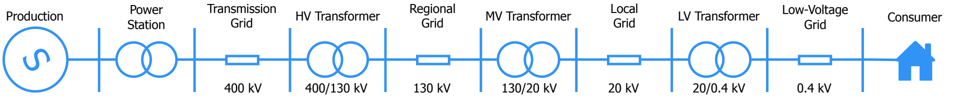


Figure 1.1: *Outline sketch of the Swedish electrical grid – From production to end consumer [1].*

The source of electricity in Sweden can generally be divided in a total of five energy sources, namely hydropower, nuclear power, wind power, bioenergy and solar power. Table 1.2 shows the production capacity of each energy source, and their gross potential [5].

Table 1.2: *Gross potential for different energy sources [5].*

Energy Source	Production Capacity Today [TWh]	Gross Potential [TWh]
Hydropower	65	100
Wind Power	15	>100
Solar Power	0.1	50
Bioenergy	20	60
Nuclear Power	65	>100

Recently, the Swedish government set the goal of producing all electricity from only RES by the year 2040 [6]. The consequence of this is that nuclear power production will gradually decrease as the production from RES will increase to compensate the liquidation of nuclear power. The term RES includes wind turbines, hydropower, solar power and bio-fuels [5].

Radial networks are normally found in rural areas. The principle of a radial network can be seen in Figure 1.2. A radial layout consists of one or more households connected to the same electrical transmission line of the grid. This layout means that the households are in series, which implies that if a fault occurs in a line, all of the households beyond the fault are disconnected from electric power supply. Another type of layout is the tied ring layout, which is basically a radial network that can be fed with electricity from both ends [7].

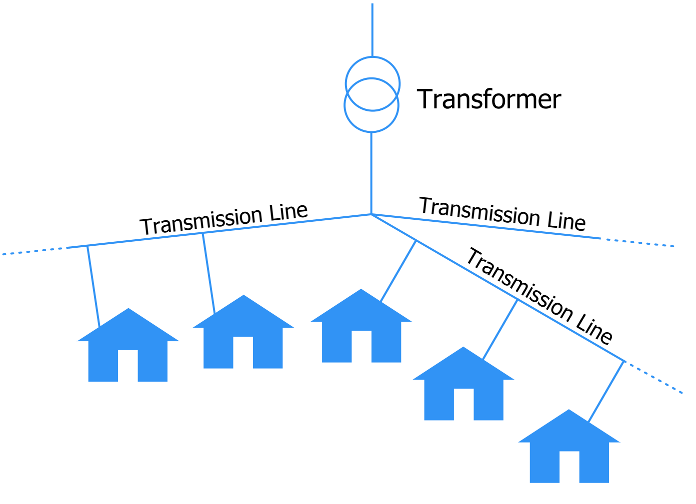


Figure 1.2: *Schematic of a radial network.*

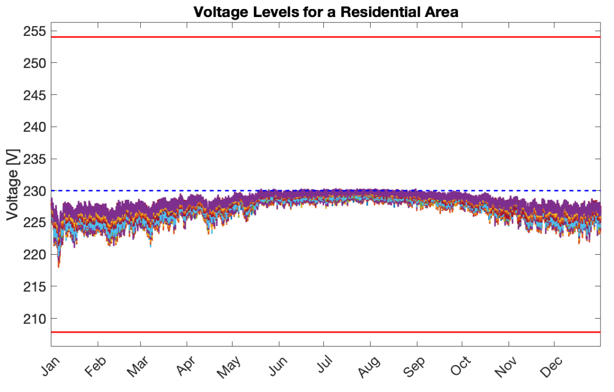
1.2.1 Ordinance and Standard

Ordinance (1999:716) [8] from the Riksdag of Sweden consists of regulations regarding measurement, calculation and reporting of transmitted electricity. The ordinance contains 34 paragraphs and applies to network concession owners i.e. EDCs such as Tekniska verken, and is only valid for measurement, calculation and reporting that the network concession owner performs on someone's behalf. Paragraphs 25 – 27 of the ordinance concern the functional requirements of the measurement systems and equipment. Overall, 25 – 27 § state that the equipment shall be able to measure current, voltage and active and reactive power. It shall also record the amount of active energy every 15 minutes. Additionally, an interface shall exist for the end customer, in which current, power (active and reactive), voltage and meter levels for in- and output of active energy can be read. Finally, the transitional provisions of the ordinance concludes among other things, that the requirements in 25 – 27 § do not need to be satisfied before the measurement year of 2025.

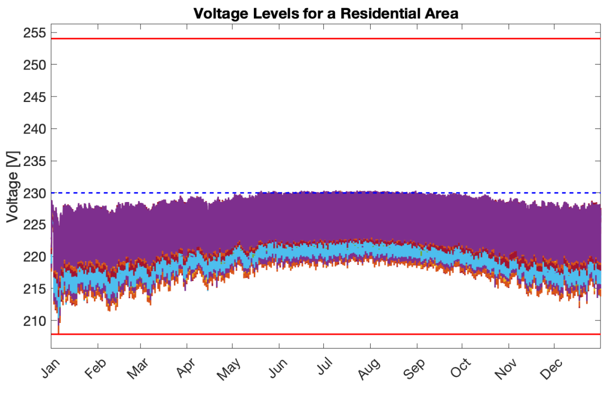
SS-EN 50160 is a Swedish Standard for the voltage characteristics of electricity supplied by public electricity networks. The standard provides guidelines, technical rules and safety regulations for EDCs. According to Section 4.2.2 of the standard, the voltage variations should not exceed ± 10% of nominal voltage level (line-to-neutral) U_n, which is illustrated in Figures 1.3a, 1.3b and 1.3c. The figures shows how the voltage levels varies during a year for 67 households located in a residential area in Sweden. Limits on the voltage are represented by the horizontal red lines. Figure 1.3c illustrates the magnitude of the problem that non-controllable EVs as well as PV production impose to the stability of the electrical grid, where it has been assumed that every household has an EV and produce PV power. It is also assumed that every EV arrives home and charges at the exact same time as each other.

As can be seen in Figure 1.3b, the introduction of non-controllable EVs lowers the voltage levels closer to the lower voltage limit. The combination of both EVs and PV production at every household, as illustrated in Figure 1.3c, gives the voltage levels a wider spectrum, as the voltages are still close to the lower limit, but also closer and above the upper limit. A possible solution for Figure 1.3b is to increase the voltage of the secondary side of the transformer as it causes the voltages to move away from the lower limit, as suggested in [9]. However, this is not a feasible solution for Figure 1.3c, since the voltages are close to both voltage limits.

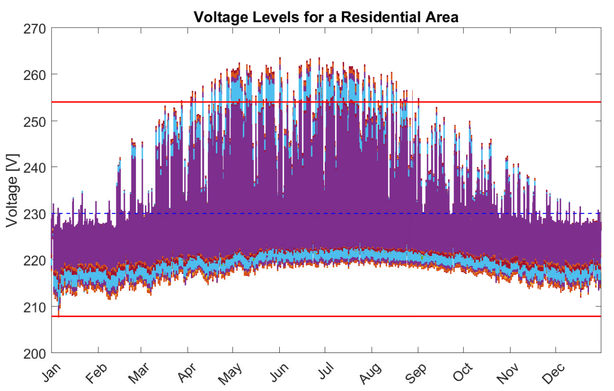
The nominal voltage level for low-voltage grids in Sweden is $U_n = 230$ V, and its nominal frequency $f_n = 50$ Hz. Also, B.6 in the appendix of the standard states that rapid voltage transients at nominal frequency level for the low-voltage grid normally do not exceed 5% of U_n, but changes up to 10% U_n for a short period of time can appear a couple of times a day under certain circumstances.



(a) *No EVs or PV production present in the grid.*



(b) *EV present at each household, no PV production.*



(c) *Each household in the grid has an EV and PV production.*

Figure 1.3: *Voltage levels for 67 houses in a residential area managed by Tekniska verken for three different scenarios **(a)**, **(b)** and **(c)**.*

1.2.2 Smart Grid and Charging

The smart grid concept implements connectivity, energy-efficiency and decentralization in the electrical grid. The current grid has been developed from a centralized production point of view, with no large scale production from RES in mind. As the self-production increases, being able to monitor electricity production and consumption will become more important. The ability of monitoring the electrical grid can bring benefits to both prosumers and EDCs. A prosumer could for instance make better decisions whether to buy or sell energy based on the energy price, or if the weather is insufficient for producing energy with RES. For an EDC, maintenance and dynamic adjustments of the production and distribution of energy can be simplified [10, 11].

In the smart grid, the increase in electricity production from RES requires a greater flexibility and that in turn requires new technical solutions. One solution which involves connectivity, energy-efficiency and flexibility is smart charging of EVs. The concept is to charge an EV at certain points in time to either take benefit of low electricity costs or to reduce peak loads [12]. Compared to scheduled charging, in which charging is limited to a specific time period with constant power, smart charging can adjust the time period and charging power to satisfy the desired objective.

1.3 Related Research

This section presents related research that has investigated similar problems.

1.3.1 Electrical Grid Stability

This thesis is a continuation of a Master's Thesis by Johan Häggblom and Jonathan Jerner. In their project, PV-power production and energy storage systems in low-voltage power grids are investigated [9]. A model of a low-voltage network was created in MATLAB. The model takes household power consumption and initial voltage guesses on each bus as input data, and computes the voltage, current and power in each of the buses of the grid. In their thesis, a bus is defined as a point in the low-voltage network, with an associated net power and voltage. A single bus can for instance be a household or connection point of two or more transmission lines i.e. cables. With the model, stability analyses for a low-voltage grid in a residential area are performed, in which PV-modules produce electricity. Parts of their project that have been used in this thesis are explained in Section 2.1.

Several Master's Theses have previously been written on the subject of the grid's capacity of EV integration. Theses on how to manage electrified vehicles and RES connected to the low-voltage grid have been investigated in [13] and [14], both from Uppsala University. The thesis in [13] looks closer how the EVs and solar panels affect the grid in terms of voltage drops and limits, as well as energy losses. It does also investigate different solutions to how the grid can meet the increasing number of EVs and RES, and how the voltage quality is affected thereby. The other thesis in [14] examines how the peak load can be reduced by implementing smart charging with or without a SBS, when charging EVs at home. The thesis does also look at which level of EV integration the requirements of the low-voltage electrical grid are breached.

In another Master's Thesis from Uppsala University [15], two case studies are performed to see the impact on the grid with an increased integration of EVs. Each case study has a specific area which is investigated, both which are urban areas. The thesis concludes that both areas are capable of handling a 100% integration of electric vehicles, without having to replace the cables of the grid. To decrease the peak load by smart charging is not implemented in the thesis, but is being highlighted as a possible solution. Two students from Chalmers University of Technology in Gothenburg investigate in their thesis the possibilities to use stationary batteries to support the electrical grid instead of cable reinforcement [16]. Their thesis studies how reinforcement by both cable and SBSs could be used in two different cases with an increase of EVs. The cases are evaluated in the software GAMS (General Algebraic Modeling System), an optimization software where their objective function were to minimize the current, total system losses and maximize the integration of EVs. The authors compared the different reinforcement solutions over multiple power demand levels and conclude that batteries are to prefer when there is a lack of power supply. Also, scheduled charging was shown to accommodate four times more EVs than uncontrolled charging.

1.3.2 Optimization Strategies

Optimal energy management in smart homes is investigated in a conference paper by Sundström, Jung and Blom [17]. In the conference paper, a model predictive controller (MPC) is implemented with the objective to achieve an optimal energy usage for a household while minimizing either the energy cost, peak power or a combination of both. The paper introduces a thermodynamic model of the house, water tanks and an EV model which all can be used for the household's energy management. Results from the implementation are compared with the optimal solution achieved by deterministic dynamic programming (DDP). An analysis of the results show that using an MPC reduces the total electric cost, as well as having a water tank installed for energy storage. Furthermore, if the objective is to reduce peak power, a long prediction horizon for the controller is of most importance to do so.

A similar smart energy management controller is developed in [18], written by Sundström and Krysander. In the conference paper, dynamic programming (DP) is implemented for vehicle charging and house heating, to investigate if reduction in electric cost can be achieved. The results from the DP are compared with an heuristic controller, and the results from the DP show that 13% in overall cost savings can be achieved compared to not using any control strategy.

A Master's Thesis from Linköping University investigates how air temperature, solar insolation and wind speed can be estimated with artificial neuron networks

(ANN), and be used in a control system to affect the electricity costs [19]. The estimations are connected to RES (wind and solar energy) that a single household might have as a prosumer, and are used in turn to estimate electricity production and consumption. In the thesis, the estimations are being input to the control system, which controls are to either sell or purchase energy, to charge or discharge a SBS, and to charge or discharge the battery of an EV. A nonlinear, constrained optimization problem is set up to select the control signals, and is solved by using the built-in MATLAB function `fmincon`. The results show that it is possible to design a control system which makes cost reductions for a househould that produces electricity by RES. Additionally, when the RES are not used, the electricity is purchased to satisfy the consumption for the househould and EV. On the other hand, when the RES are active and are producing electricity, the electricity is being sold or purchased, depending on the solution of the optimization problem.

1.4 Purpose and Goal

Tekniska verken i Linköping AB is a company that works with electric distribution, as well as regional energy and waste management, such as district heating, recycling and biogas production [20]. The authors of this report have conducted this Master's Thesis in cooperation with Tekniska verken Linköping Nät AB, which is the EDC affiliate of Tekniska verken.

The purpose of this thesis is to analyze alternative solutions to support the existing electrical grid as the use of EVs and PV-modules increases, instead of conventional cable reinforcement. The problem EVs and PV-modules imposes to the electrical grid can be seen in Figures 1.3b and 1.3c. More specifically, the thesis looks deeper into how batteries (mainly of EVs) can be used to reduce peak load power by smart charging and reduce voltage variations that can occur in the electrical grid.

The goal of this Master's Thesis is to develop and implement an optimization tool which can be used to determine how batteries can be used for reducing peak load power of a household, and reduce voltage variations that can occur in the electric grid with the increase in production from RES and number of EVs.

1.5 Problem Formulation

Based on the purpose and goal of Section 1.4, the problem formulation can be summarized by the following bullet points:

- Can smart charging of batteries (of EVs) be applied to lower peak loads and thereby smoothen out the load profile of a household in a low-voltage electrical grid, with existing electric power production from PV-modules?
- Can the usage of EV batteries be used to lower voltage variations that may occur in the low-voltage electrical grid, with existing electric power production from PV-modules?
- How are the peak loads and voltage variations in the electrical grid affected by the use of SBSs?
- What is the maximum integration level of EVs that certain low-voltage grids areas managed by Tekniska verken can handle, with existing electric power production from PV-modules?

1.6 Delimitations

The low-voltage grid model used in this thesis uses hourly-based consumption data from households supplied by Tekniska verken. Since the data is on an hourly-basis, shorter sample times can not and will not be investigated. Consequently, it will not be possible to investigate voltage transients that can occur in the electrical grid, as the low-voltage grid model would need data of shorter sample time. Additionally, the model used in this thesis assumes symmetrical loads in all three phases, and calculations are thereby performed for a one three-phase equivalent line.

The behaviour of the battery is assumed to be equivalent for both the electric vehicle and the stationary battery. Therefore, only one battery model is used throughout the thesis. The battery model is also assumed to be linear, due to linear efficiency. Also, temperature effects are not considered for the battery and the type of battery is lithium-ion.

This thesis focuses solely on the impact on the low-voltage grid by introducing smart battery management for EVs and SBSs. This is due to the fact that the grid model developed in [9] is a low-voltage grid model. Other delimitations regarding the grid model can be found in [9].

1.7 Thesis Outline

In this report, **Chapter 1** and the following chapters are included:

Chapter 2 – Modeling
This chapter presents the models used in the project.

Chapter 3 – Optimization Problem
In here, the optimization problem is explained and set up. Also, it introduces the concept of nonlinear programming to the reader for a better understanding of the optimization problem setup.

Chapter 4 – Results and Analysis
Includes the results and presents analyses that have been achieved in the project. Numerical results and figures are displayed here.

Chapter 5 – Discussion
Discussion about the results and parts that have not been enlightened previously in the thesis.

Chapter 6 – Conclusions and Future Work
This chapter summarizes the Master's Thesis, as well as the results and analyses of Chapter 4. Suggestions of future work are presented.

2

Modeling

The purpose of this chapter is to present the applied models of this Master's Thesis project. Section 2.1 presents the low-voltage grid model that is used in this thesis. In Section 2.2, the battery model is presented, and the final section of this chapter, Section 2.3 brings up the PV-module model.

2.1 Low-Voltage Grid Model

In this thesis, the low-voltage grid model created by Johan Häggblom and Jonathan Jerner has been used for optimization purposes [9]. This section will provide a more thorough description of the parts of the grid model relevant to this thesis, as a complement to the brief description in Section 1.3.1. The electrical grid examined in this thesis can be seen in Figure 2.1, which is based on a residential area in Sweden, and is managed by Tekniska verken. This electrical grid has a total of 120 buses, where 67 of these buses are households and are represented by the red markers in Figure 2.1. The transformer is located between bus one and bus two. The remaining blue buses are different cables being joined together. For instance, a blue bus can be a cable distribution cabinet. Figure 2.2 is another version of Figure 1.1, and specifies which section of the electrical grid that is analyzed in this thesis. Note that the faded part of Figure 2.2 is not considered in this thesis.

The model in [9] assumes symmetrical loads in all three phases, and calculations are thereby performed for a one three-phase equivalent line. As inputs, the grid model uses power consumption data, provided by Tekniska verken, as well as an initial voltage guess on each bus. The provided power consumption data does only include data for each household from the year of 2017 on an hourly basis.

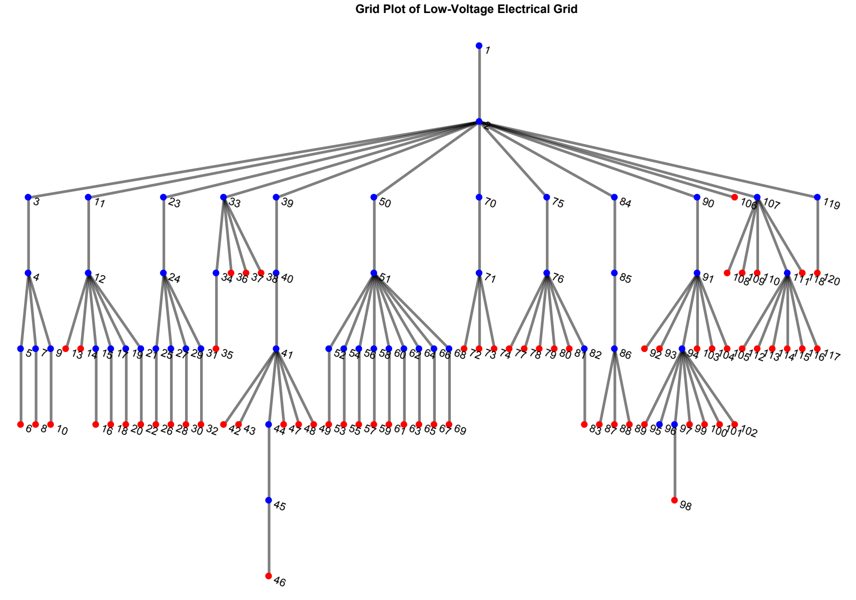


Figure 2.1: *Grid plot of the grid used in this thesis. All connections are represented by the black lines, load buses in red and other buses in blue. A single branch in the grid plot contains the buses and connections from one household to the transformer (bus 2) [9].*

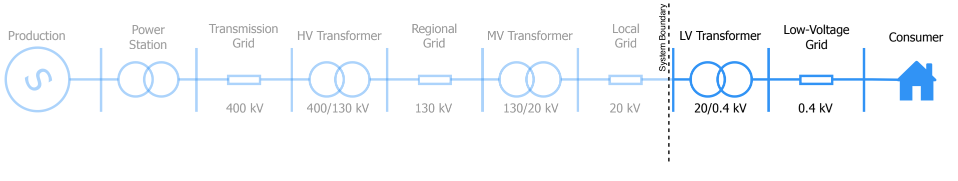


Figure 2.2: *Illustration of which part of the electrical grid that is analyzed.*

The power consumption of the remaining buses are initially set to zero. All calculations are performed in a Per-Unit System (p.u.), meaning that all computed entities are normalized to a nominal value, e.g. the nominal voltage $U_n = 230$ V. The initial voltage guesses are set to 0.99 p.u. (99 % of U_n) for buses that are households and 1.00 p.u. for the remaining buses [21].

To illustrate the impact a conventional EV, that only is capable of charging its battery, has on a household, an EV has been added to one of the houses in the electrical grid. This is done by altering the power consumption data for a household bus by adding an external load, which represents an EV. Figure 2.3 illustrates the impact of the EV, where it can be seen how periodic charging of an EV affects the voltage level and the power consumption of a household. Note that the EV is assumed to be at home during the weekends, resulting in no effect during Saturdays nor Sundays. In the figure, the timeline used in the simulation was set to two weeks in January.

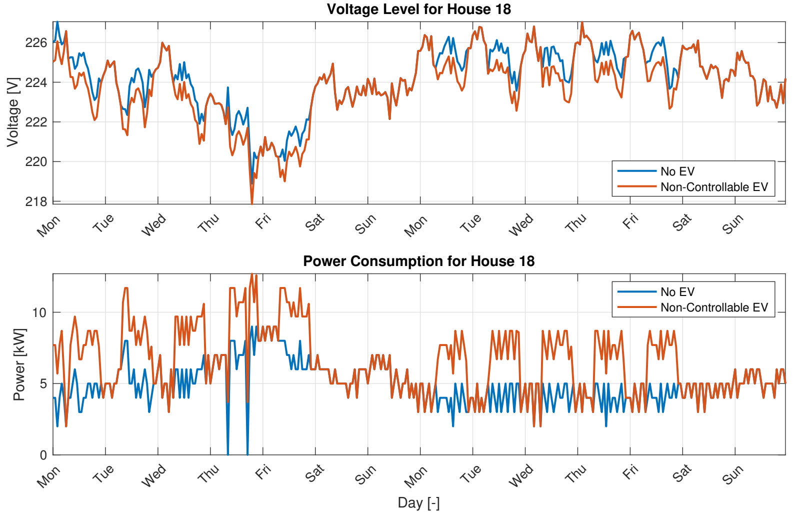


Figure 2.3: *The effect of having a non-controllable EV on a household's voltage level and power consumption.*

2.1.1 FBSM-Solver

The solver function of the model uses the Forward Backward Sweep Method (FBSM), which is an iterative method that computes the outputs of the model, namely the voltage, current and power of each bus in the grid [9, 22]. In [9], the authors makes use of the results from [22], which is an article that concludes FBSM to be the most efficient method among other solver methods for radial networks. Note that during the backward sweep, the calculation begins at the load buses and continues upwards. The forward sweep begins at the transformer bus and continues downwards to the load buses.

The solver function is implemented to start with the backward sweep to determine the current, power and power losses at the connections as well as the power at the buses. When the backward sweep is completed, the algorithm continues and begins calculating forward to determine the voltage drops over the connections and the voltage at the buses. As the algorithm has completed both the backward and forward sweep, it now compares the results from this iteration with the iteration before to determine if the convergence criteria are fulfilled or not. If the criteria are fulfilled, the algorithm stops. However, if the criteria are not fulfilled the algorithm starts over until the convergence criteria is fulfilled or if the maximum number of iterations is exceeded.

The power consumption of the households, which is one of the inputs to the model, remains the same when the solver has completed a calculation. This is due to the fact that the main purpose of the model is to determine the power in the buses that are not households as well as the current and voltage of all 120 buses. A more thorough description of the model and its solver can be found in [9].

2.1.2 Power-Voltage Correlation

Figure 2.4 illustrates how a household is connected to the low-voltage transformer via a cable. The transformer can also be cable distribution cabinet. The cable is represented by the line that goes from $\overline{U}_1$ to $\overline{U}_2$, and is assumed to consist of an inductor with inductance L and resistor with an internal resistance R_i. This cable model is the one implemented in the low-voltage grid model developed in [9]. The voltage at the end consumer $\overline{U}_2$ can be expressed as follows

$$\overline{U}_2 = \overline{U}_1 - \overline{U}_{cable} = \overline{U}_1 - (R_i\overline{I} + j\omega L) \tag{2.1}$$

where $\overline{U}_1$ is the voltage level at the transformer bus and $\overline{U}_{cable}$ is the voltage drop over the cable. When the electric power consumption of the consumer increases, for instance at peak loads, the current demand $\overline{I}$ increases. Thus, the term $R_i\overline{I}$ of (2.1) grows, which reduces the voltage magnitude at the consumer, $\overline{U}_2$.

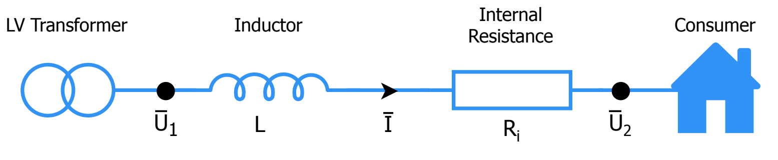


Figure 2.4: *Outline sketch of a cable connecting a consumer to the low-voltage transformer.*

2.2 Battery Model

The State of Charge (SoC) is the ratio of a battery's current capacity to its nominal capacity [23]. It is a measure how much battery capacity is left before it is fully depleted. A battery model can be expressed as

$$\mathrm{SoC}(t+1) = \mathrm{SoC}(t) + \eta_{batt} \cdot \frac{P_{batt}(t)}{Q_{batt}} \tag{2.2}$$

where $\mathrm{SoC}(t+1)$ is the SoC of the next point in time, $\mathrm{SoC}(t)$ the current SoC, η_{batt} the efficiency of the battery, $P_{batt}(t)$ the battery power and Q_{batt} the total capacity of the battery. The expression in (2.2) is a linear one, but can be seen as nonlinear due to lithium-ion batteries' discharge characteristics, which are displayed in Figure 2.5 [24]. A battery's life is affected by a number of factors, such as elevated temperature and the amount of dis-/charge cycles. Whenever a battery is said to be at the end of its lifetime, its capacity has typically decreased to 80 % of its nominal capacity rating [25]. The battery degradation of lithium-ion batteries can be seen in Figure 2.6, where an increase in Dynamic Stress Test (DST) cycles degrade the capacity of the battery [26]. Also, the figure shows how the actual SoC range of a test affects the capacity retention. For instance, by letting SoC $\in [25\%,\ 100\%]$ degrades the battery to a greater extent than SoC $\in [65\%,\ 75\%]$.

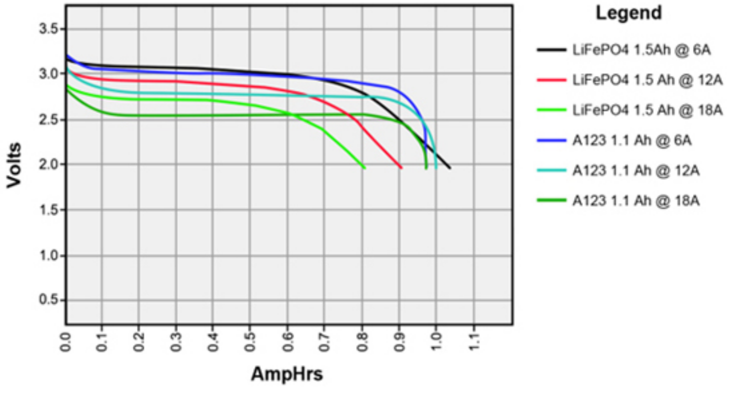


Figure 2.5: *Discharge profile of lithium iron phosphate. The image is from Battery University [24].*

2.2.1 Battery Parameters

To create the model of an EV, (2.2) was used. The parameters that define the battery are the efficiency η_{batt} and its total capacity Q_{batt}. In this thesis, two different types of EVs have been implemented: the Renault ZOE [27] and the Tesla Model S P100D [28]. These specific models were selected to represent EVs

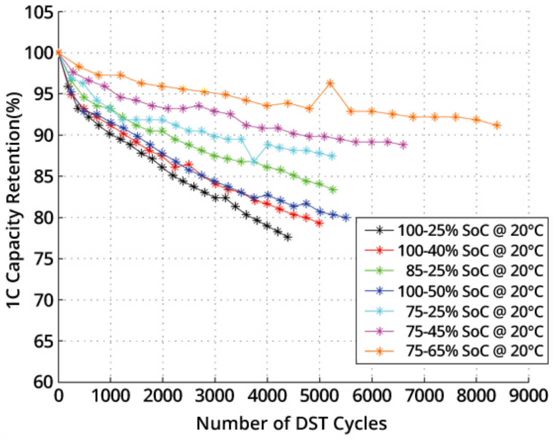


Figure 2.6: *Capacity loss of lithium-ion battery as a function of charge and discharge cut-off points. The image is from Battery University [26].*

with distinct battery capacities. Both are full EVs i.e. they rely solely on electrical power for propulsion. Each EV has a lithium-ion battery and the batteries were assumed to have an efficiency of 99 %. It is a typical charge efficiency value of lithium-ion batteries [29], and has been used in this thesis for dis-/charging. For the results and analysis in Chapter 4, the Tesla and its characteristics were analysed the most and are therefore presented in that chapter. The Renault was implemented for comparison purposes only, and is highlighted in Chapter 5.

In this thesis, an EV is said to be controllable if it can be charged and discharged i.e. electric power can flow into or out of the battery. On the contrary, a non-controllable EV can only be charged with a specific electric power until it reaches a desired SoC level. Hence, a controllable EV allows for smart charging as well as reducing peak loads, while a non-controllable can only experience scheduled charging. Throughout this thesis, charging of the battery takes positive values i.e. $P_{batt}(t) > 0$, and discharging of the battery takes negative values, that is $P_{batt}(t) < 0$. The maximum allowed dis-/charging power is set to 11 kW for the Renault, and 16.5 kW for the Tesla. These values are based on common home charging applications for each EV [30, 31]. A non-controllable EV is set to charge with 11 kW, unless its SoC exceeds 90 %. If that is the case, it adjusts its scheduled charging power accordingly until the battery has reached the desired SoC value.

In the analysis, the EV(s) is (are) set to be away from the household in between 08:00-17:00 to represent an average working day, which applies for the weekdays. It is assumed that the EV will drive a total of 33 km each day as it is away from the household, resulting in a lower SoC when the EV arrives home. The distance driven each day is based on the average distance driven by a private car in 2017 [32]. This makes the EV(s) available for control during the remaining hours. Furthermore, it is assigned that the SoC of the EV(s) should be at least 80 %

each weekday morning between 07:00–08:00, before leaving to work. During the weekend, the EV(s) remains(-s) at the household(s). Figure 2.3 shows these characteristics for a non-controllable EV. Whenever the car is away, it is assumed that its SoC decreases linearly with an specific power consumption. The power consumption for each EV model was collected from *Spritmonitor.de*, a German website where users log and upload the fuel-consumption data of their vehicles under real-life conditions.

The SBS model was also created by using (2.2), and the same battery capacities of the EVs were applied. The only difference implemented was that the battery of the SBS remains at the household and its only controllable. Specific data for the EVs and SBS are found in Table 2.1.

Table 2.1: *Battery Characteristics.*

Battery Type	Capacity [kWh]	Efficiency [-]	Power Cons. [kWh/100 km]	Max. Power [kW]
EV (Renault ZOE)	41	99 %	16.7	11
EV (Tesla Model S P100D)	100	99 %	24.0	16.5
SBS	41/100	99 %	N/A	11/16.5

2.3 Photovoltaic Module Model

A PV-module is an array of photovoltaic cells, which can produce electrical power by the sun's irradiance. PV-modules are therefore a renewable energy source, which make them a part of the transition to a more green energy production [33]. A single PV-cell has similar characteristics to that of an electrical diode and produces power according to

$$P_{PV} = U_{PV} \cdot I_{PV} \tag{2.3}$$

The voltage and current of the PV-module (U_{PV} and I_{PV} respectively) depend on a number of factors, such as irradiance, cell temperature, tilt angle and the number of PV-cells [34]. Since this thesis does not focus on modeling of PV-modules, these relations are not explained in detail. Instead, a PV model developed in a Master's Thesis [35] has been implemented in this thesis. The model is implemented in MATLAB and can compute the produced electrical power (P_{PV}) from a PV-module by the input of its location, orientation to the sun, tilt angle and solar irradiance data. The calculated power P_{PV} by the model is expressed in hourly data, which makes it suitable to combine with the hourly consumption data. Also, the peak PV-power produced by the model is slightly greater than 8 kW, which is close to the total power capability of a PV system for a typical residential household [36].

The location was set to Norrköping, since it has the closest weather station to the investigated residential area. Orientation to the sun was set to south and the tilt angle to 22°. These settings were chosen since a PV-module facing south will generally receive the most sunlight, and it was noticed that other tilt angle values had a minor impact on the produced power by the PV-module. Solar irradiance data from 2017 was provided by the Swedish Meteorological and Hydrological Institute (SMHI)[2].

[2]Data was sent to the authors by E-mail from Tomas Carlund, meteorologist at SMHI.

3

Optimization Problem

Now that all models used in this thesis have been presented, the optimization problem is explained and set up. The optimization problem is designed to satisfy the purpose and goal in Section 1.4, and to provide answers to the questions of the problem formulation in Section 1.5.

3.1 General Setup

This section and its subsections present the general setup for the optimization problem, which originates from the general structure displayed in (3.1). The optimization problem is implemented in MATLAB and the optimization makes use of the built-in nonlinear programming solver `fmincon`.

3.1.1 Nonlinear Programming

Nonlinear programming is the concept of optimizing a nonlinear objective function subjected to a number of constraints, where some of them or all can be nonlinear. Depending on the problem which is to be solved, the optimization problem is set up differently as well as the applied method. For instance, if the problem is unconstrained, methods such as quasi-Newton, Nelder-Mead and trust-region are applicable. When there are constraints involved, common methods to solve the optimization are the interior-point, sequential quadratic programming and trust-region reflective method [37].

In general, a constrained nonlinear programming problem in which the objective function $f(x)$ is to be minimized, can be put on the form

$$\begin{aligned} \min_{x} \quad & f(x) \\ \text{s.t.} \quad & c(x) \leq 0 \\ & c_{eq} = 0 \\ & A \cdot x \leq b \\ & A_{eq} \cdot x = b_{eq} \\ & lb \leq x \leq ub \end{aligned} \tag{3.1}$$

where x is a vector containing the decision variables i.e. the minimizers and the variables of the nonlinear objective function $f(x)$, $c(x)$ and $c_{eq}(x)$ can be nonlinear functions typically used to set nonlinear inequality and equality (eq) constraints, respectively. The matrices A and A_{eq} together with the vectors b and b_{eq} are used to set linear inequality and equality constraints respectively, that are linearly dependent to x. The lower bound is lb and ub is the upper bound for x [38].

3.1.2 Constraints and Bounds

To set up the optimization problem, the purpose and goal in Section 1.4 need to be translated mathematically to (3.1), which is the basic structure of `fmincon`. There is a number of constraints that needs to be taken into consideration when optimizing. The voltage variation limits for the buses of $U_n \pm 10$ % from the standard SS-EN 50160 are set as nonlinear constraints, due to that the voltage levels of all buses in the grid U_{bus}, are computed by the FBSM-solver, which is a nonlinear function. The bus currents I_{bus} are also computed by the FBSM, so the maximum allowed current $I_{house,max}$ is also defined as a nonlinear constraint. Its maximum value is determined by the electrical fuse of a household, which in turn is set by the annual power consumption of a household. It was found out that the consumption was between $20,000 - 25,000$ kWh for the households of the investigated residential area. This corresponds to $I_{house,max} = 20$ A, according to [39].

Firstly, the SoC of the battery is set to take values in the range of SoC $\in [10\%,\ 90\%]$. The maximum SoC of 90 % is chosen since limiting a full charge prolongs the life of the battery [26], and the aging of the battery increases when it is stored with a SoC beyond this value [40]. The value of 10 % is selected to avoid full discharging of the battery, which otherwise shortens the battery's life [26].

Secondly, the SoC is restricted to take a too high or low value from a point in time (t) to the next, $(t+1)$. This is confirmed by (2.2) on page 17. When the battery power $x(t) = \pm P_{batt,max}$, depending if the car is charging or discharging, SoC$(t+1)$ is assigned its maximum allowed value from (t) to $(t+1)$. The maximum allowed power to or from the battery $P_{batt,max}$, is determined by maximum allowed power of the specific EV, see Table 2.1, and the electrical fuse of the household. For this thesis, it assumed that all houses use an electrical fuse of 20 A, which yields a maximum power outtake of 13.8 kW ($P_{house,max} = 3 \cdot U_n \cdot I_{house,max} = 3 \cdot 230 \cdot 20 = 13.8$ kW). Power from PV-production is also included in the maximum power outtake of a household. Finally, the lower and upper bound for the battery power x are therefore extracted from the expression $|P_{house}(t) + x(t)| \leq P_{batt,max}$.

The general structure of (3.1) can be modified with the addition of the general constraints and bounds, which results in the following structure

$$
\begin{aligned}
\min_{x} \quad & f(x) \\
\text{s.t.} \quad & \text{SoC}_{min} \leq \text{SoC}(t) \leq \text{SoC}_{max} \\
& -\frac{P_{batt,max}}{Q_{batt}} \eta_{batt} \leq \text{SoC}(t+1) - \text{SoC}(t) \leq \frac{P_{batt,max}}{Q_{batt}} \eta_{batt} \\
& 0.9\ U_n \leq U_{bus}(t) \leq 1.1\ U_n \\
& I_{bus}(t) \leq I_{house,max} \\
& -P_{batt,max} - P_{house}(t) \leq x(t) \leq P_{batt,max} - P_{house}(t) \\
& -P_{house,max} \leq P_{house}(t) \leq P_{house,max} \\
& \text{SoC}(t+1) = \text{SoC}(t) + \eta_{batt} \cdot \frac{x(t)}{Q_{batt}} \\
& [P_{bus}(t), U_{bus}(t), I_{bus}(t)] = \text{FBSM}(x(t), P_{house}(t), U_{guess}(t))
\end{aligned}
\tag{3.2}
$$

3.1.3 Cluster Definition

A cluster is defined as the households that are on the same branch initiating from the transformer at bus 2, as shown in Figure 3.1. The only exceptions are the branches emerging from bus 90 and 107, which consist of two clusters each (one cluster for bus 89 and 97-102, and one cluster for bus 92, 93 and 103-105). Throughout the optimization problem, the optimization of EV battery power is performed with respect to the voltage levels of the cluster households $U_{cluster}(x)$, and not all households of the residential area. The reason behind this is that it requires far more computational power to include all households, and it was noticed that doing so had little or no effect on the optimal solution.

Another reason to why only the households in the cluster were considered is due to how the solver of the low-voltage grid model computes the power and voltage at each bus. Assume that an external load, i.e. a PV-module or an EV, is present at bus 8 in Figure 3.1. The external load would affect the power consumption in bus 8, which during the backward sweep of the solver affects the power of all buses that are above bus 8. For this given example, the affected buses are namely 7, 4, 3 and 2. As the backward sweep is completed, the solver begins the forward sweep to determine the voltages at each bus. Due to the relation between power and voltage, as explained in Section 2.1 on page 13, the largest changes in voltage will be noticed in the buses that are present in cluster since the power will only be affected in these buses. Therefore, it becomes natural to only consider the voltage levels of the households in the cluster when optimizing.

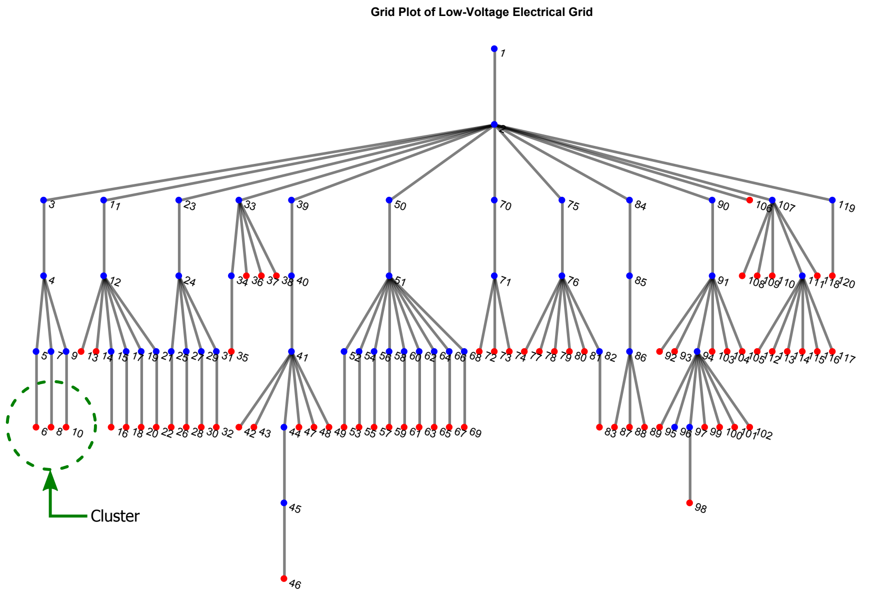


Figure 3.1: *Definition of a cluster of households in the low-voltage network.*

3.2 Objective Function

The objective function of the optimization problem was designed as sums of squared errors, that considers both smoothing of the power consumption profile, and to simultaneously reduce voltage variations of the adjacent households in the cluster. Consequently, this results in a single objective function $f(x)$ consisting of two parts, and is expressed as

$$f(x) = (1-\lambda)\sum_{i=1}^{n_{EV}}\sum_{t=1}^{n_{hours}}(P_{house,it} + x_{it})^2 + \lambda \sum_{j=1}^{n_{cluster}}\sum_{t=1}^{n_{hours}}(U_{mean,jt} - U_{cluster,jt}(x_{jt}))^2 \tag{3.3}$$

where λ is a weight parameter, P_{house} is the net power consumption of the household (PV power production included) before the optimization, x is the power flow to and from the battery of the EV ($x_t = P_{batt}(t)$, in (2.2)), U_{mean} contains the mean values of the voltage levels of the households before optimizing (no EV present), and $U_{cluster}(x)$ the voltage levels of the households adjacent to households with an EV. The total number of controllable EVs is denoted as n_{EV}, the hours of the investigated timeline is n_{hours}, and the number of adjacent households in the cluster is set to $n_{cluster}$. For variables with indexing $(\cdot)_{it}$ or $(\cdot)_{jt}$, the size of i is based on n_{EV}, t is based on n_{hours} and j is based on $n_{cluster}$. By combining the objective function in (3.3) with the constraints and bounds in (3.2), the optimization problem can be set up as

$$
\begin{aligned}
\min_{x} \quad & (1-\lambda)\sum_{i=1}^{n_{EV}}\sum_{t=1}^{n_{hours}}(P_{house,it}+x_{it})^2+\lambda\sum_{j=1}^{n_{cluster}}\sum_{t=1}^{n_{hours}}(U_{mean,jt}-U_{cluster,jt}(x_{jt}))^2 \\
\text{s.t.} \quad & \mathrm{SoC}_{min} \leq \mathrm{SoC}(t) \leq \mathrm{SoC}_{max} \\
& -\frac{P_{batt,max}}{Q_{batt}}\eta_{batt} \leq \mathrm{SoC}(t+1)-\mathrm{SoC}(t) \leq \frac{P_{batt,max}}{Q_{batt}}\eta_{batt} \\
& 0.9\ U_n \leq U_{bus}(t) \leq 1.1\ U_n \\
& I_{bus}(t) \leq I_{house,max} \\
& -P_{batt,max}-P_{house}(t) \leq x(t) \leq P_{batt,max}-P_{house}(t) \\
& -P_{house,max} \leq P_{house}(t) \leq P_{house,max} \\
& \mathrm{SoC}(t+1)=\mathrm{SoC}(t)+\eta_{batt}\cdot\frac{x(t)}{Q_{batt}} \\
& [P_{bus}(t), U_{bus}(t), I_{bus}(t)] = \mathrm{FBSM}(x(t), P_{house}(t), U_{guess}(t))
\end{aligned}
\tag{3.4}
$$

3.2.1 Pareto Optimal Solutions

To adjust the trade-off between the two parts of the objective function in (3.3), the weight parameter $\lambda \in [0,1]$ is included in (3.4). Also, this enables the questions in Section 1.5 to be analyzed separately. A λ-value closer to one results in greater reduction of voltage variations and little to no consideration of reducing peak loads. If λ takes a value closer to zero, it results in the opposite, namely a greater reduction of peak loads and little to no consideration of reducing the voltage variations. Therefore, no solution is optimal for both peak load and voltage variation reduction, but the solution is basically a trade-off between the objective of each part.

The trade-off between different objectives introduces the concept of Pareto optimality, which is mainly used in economics. A Pareto optimal point is the point of allocation of resources, where a certain preference can not me made better off without making another one worse off [41]. To exemplify, a preference might be to prioritize reduction of voltage variations and making them better off, but that might make the load profile worse off. This example can be seen as to penalize high voltage variations, associated to a certain cost function. Multiple Pareto optimal points can exist, and together they can be visualized in a Pareto optimality curve, as shown in Figure 3.2.

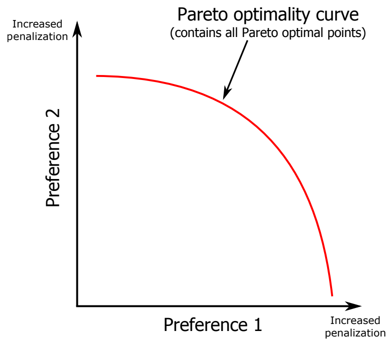


Figure 3.2: *Example of a typical Pareto optimality curve. The figure is made by the authors.*

3.3 Implementation of Algorithm

As mentioned earlier, the implemented optimization makes use of MATLAB's built-in solver `fmincon`, and the standard tolerances for `fmincon` were used. When performing an optimization, a specific timeline in 2017 e.g. a week in October is selected, for which the optimization is executed. By having this function, seasonal differences in the stability of the grid can be analyzed. An optimization is executed by the inputs of:

- a selected timeline
- value of the weight parameter λ
- the current EV model and if it is controllable or not
- if solar power production exists
- which house(s) that has (have) a battery to use
- if the battery is part of a SBS or an EV.

The output of an optimization is the minimizer and battery power x, which is the solution to how the battery should operate to achieve the optimal solution of the objective function $f(x)$ in (3.4).

A flowchart of how the optimization works is shown in Figure 3.3. The iterative section of the flowchart in the figure calls the FBSM-solver in order to check if all constraints on the optimization are fulfilled. The number of calls to the solver for one iteration is determined by the amount of houses that have a controllable EV and the amount of hours that are included in the input timeline. As the optimization problem grew by optimizing over longer timelines and by adding more controllable EVs, it was deemed that the calculation time of the implemented FBSM-solver in MATLAB was too high. This became an issue, which was solved by translating the FBSM-solver to C++ code. The improvement in calculation time can be seen in Figure 3.4, where a simulation with a timeline of one day was executed ten times in both MATLAB and C++. As Figure 3.4 shows, C++ is roughly 50 times faster than MATLAB.

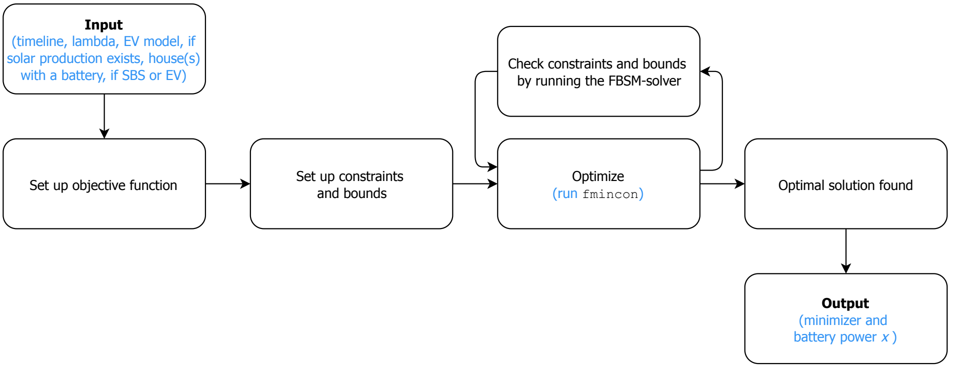


Figure 3.3: *Flowchart of the optimization process.*

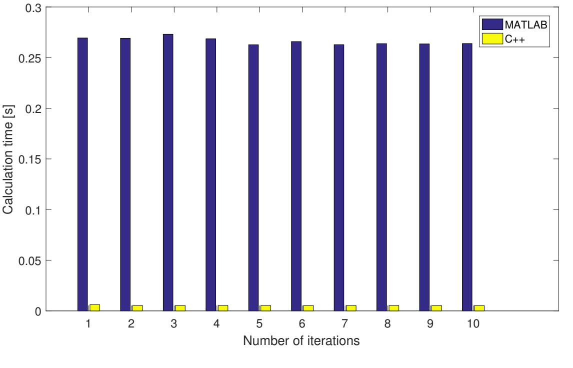


Figure 3.4: *Comparison in calculation time of the FBSM-solver implemented in MATLAB and C++*

4

Results and Analysis

In this chapter, the results from the analyses are presented. Firstly, a Pareto optimality curve was generated for the given optimization problem presented in (3.3). The purpose was to analyze how different values on the weight parameter affects the solution of the optimization.

Secondly, the seasonal differences were investigated for $\lambda = 0$ and $\lambda = 1$. These analyses were conducted by only using one controllable EV, with existing PV production. The selected seasons were winter and summer. Also, the EV was replaced with a SBS for performance comparison.

Thirdly, multiple controllable batteries were introduced in the grid as well as non-controllable EVs. Optimizations were performed to investigate how the controllable batteries could reduce the voltage variations in the grid. The controllable batteries were either EVs or SBSs, and a performance comparison of them was made.

Finally, the maximum EV integration capability was investigated. The purpose of this analysis was to find the maximum number of non-controllable EVs the grid could manage in terms of voltage, for different charging powers.

4.1 Pareto Optimality Curve

Figure 4.1 shows the Pareto optimality curve, which is basically the trade-off between load profile smoothing versus voltage variation reduction. The total sum of the load profile smoothing is located on the y-axis, and the total sum of the voltage variation reduction on the x-axis. The figure was produced by performing several optimizations for the optimization problem in (3.4) on page 25, assigning λ with a different value in the range of $[0, 1]$ for each optimization. The controllable EV was placed on the household with bus number 18, and the optimization problem in (3.4) was applied to analyze a winter week in February. It was noticed that a step in λ of 0.1 resulted in a coarse Pareto curve. Thus, finer steps of 0.01 were taken for $\lambda \in [0.7, 1]$ to see how it affected the Pareto curve and therefore the trade-off.

It can be seen in Figure 4.1 that a step in λ from 0.9 to 1 greatly increases the sum related to the load profile. Numerically, it is an increase by nearly 20 %. The voltage variation sum is decreased by 10 % for the same step. On the other hand, steps in λ from e.g. 0.4 to 0.5 to prioritize load profile smoothing further, increases the load profile sum by 0.3 %, and decreases the voltage variation sum by approximately 3 %. From this result, it can be said that steps in λ closer to 1 clearly have an impact how each part of the objective function is penalized. More specifically, the sum connected to load profile smoothing increases to a greater degree than the decrease in the voltage variation sum when λ. This also means that when voltage variations are penalized more, the battery power usage is increased.

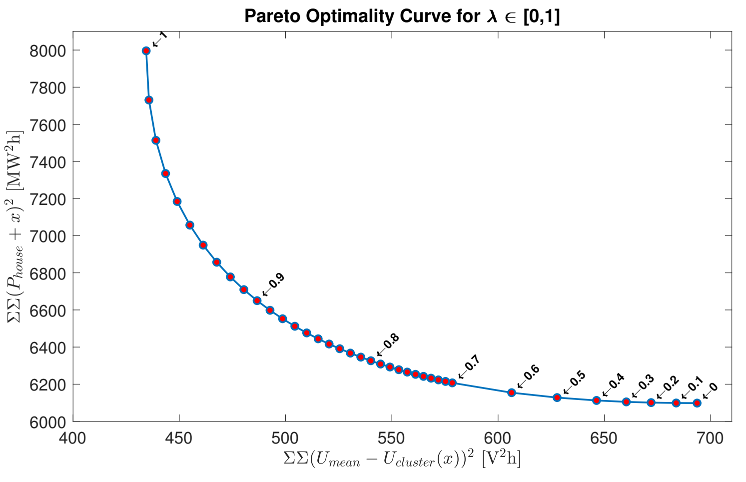


Figure 4.1: *Pareto optimality curve for the objective function with both load profile smoothing (y-axis) and voltage variation reduction (x-axis).*

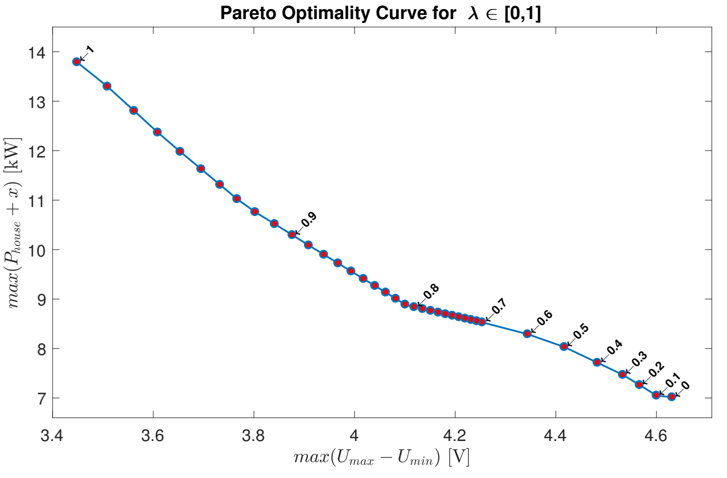


Figure 4.2: *Pareto optimality curve with axes representing the maximum power of the household (y-axis) and the maximum difference between the maximum and minimum voltage level in the cluster (x-axis).*

A more tangible version of Figure 4.1 is shown in Figure 4.2, which shows how different values of the weight parameter λ affect the maximum power consumption of a household, and the maximum difference between the maximum and minimum voltage level in the cluster. By comparing it to Figure 4.1, the relation is a more linear one. However, once again it can be said that steps in λ closer to 1 has an greater impact how each part is penalized. For instance, a step from 0.9 to 1 results in a increase by 34 % in maximum power, and the same step makes a decrease in maximum voltage difference by 11 %. It can also be said from Figure 4.2 that if the maximum difference between the maximum and minimum voltage level wants to be reduced as much as possible ($\approx$ 1.2 V), the maximum power of the household nearly doubles.

The impact of the parameter λ is also illustrated in Figure 4.3, where the investigated values of λ is set to four different values, namely 0, 0.7, 0.9 and 1. When the weight parameter is set to zero, the objective function clearly succeeds in minimizing variations in the load profile of the household, but takes little to no consideration to the voltage variations. As the weight parameter increases, the variations of the load profile increases accordingly since the objective function chooses to prioritize the second term, which penalizes variations in voltage.

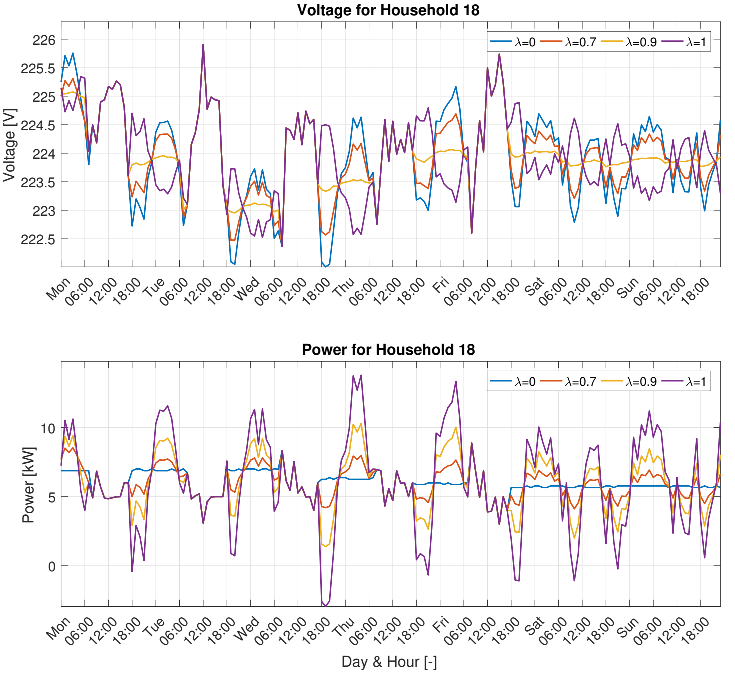


Figure 4.3: *The voltage and power levels for different values on the weight parameter λ.*

The difference in performance of having $\lambda = \{0.9, 1\}$ is shown in Figure 4.4 and Figure 4.5, respectively. These figures show how much the voltage variations have reduced in each bus after the optimization, which is done by using the following performance measure

$$U_{var} = 100 \cdot \left(1 - \frac{\text{var}(U_{opti})}{\text{var}(U_{bef})}\right) \tag{4.1}$$

where the variance of the voltage level after the optimization, U_{opti} is compared with the voltage variance before the optimization, U_{bef}. The performance measure U_{var} is yielded as a percentage which describes the improvement, or deterioration, of the variance. Both Figure 4.4 and Figure 4.5 include the performance measure, which can be seen on the right side of the figures, and is used to determine the color of each bus. As one can see in these figures, having the weight parameter equal to 1 results in a greater reduction of voltage variation for the cluster, and for the remaining buses outside the cluster. However, the reduction for the household with an EV is lower when $\lambda = 1$. The reason for this is that load profile smoothing is not considered at all, causing more battery power to be used for greater reduction of voltage variation in the cluster.

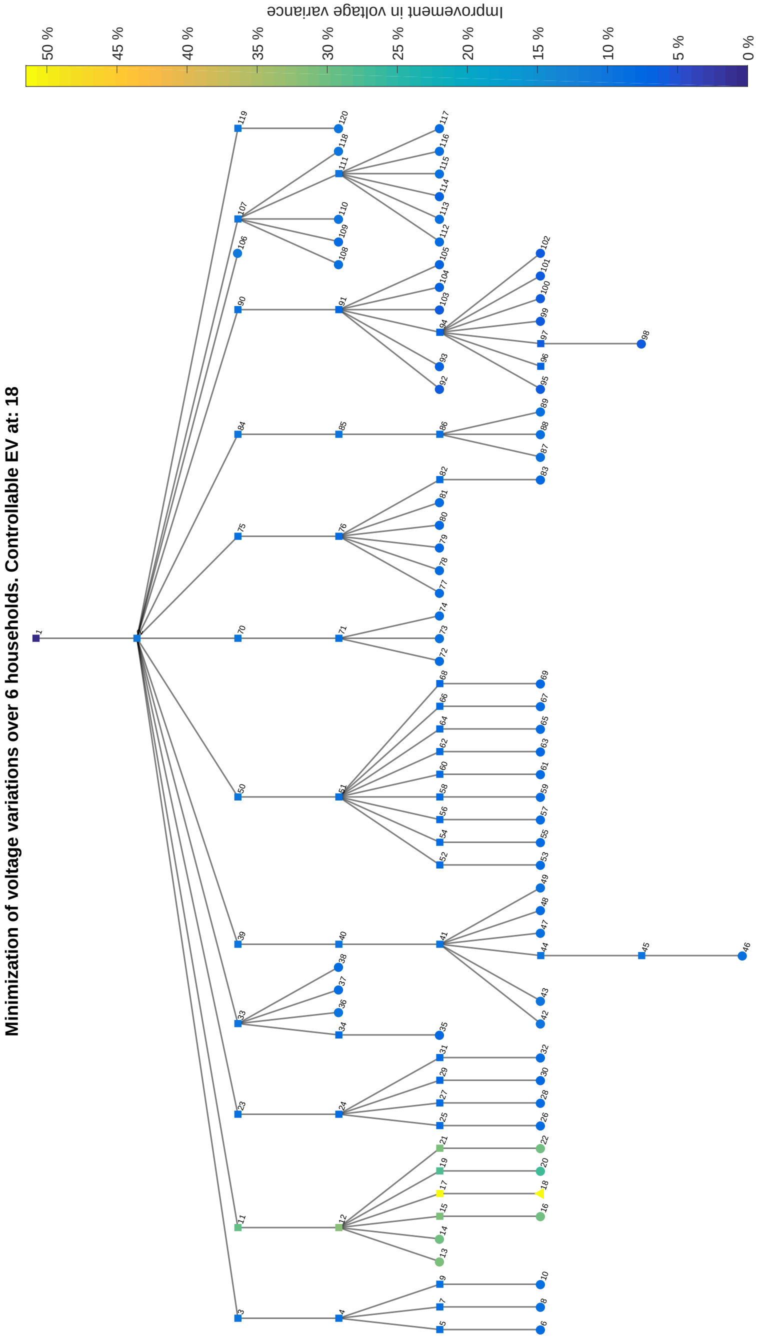


Figure 4.4: *Improvement of voltage variations with λ set to 0.9.*

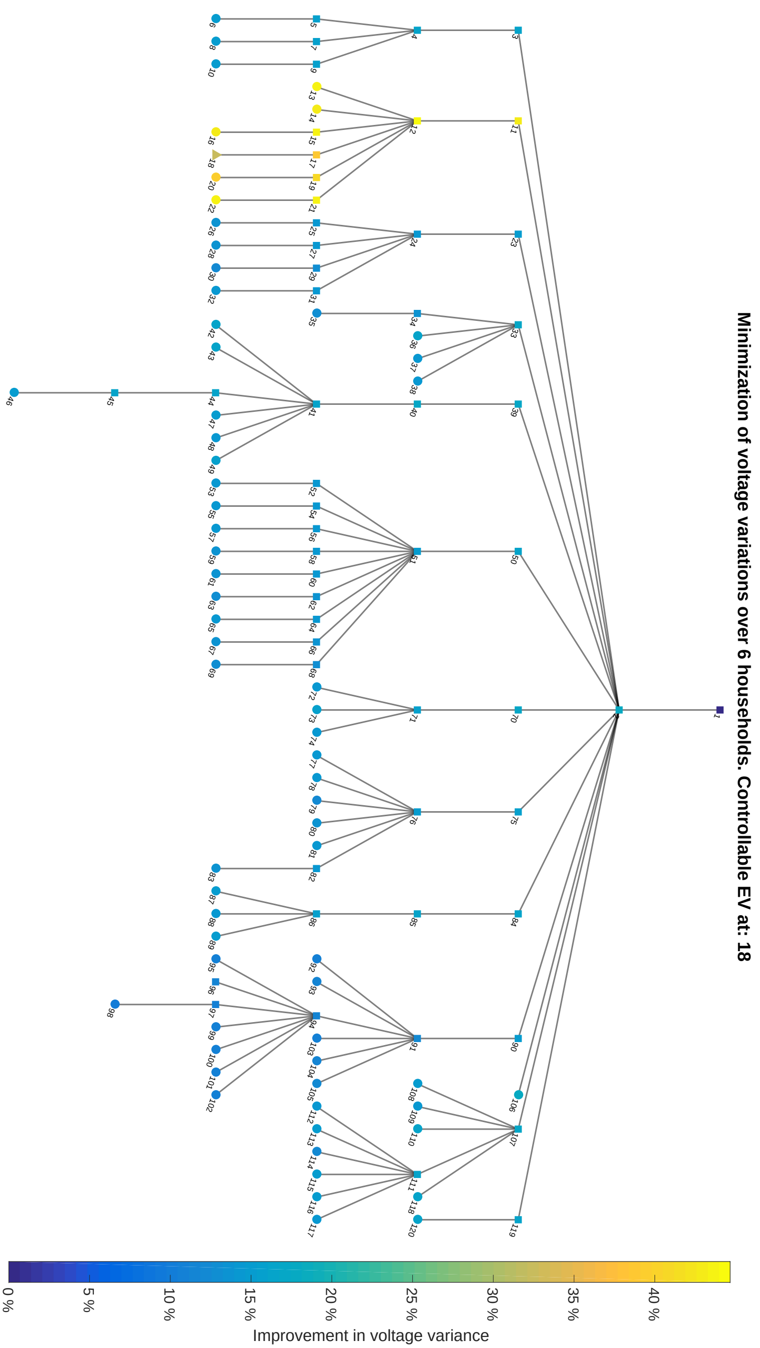


Figure 4.5: *Improvement of voltage variations with λ set to 1.0.*

4.2 Seasonal Differences

This section presents how seasonal differences in power consumption and production affect the solution of the optimization problem, and in turn the stability of the electric grid. One week during winter (February 6-12) and summer (June 5-11) were analyzed. These weeks were selected due to the fact that during the year, the highest and lowest mean power consumption occurred during on these weeks.

Both voltage variation reduction and load profile smoothing were considered. The weight parameter was set to either $\lambda = 0$ or $\lambda = 1$, since each choice of λ penalized the respective part of the objective function in (3.4) on page 25 the most. This is supported by the Pareto curve in Figure 4.1. Four optimizations were therefore executed, where each optimization had a cluster in the grid containing one controllable EV and PV-modules existed on all households of the cluster. For the winter optimizations, the household with a controllable EV was set to household 18, as it had the highest annual power consumption. The selected household with an EV in the summer season was bus 59, and was chosen since it had the lowest annual power consumption of all households.

The EV was also replaced by a SBS in the four optimizations, which was done to compare the performance of a SBS to an EV. For both the EV and SBS, the initial and final SoC of the analyzed timeline were selected to be 70 %. In Section 4.2.3, the SBS optimizations are presented and analyzed.

4.2.1 Load Profile Smoothing

Seasonal differences for the objective function prioritizing load profile smoothing are presented in this section. The inputs to the optimizations penalizing peak loads are presented in Table 4.1.

Table 4.1: *Input for the optimizations penalizing peak loads.*

Timeline	λ	EV Model	PV Prod. Exists	Household with Batt.	SBS
6 – 12 of Feb	0	Tesla	Yes	18	No
5 – 11 of June	0	Tesla	Yes	59	No

Winter

During winter, the power consumption of a household is generally higher than during summer and the PV production is typically lower. Thus, one can expect higher peak loads during the winter season. However, in upper plot in Figure 4.6, some voltage levels are actually improved. It is especially noticeable in the weekend, which is a consequence of the flat load profile created by the battery of the EV. With lower power magnitude at peak loads, the voltage level increases and vice versa. Thus, load profile smoothing can actually reduce voltage variations as well to a certain degree, even though it is not to be prioritized in the objective function.

The SoC and battery power $P_{batt}(t)$ for peak load penalization are found in Figure 4.7. By having the weight parameter set to zero, the EV will choose to charge and discharge in a way that results in a smooth power consumption profile for the household. Thus, the battery power profile in the figure is basically the mirror image of the power consumption of the household without an EV. As mentioned in Section 2.2, the EV is set to be away on weekdays between 08:00–17:00, i.e. $P_{batt} = 0$, which is represented by the red asterisks in the figure.

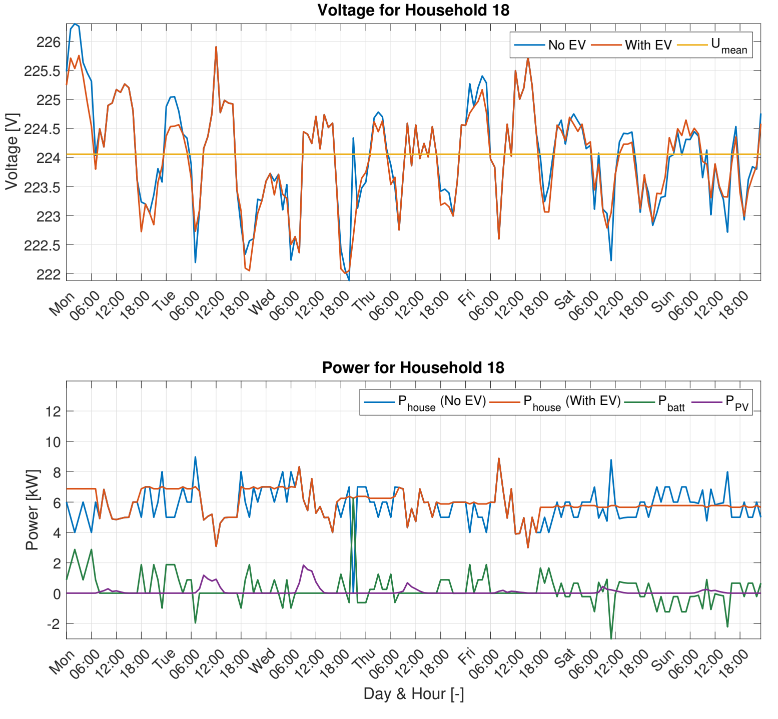


Figure 4.6: Voltage and power consumption levels of a winter week optimization. Only peak loads are penalized, i.e. $\lambda = 0$.

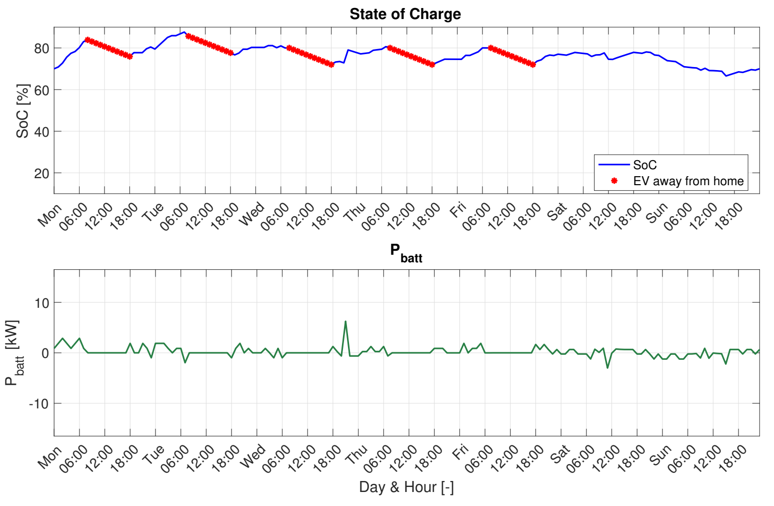


Figure 4.7: *State of charge and battery power levels of a winter week optimization. Only peak loads are penalized i.e.* $\lambda = 0$.

Summer

During the summer, PV power production is generally higher than in the winter. Thus, one can expect voltage peaks during the days. As can be seen in lower plot in Figure 4.8, the PV-module is generating electrical power during the sunny hours of the days. Consequently, voltage peaks are found during these hours, which mostly occur whenever the EV is away from home. The EV is home a couple of these hours during the weekdays, which can be noticed by that the EV uses the PV power to charge. As during winter, the figure shows that some voltage levels also improve when the load profile is smoothed out.

Due to a low power consumption during the summer, the household may have a negative power consumption at some time instances, which can be seen in the lower plot in Figure 4.8. This negative power flow travels back into grid and affects all buses that are above the bus with an EV, as explained in Section 3.1.3 on page 23.

Figure 4.9 shows the SoC and battery power of the EV. Due to the low consumption, there will generally be a small number of peak loads to be minimized. However, the high PV production causes large power peaks during the day, which the EV manages to minimize.

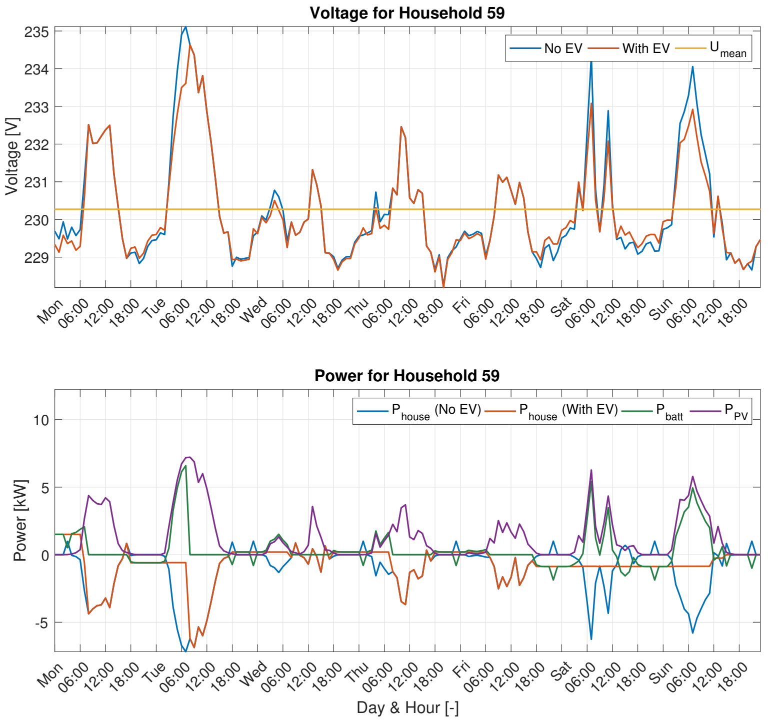


Figure 4.8: *Voltage and power consumption levels of a summer week optimization. Only peak loads are penalized i.e.* $\lambda = 0$.

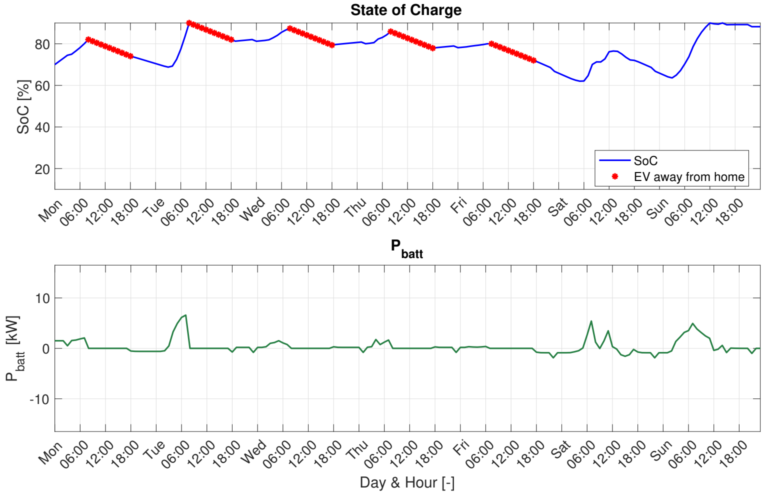


Figure 4.9: *State of charge and battery power levels of a summer week optimization. Only peak loads are penalized i.e.* $\lambda = 0$.

4.2.2 Reduction of Voltage Variations

This section presents seasonal differences for the objective function prioritizing reduction of voltage variations. In Table 4.2, input data for the optimizations penalizing voltage variations are found.

Table 4.2: *Input for the optimizations penalizing voltage variations.*

Timeline	λ	EV Model	PV Prod. Exists	Household with Batt.	SBS
6 – 12 of Feb	1	Tesla	Yes	18	No
5 – 11 of June	1	Tesla	Yes	59	No

Winter

The voltage level and power consumption of household 18 can be seen in Figure 4.10, and Figure 4.11 shows the SoC of the battery and the battery power. One thing that is noticeable in both lower plots in Figure 4.10 and 4.11, is that the battery discharges immediately when the EV arrives home, enabling voltage variations to be reduced. Then, during the hours of night when the consumption is typically lower, it charges to satisfy the minimum SoC of 80 %.

By comparing Figure 4.6 to Figure 4.10, the load profile of the household is considerably more uneven in Figure 4.10. Also, the battery power of the same figure has higher magnitudes while dis-/charging. Consequently, the capacity of the battery is used to a greater extent. The reason for this is that load profile smoothing is not penalized in the objective function.

Histograms of the voltage levels before and after an optimization of a winter week can be seen in Figure 4.12. Clearly, when penalizing voltage variations in the objective function, the voltage levels shift towards the mean value U_{mean} and the number of outliers decrease. However, it can be seen that there still exist outliers and the reason for this is that the EV is away from home during certain hours, making control of voltage variations not applicable. Note that not all households of the specific cluster are shown in the figure, but only a few to visualize the impact of the shift in voltage level. Nevertheless, all households in the cluster experienced the same behaviour.

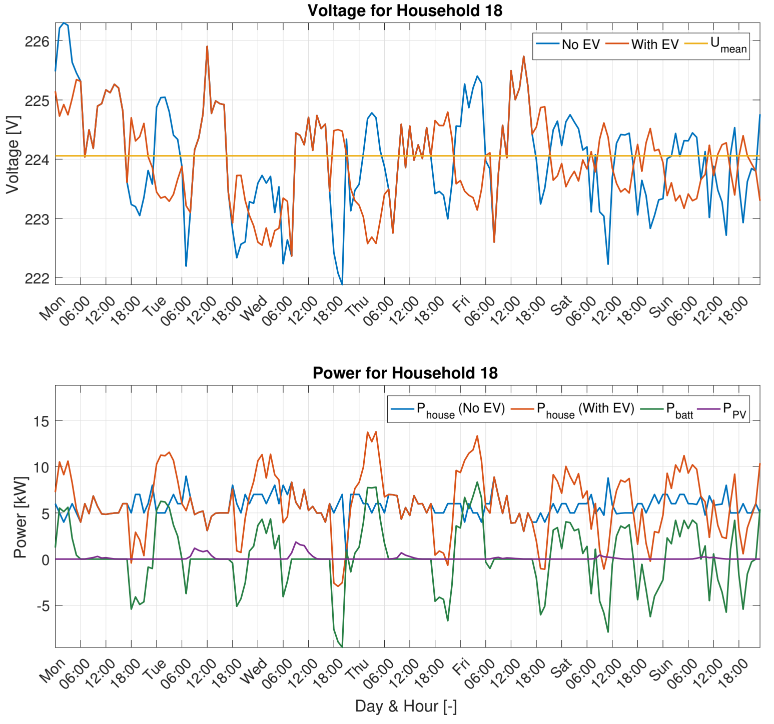


Figure 4.10: *Voltage and power consumption levels of a winter week optimization. Only voltage variations are penalized i.e.* $\lambda = 1$.

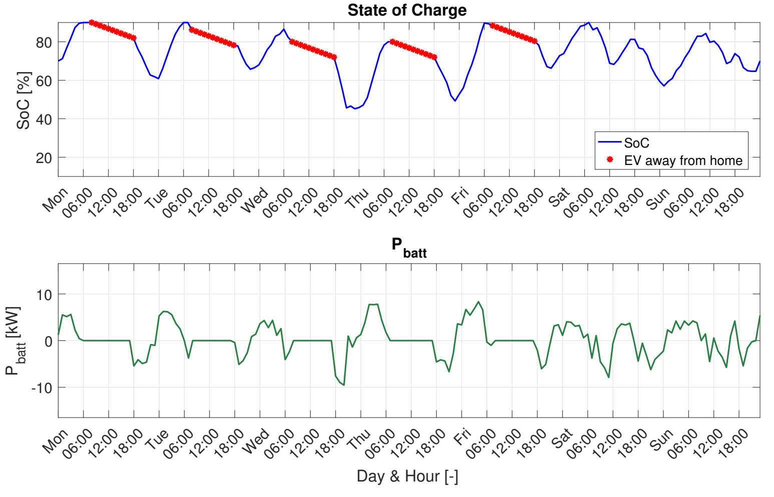


Figure 4.11: *Voltage and power consumption levels of a winter week optimization. Only voltage variations are penalized i.e.* $\lambda = 1$.

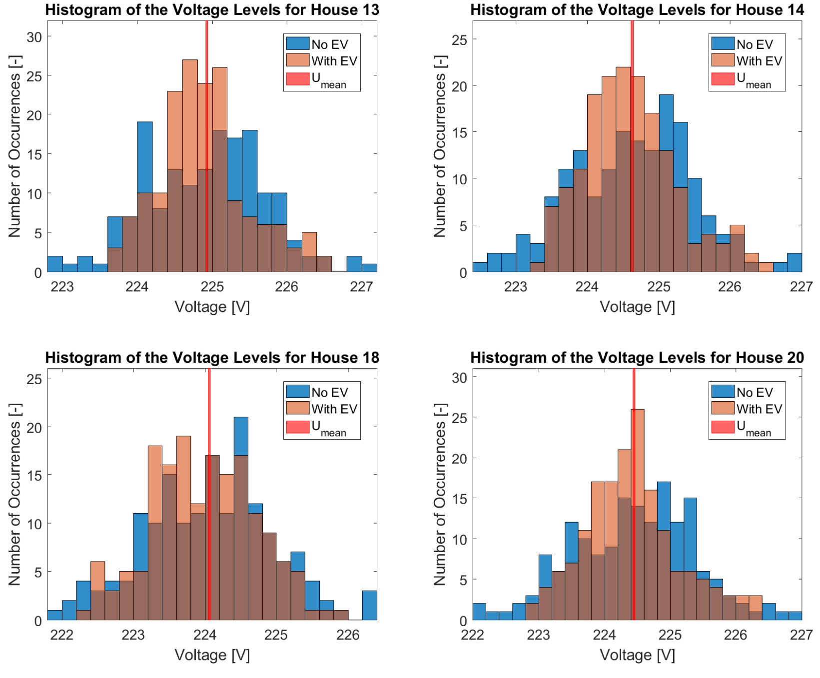


Figure 4.12: *Histograms of a winter week optimization. Only voltage variations are penalized i.e.* $\lambda = 1$.

Summer

Figure 4.10 shows that the outcome of the summer optimization is quite similar to the winter optimization, where the EV chooses to discharge its battery as soon as it arrives home. One major difference to the winter optimization is that PV production is now higher. As a consequence of this, higher voltage peaks exist and the battery is used to a greater extent. The SoC and power of the battery can be seen in Figure 4.14. In particular, the battery is highly active in the weekend, since it is available throughout the day. Thus, it can therefore adjust the voltage variations when the solar irradiance is at its maximum.

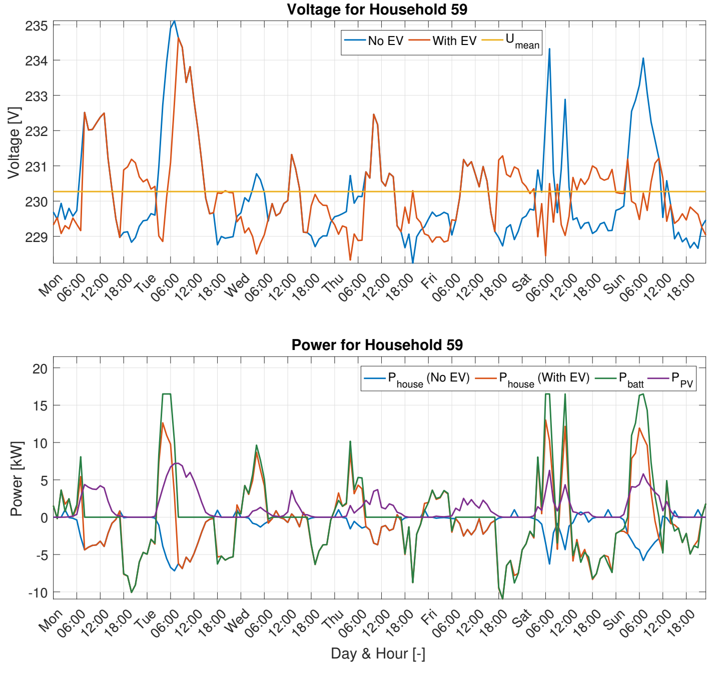


Figure 4.13: *Voltage and power consumption levels of a summer week optimization. Only voltage variations are penalized i.e.* $\lambda = 1$.

Figure 4.15 shows voltage histograms for some of the adjacent households to household 59. As in Figure 4.12, the number of voltage outliers has been reduced and the number of voltage occurrences closer to U_{mean} has increased. Once again, this fact is explained by an objective function that purely penalizes voltage variations. When comparing the voltage level of the households with an EV for the two objective functions i.e. Figure 4.6 to 4.10, and Figure 4.8 to 4.13, one can confidently say that when prioritizing reduction of voltage variations, the voltage levels are affected accordingly. Numerical results regarding the voltage levels for the four optimizations are summarized in Tables 4.4 and 4.5.

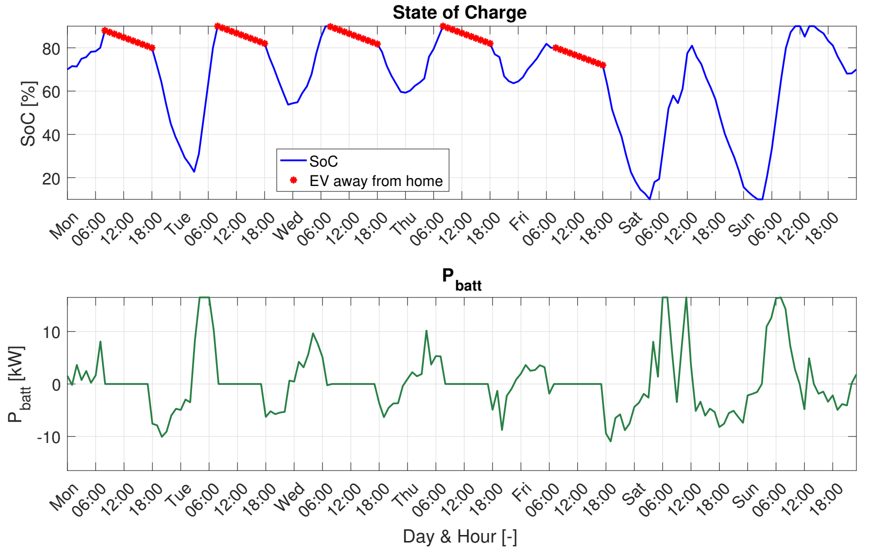


Figure 4.14: *State of charge and battery power levels of a summer week optimization. Only voltage variations are penalized i.e.* $\lambda = 1$.

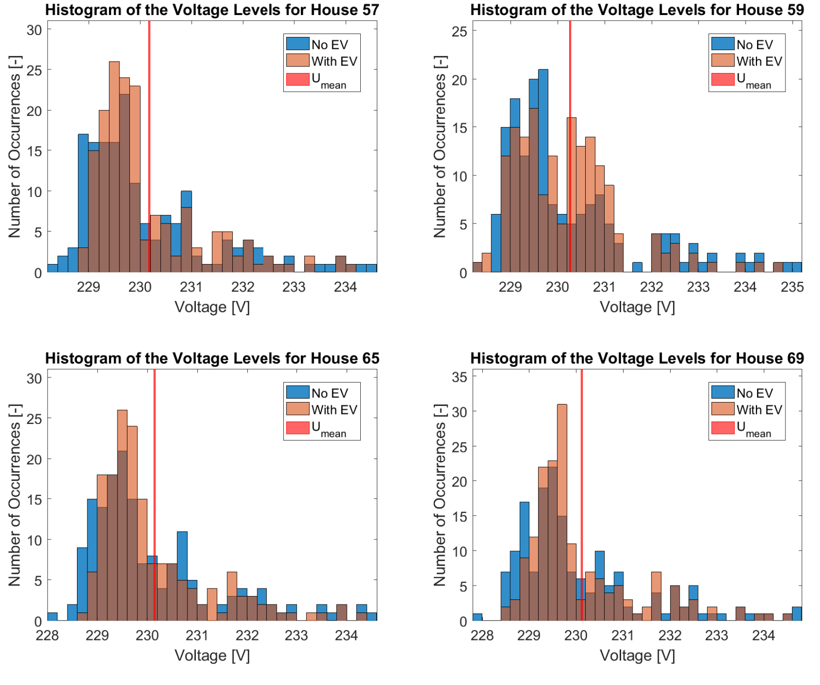


Figure 4.15: *Histograms of a summer week optimization. Only voltage variations are penalized i.e.* $\lambda = 1$.

4.2.3 Electric Vehicle versus Stationary Battery System

An issue regarding EVs is that the vehicles become unavailable during the day, which coincides with the time of day where PV production is at its highest. Another issue is that both the controllable and the non-controllable EVs arrive home at the exact same time. Therefore, the voltage levels drops further as the non-controllable EVs charge, which in turn means that the controllable EVs need to utilize the capacity of their batteries considerably more. Due to these issues, this analysis was made to feature optimizations where the EV was replaced by a SBS. In Table 4.3, input data for the four SBS optimizations is displayed.

Table 4.3: *Input for the SBS optimizations.*

Timeline	λ	Batt. Cap. [kWh]	PV Prod. Exists	Household with Batt.	SBS
6 – 12 of Feb	[0,1]	100	Yes	18	Yes
5 – 11 of June	[0,1]	100	Yes	59	Yes

Tables 4.4 and 4.5 display the numerical data for the variance reduction of the four seasonal optimizations. Table 4.4 presents data connected to the winter season, and Table 4.5 to the summer season. The reduction is expressed in percent and is denoted with the variable U_{var}, which was defined in (4.1). The highest reduction in voltage variance occurs when $\lambda = 1$ i.e. only voltage variations are penalized in the objective function. This is true for both the EV and SBS. By looking at Tables 4.4 and 4.5, it is clear that the single SBS performs better than the EV in reducing voltage variations.

Figures 4.16 and 4.17 show how much an EV or a SBS reduces voltage variations in the grid, respectively. These figures show that the SBS reduces voltage variations to a greater extent than the EV during the summer week. It was also found out that both the SBS and EV gave greater improvement in voltage levels for the entire grid during the summer week, than for the winter week. An explanation for this is that PV production exists on all cluster households before the optimization, which deteriorates the voltage levels of the remaining buses. As a controllable battery is introduced in the optimization, the battery will try to reduce the voltage variations of the cluster households, where all PV-modules are located. This in turn affects the voltage variations of the remaining buses positively.

Table 4.4: *Improvement in voltages for all cluster household buses, when using $\lambda = 0$ and $\lambda = 1$ for the winter week optimizations.*

	Household					
No Battery	**13**	**14**	**16**	**18**	**20**	**22**
$U_{max} - U_{min}$	4.1	4.6	4.2	4.4	4.8	4.5
EV ($\lambda = 0$)	**13**	**14**	**16**	**18**	**20**	**22**
U_{var}	3.7%	3.9%	3.8%	11.9%	3.0%	3.3%
$U_{max} - U_{min}$	3.9	4.3	4.0	3.9	4.6	4.4
SBS ($\lambda = 0$)	**13**	**14**	**16**	**18**	**20**	**22**
U_{var}	9.1%	8.5%	9.4%	27.6%	7.6%	8.3%
$U_{max} - U_{min}$	4.0	4.4	4.1	3.9	4.7	4.5
EV ($\lambda = 1$)	**13**	**14**	**16**	**18**	**20**	**22**
U_{var}	43.8%	43.0%	42.8%	32.6%	39.6%	43.3%
$U_{max} - U_{min}$	2.8	3.0	3.0	3.5	3.4	3.1
SBS ($\lambda = 1$)	**13**	**14**	**16**	**18**	**20**	**22**
U_{var}	69.7%	65.8%	69.1%	62.1%	63.2%	68.2%
$U_{max} - U_{min}$	2.4	2.8	2.5	2.2	3.1	2.9

Table 4.5: *Improvement in voltages for all cluster household buses, when using $\lambda = 0$ and $\lambda = 1$ for the summer week optimizations.*

	Household								
No Battery	**53**	**55**	**57**	**59**	**61**	**63**	**65**	**67**	**69**
$U_{max} - U_{min}$	6.1	6.4	6.2	6.9	6.9	7.9	6.4	6.5	6.7
EV ($\lambda = 0$)	**53**	**55**	**57**	**59**	**61**	**63**	**65**	**67**	**69**
U_{var}	8.6%	8.1%	8.2%	23.2%	7.4%	6.6%	8.0%	7.7%	7.7%
$U_{max} - U_{min}$	5.8	6.1	5.9	6.4	6.6	7.5	6.2	6.2	6.5
SBS ($\lambda = 0$)	**53**	**55**	**57**	**59**	**61**	**63**	**65**	**67**	**69**
U_{var}	15.5%	14.8%	14.9%	42.7%	13.5%	12.2%	14.5%	14.0%	13.9%
$U_{max} - U_{min}$	5.7	6.0	5.8	5.4	6.5	7.5	6.0	6.1	6.3
EV($\lambda = 1$)	**53**	**55**	**57**	**59**	**61**	**63**	**65**	**67**	**69**
U_{var}	33.1%	31.5%	31.6%	41.6%	29.1%	26.0%	31.4%	30.1%	30.4%
$U_{max} - U_{min}$	5.2	5.5	5.3	6.3	6.0	6.7	5.6	5.6	5.9
SBS($\lambda = 1$)	**53**	**55**	**57**	**59**	**61**	**63**	**65**	**67**	**69**
U_{var}	54.0%	51.8%	52.0%	64.5%	48.0%	43.6%	51.2%	49.9%	49.9%
$U_{max} - U_{min}$	4.3	4.6	4.4	4.7	5.0	6.0	4.6	4.8	4.9

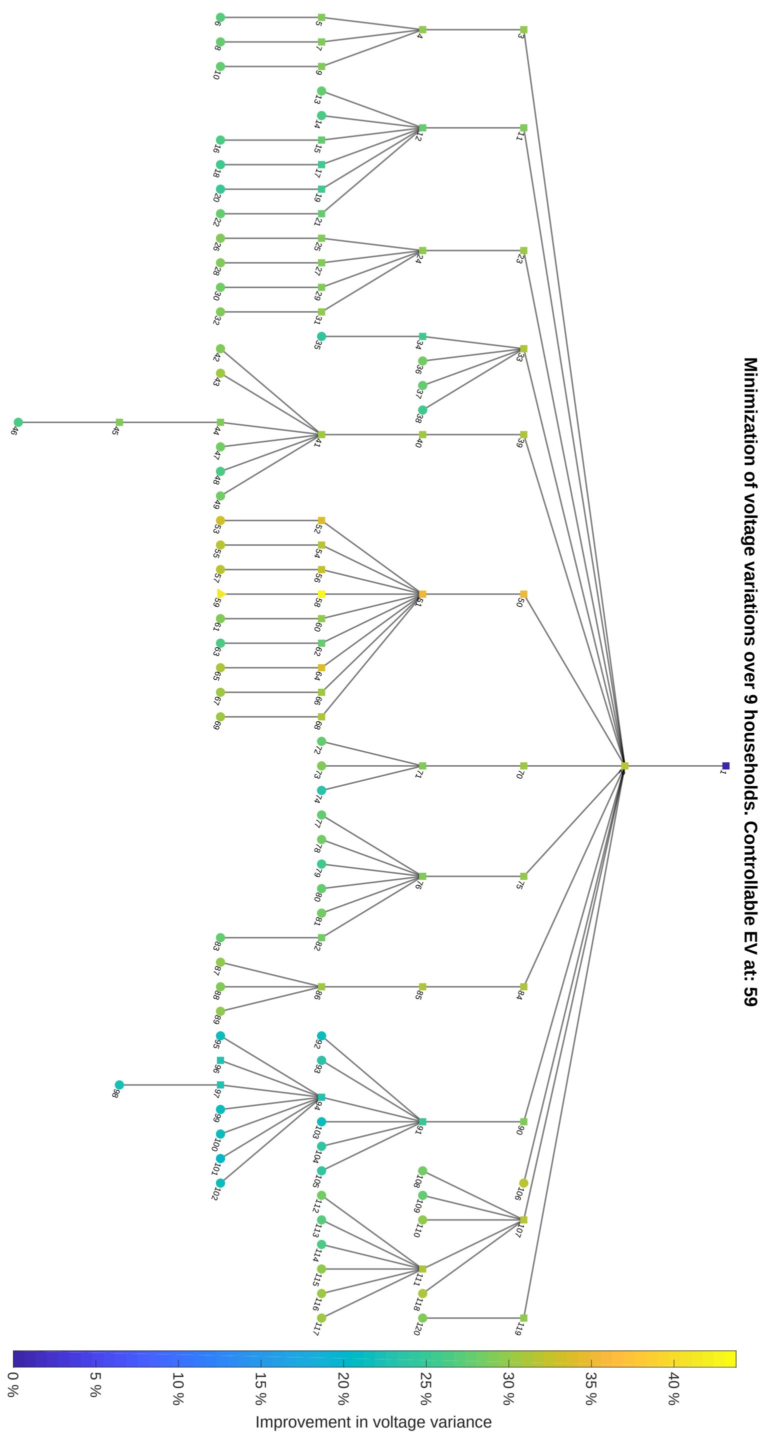


Figure 4.16: *Improvement of voltage variations with λ set to 1.0 for a summer week optimization with an EV.*

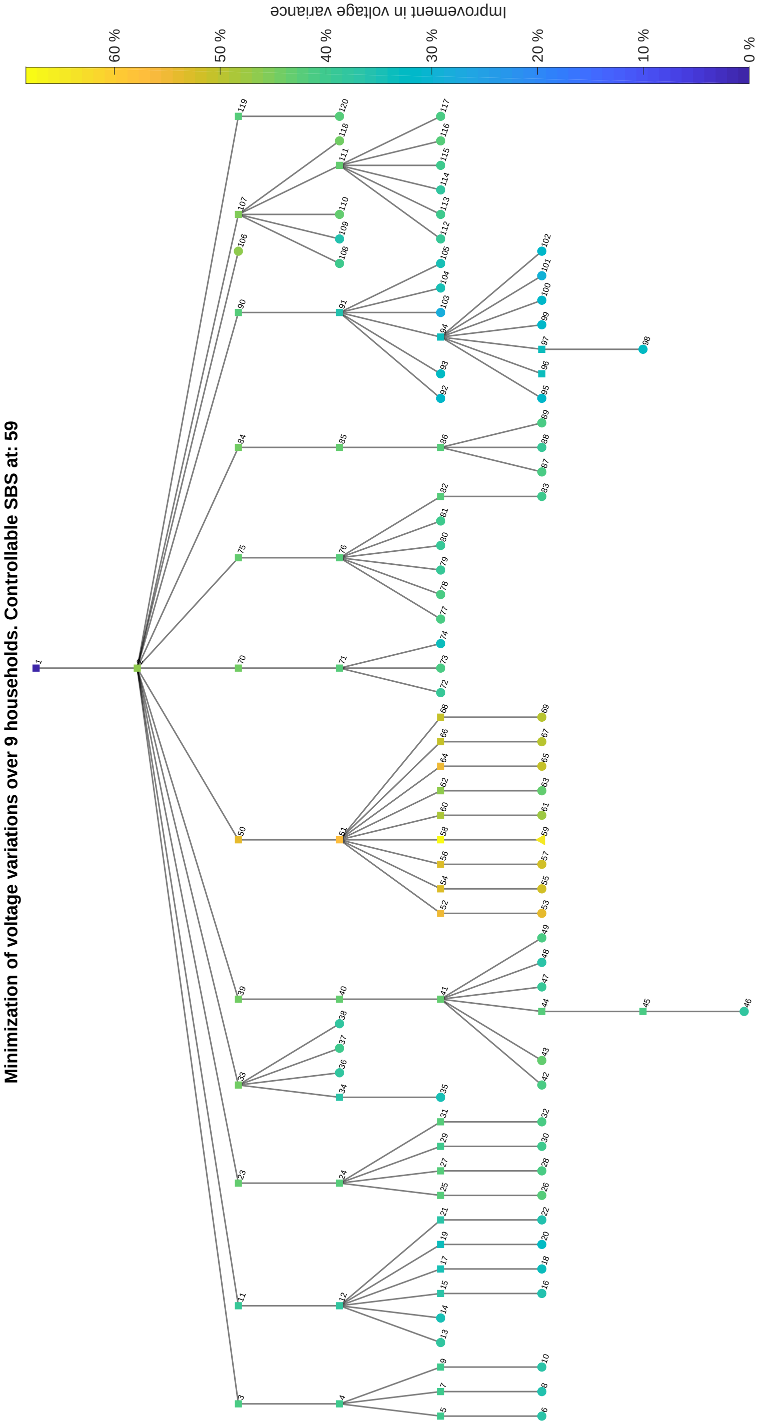


Figure 4.17: *Improvement of voltage variations with λ set to 1.0 for a summer week optimization with a SBS.*

4.3 Multiple Batteries

The effect of introducing multiple controllable and non-controllable EVs, and PV-modules in the grid was investigated. This is of certain interest for Tekniska verken, since the increase in EVs and PV-modules impose problems to the electrical grid as mentioned in Chapter 1 and seen in Figure 1.3. To represent the increase in EVs, the forecast by Power Circle mentioned on page 2 was used. Out of the 67 households in the low-voltage grid, 35 were assigned with EVs of which five were controllable. Thus, the share of EVs turned to be slightly above 50 % ($\approx$ 52 %). The five controllable EVs were placed into five separate clusters in the grid, and non-controllable EVs were positioned at their neighbouring households. Also, every household in the five clusters had PV production.

Both seasons were investigated, but the results from the summer week are the ones presented. This decision was taken since the summer season generated higher differences in magnitudes for voltage peaks and drops, which can be seen in Figure 4.18. Input data for the multiple EV and SBS optimizations is found in Table 4.6.

Table 4.6: *Input for the optimizations penalizing voltage variations.*

Timeline	λ	Batt. Cap. [kWh]	PV Prod. Exists	Households with Batt.	SBS
5 – 11 of June	1	100	Yes	18, 37, 59, 79, 114	No
5 – 11 of June	1	100	Yes	18, 37, 59, 79, 114	Yes

By looking at Figure 4.18, it is clear that the SBSs can reduce the voltage variations further than the controllable EVs. However, both the controllable EVs and the SBSs perform equally whenever the EVs are home. This can be seen in the two rightmost plots in the same figure, when the EVs arrive home at the evening and during the weekends. Figure 4.19 shows voltage level histograms of all cluster households, before and after an optimization. In this figure it can be seen that the high voltage levels that occur are more reduced by the SBS.

Finally, the improvement in voltage variance of all buses in the grid when using either five controllable EVs or five SBSs can be seen in Figure 4.20 and 4.21, respectively. Buses marked with an asterisk are households that have a non-controllable EV.

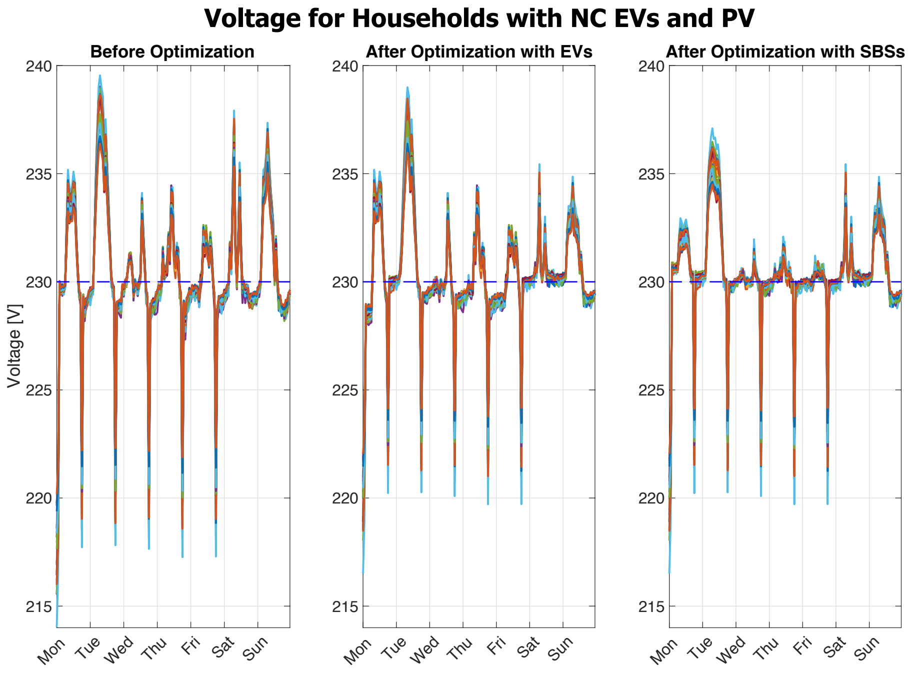


Figure 4.18: *Voltage levels of households with non-controllable EVs before and after optimization. Five controllable EVs or SBSs were introduced in the optimization.*

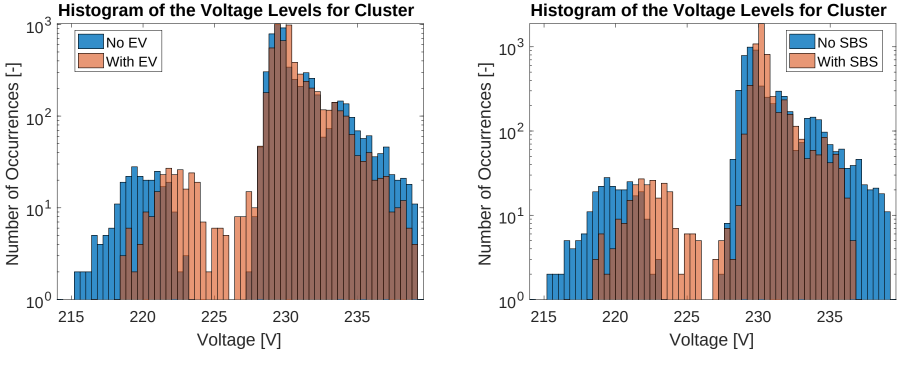


Figure 4.19: *Voltage levels of all cluster households before and after optimization. Note that the y-axes are in logarithmic scale.*

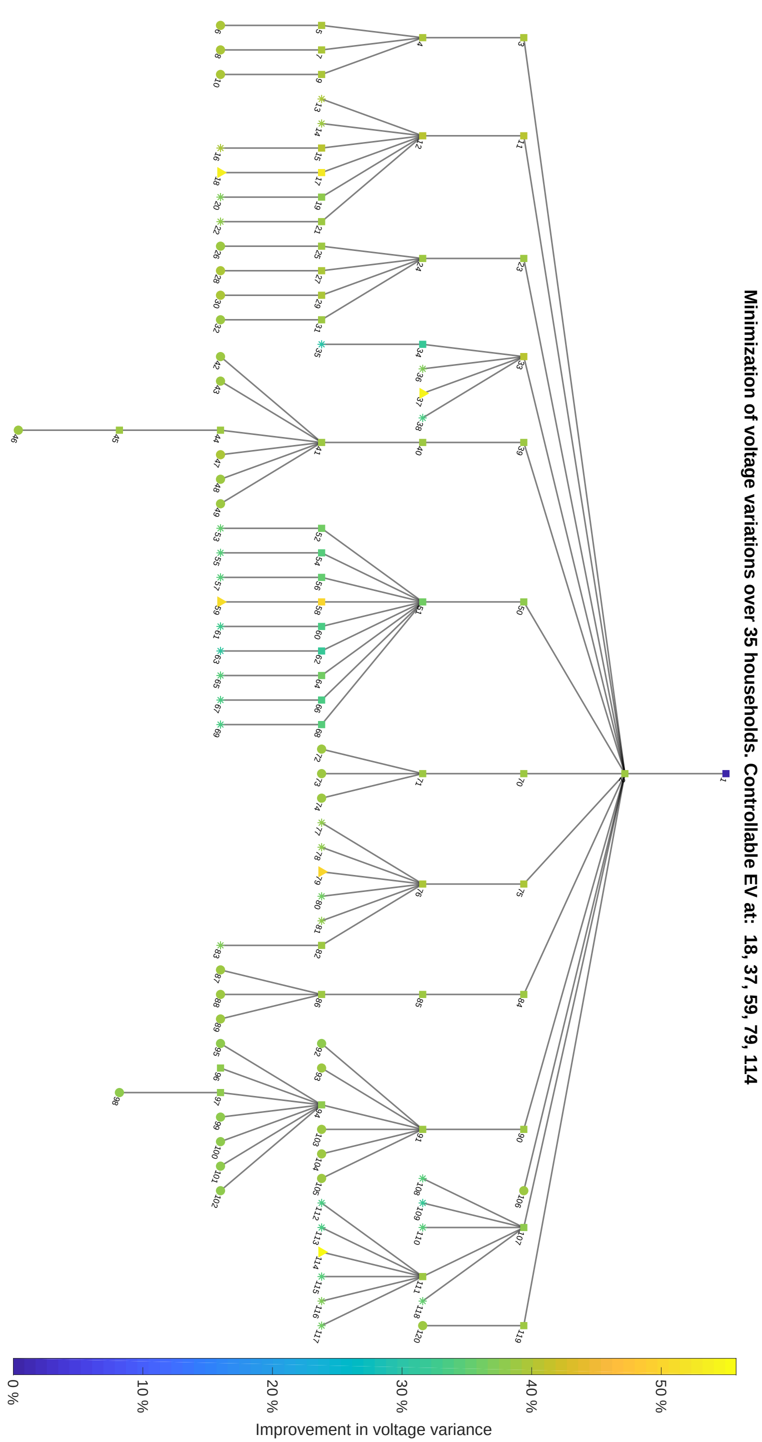


Figure 4.20: *Improvement in voltage variance for the entire grid. Summer week optimization with five EVs.*

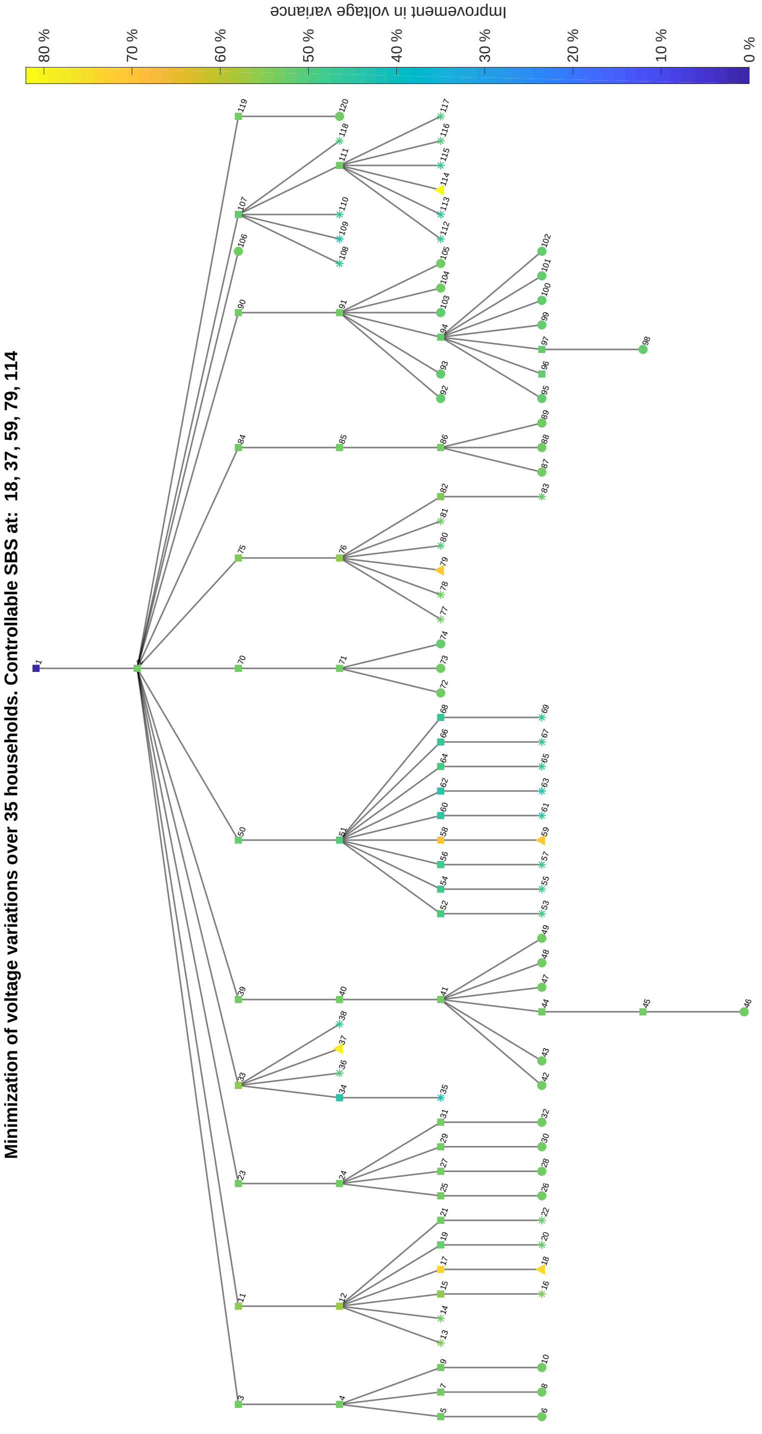


Figure 4.21: *Improvement in voltage variance for the entire grid. Summer week optimization with five SBSs.*

4.4 Maximum EV Integration Capability

Simulations with non-controllable EVs were performed from January to February to find out the maximum EV capability. The approach was to investigate the minimum voltage level of all buses in the grid, and the maximum number of EVs was found when the minimum voltage level breached the lower voltage limit. Basically, one non-controllable EV was gradually added at a household until all households had an EV. This was done in two different ways, where the EVs were added from the leftmost household in the grid (bus 6) to the rightmost household bus in the grid (bus 120), and vice versa. For the simulations, a total of six different charging powers were used, which can be seen in Table 4.7.

Assumptions in these simulations were that all EVs were of the same EV model, the distance driven during the day by each EV was the same and that all EVs arrive home and begin to charge simultaneously. To obtain worst-case conditions for the voltage drops, the distance driven was not set to 33 km as previously done, but to 99 km in order to keep the EVs charging for a longer period of time.

Figure 4.22 shows how the minimum voltage level of any bus in the entire grid drops as the number of non-controllable EVs increases for different charging powers. As can be seen in the figure and Table 4.7, the number of EVs that the grid is capable of managing decreases when the charging power increases. It is also noticeable that at higher powers, the capability is greater when placing the EVs from right to left (R2L) in the grid, than from left to right (L2R). This is true for both house fuses.

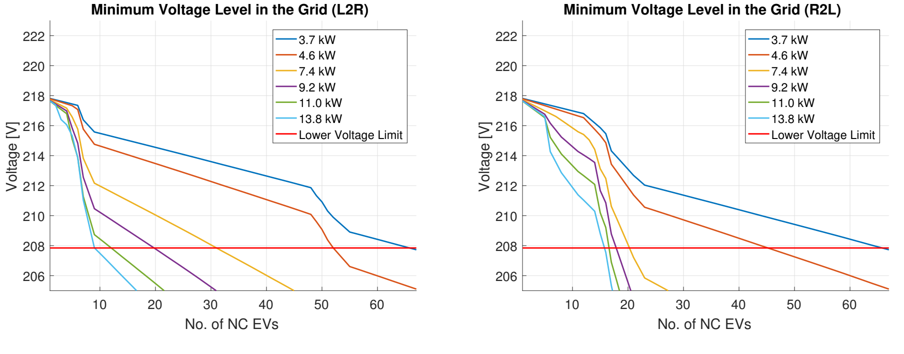


Figure 4.22: *The minimum voltage level in the grid as a function of the number of non-controllable EVs for different charging powers.*

Table 4.7: *Data regarding the maximum EV integration capability.*

House Fuse [A]		16			20		
Charging Power [kW]		3.7	7.4	11.0	4.6	9.2	13.8
No. of EVs	L2R	65	31	12	52	19	9
	R2L	65	20	16	45	17	15

5 Discussion

Discussions regarding several parts of this thesis are found in this chapter. This chapter begins with discussing the analyses and results presented in Chapter 4 with account of the problem formulation of this thesis. The end of this chapter discusses the validity of the results and the models used in this thesis.

To assist the reader, the problem formulation is presented once again:

- Can smart charging of batteries (of EVs) be applied to lower peak loads and therefore smoothen out the load profile of a household in a low-voltage electrical grid, with existing electric power production from PV-modules?
- Can the usage of EV batteries be used to lower voltage variations that may occur in the low-voltage electrical grid, with existing electric power production from PV-modules?
- How are the peak loads and voltage variations in the electrical grid affected by the use of SBSs?
- What is the maximum integration level of EVs that certain low-voltage grids areas managed by Tekniska verken can handle, with existing electric power production from PV-modules?

5.1 Load Profile Smoothing

The purpose of optimizing a controllable EV that focuses on smoothing the load profile of a household, was to simply investigate how an optimization strategy like this affects the grid and household in question. The results seen in Figure 4.6 and 4.8 clearly shows that the EV performs well, as the load profile of the household in the lower plots in both figures is smoothed out.

From the figures that show the SoC of the EV, namely Figure 4.7 and 4.9, it can be seen that the EV is used to a greater extent during summer. An explanation to this is that during winter, the EV flattens the load profile and power peaks of an already high consumption. During the summer however, high PV production causes large power peaks during the day, since the consumption is low. The EV uses the large power peaks from the PV-module to its best extent, as this flattens the load profile of the household.

The impact this optimization strategy has on the grid is quite small, since having $\lambda = 0$ only focuses on the household with a controllable EV. The reason for this is that only power consumption is regarded in the optimization, and a controllable EV can only affect the power consumption of the household where it is located.

5.2 Reduction of Voltage Variations

The reduction of voltage variations is of most interest to Tekniska verken that the authors have collaborated with. From the results presented in Chapter 4, it is clear that voltage variations are reduced the most when $\lambda = 1$ in the objective function in (3.4). As Figures 4.5, 4.16 and 4.17 show, the voltage variation reduction is greatest for the cluster where the EV is present. However, there are actually improvements for the other buses of the grid as well. By this result, it can be said that even a single controllable EV can contribute in a positive manner to the voltage levels of the entire grid, despite only optimizing for the households in the cluster. Figure 4.20 shows similar behavior as presented in Figures 4.16 and 4.17, where the main difference is that the improvement in voltage variance for the entire grid increases as more controllable EVs are introduced.

By comparing the voltage variation reduction performance of a SBS at a household to an EV, the SBS performs better, which is shown in Tables 4.4 and 4.5. The tables also show that the SBS reduces variations in the cluster even more than the EV in the winter week. The voltage variations were however further reduced for the entire grid during the summer week, which is explained by the fact that the nominal case gets worse in terms of voltage peaks due to the increased PV power production. The reason why the SBS outperforms the EV is that is constantly at home, allowing it to reduce the voltage peaks that occur at the time of the day when the EV is away from home. This is especially noticeable during the summer season when voltage peaks occur as a consequence from the high PV power production.

5.3 Maximum EV Integration Capability

Figure 4.22 shows that the charging power strongly affects the number of EVs that can charge simultaneously. With the increasing demand of EVs and larger battery sizes, as well as higher charging power, the simulations in the figure that breach the lower voltage limits at lower EV capabilities might very well occur in reality. The figure shows when the voltage level of at least one bus in the entire grid has breached the lower voltage limit. Exactly at which bus this occurs has not been investigated, and it is therefore not necessarily the same bus that breaches the limit in every simulation.

By placing the EVs from left to right, or right to left gave different results as Table 4.7 shows. A possible explanation might be that the households of the left part of the low-voltage grid already have a high power consumption, and the addition of an EV with high charging power makes the voltage drop even further. Another explanation might be that the characteristics of the cables of the left part are not as susceptible to multiple EVs, as the cables of the right part.

5.4 Validity of Results

This section discusses the validity of the achieved results from Chapter 4.

5.4.1 Seasonal Differences

The authors did perform a few optimizations for longer timelines. The longest timeline investigated was a month, and was done for both seasons. Each optimizations included a single EV or SBS at either household 18 or 59, with existing PV production. From these optimizations, it was noted that the behaviour of the battery was highly similar to the presented results in Section 4.2.

5.4.2 Multiple Batteries

For the optimizations with multiple batteries, there was only one controllable battery in each of the five clusters. The effect of having two or more in a single cluster was not investigated. Hypothetically, it could affect the voltage variations in a positive manner, since controllable batteries are not bound to charge with a specific power as non-controllable EVs.

The maximum EV integration capability was presented in Section 4.4, and it concerns non-controllable EVs. However, if controllable EVs were to replace all of the non-controllable, the low-voltage grid might be capable of managing a larger number of EVs. This is supported by the fact that they are not bound to a specific charging power as a non-controllable EV, and can be used to reduce voltage variations in the grid.

5.4.3 Maximum EV Integration Capability

The simulations connected to the EV capability of the grid were based on non-controllable EVs with the same characteristics, and that all EVs arrived home at the exact same time. Also, the charging power was exactly the same for all EVs. In reality, these assumptions are however not likely to occur simultaneously, but were chosen to represent a worst-case scenario for the lower voltage limit.

5.4.4 Battery Degradation

For the different optimizations that were performed, the battery of the EV or SBS used its capacity to various degrees. For instance, by comparing the battery behaviour in Figures 4.7 and 4.11, it is clear that the battery is being used to a greater extent in Figure 4.11, which is for a winter week and $\lambda = 1$. The SoC in the same figure varies in the range of approximately $90 - 45$ %, while the SoC in Figure 4.7 (winter week, $\lambda = 0$) has an approximate SoC range of $85 - 70$ %. Thus, when only voltage variations are considered in the objective function, deeper discharges are present. Furthermore, more battery power is used when voltage level improvement is desired. This is supported by the Pareto curve in Figure 4.2, which shows that the maximum power of the household nearly doubles when the maximum difference between the maximum and minimum voltage level is the lowest possible.

A larger dis-/charging range can reduce the battery's life faster, according to Figure 2.6 on page 18. In the figure, the red line of $100 - 40$ % as well as the blue line of $100 - 50$ %, are closest to the achieved SoC range $90 - 45$ %. The orange line of $75 - 65$ % in the figure is closest to the SoC range of $85 - 70$ %. Already after 500 DST cycles, the capacity loss is around 10 % higher for the red and blue line. In Figure 4.11, the battery experiences around seven dis-/charging cycles in a week, which roughly translates into a 7 % total capacity loss after 72 weeks by looking at Figure 2.6. The capacity loss after 500 DST cycles for the battery behaviour in Figure 4.7 (SoC range of $85 - 70$ %) would roughly be 2 % after 72 weeks. Both capacity losses however would most likely be even greater in practice, since Figures 4.7 and 4.11 are only for a winter week, and the battery's capacity is used even more during the summer season which is seen in Figure 4.14. Also, the dynamic stress tests performed in Figure 2.6 were all conducted at 20 °C. Higher temperatures than this might very well occur in the summer season, and as mentioned in Section 2.2, elevated temperature can reduce the battery's life.

5.5 Validity of Modeling

The validity of the modeling that were presented in Chapters 2 and 3 is discussed in this section.

5.5.1 Battery Model

The capacity of the batteries used in the optimizations and simulations in Section 4 were based on a Tesla Model S P100D, which has a capacity of 100 kWh. This is quite large compared to other EVs and SBSs destined for private use, since a capacity of this size for a SBS is typically intended for industrial applications. The reasoning behind choosing a size of 100 kWh for both the EVs and SBSs, was to obtain a fair performance comparison between them. However, a battery capacity of 41 kWh for the SBS was analyzed and compared to a controllable EV with a capacity of 100 kWh, but was not presented in this thesis. These analyses showed that the SBS still performed better than the EV during the winter, but not during the summer.

5.5.2 PV-module

The model used for the PV-modules uses actual irradiance data from a single location in Sweden. An issue with this is that all PV-modules added to the grid will technically produce the same amount of PV power, which is highly unlikely. For this to happen in reality, clouds would have to block the solar radiance at all PV-modules at the same time, all PV-modules would have the same specifications and installed with the same tilt and orientation.

5.5.3 Power Consumption

A problem with the power consumption data used in this thesis is that it is not fully representative of the reality, since the data is stored as accumulated integer values. This means that if the household consumption has a value of zero at a specific hour, it would in reality be anywhere between 0 kWh and 0.9 kWh. This becomes an issue as the consumption data becomes pointy, which in turn makes the battery usage pointy resulting in greater wear of the battery.

5.5.4 Optimization Problem

Prior to an optimization, the actual power consumption of the households is known for the entire timeline. In reality, this data is not known in advance. The optimizations performed are therefore based on the assumption that the hourly power consumed are available. As described in Section 1.2.1 on page 5, the measurement equipment installed by the year of 2025 shall record the active energy every 15 minutes. This can allow having data of shorter sample time for the households' power consumption, which in turn might provide a more optimal solution to how the battery should be used to solve the objective function.

6

Conclusions and Future Work

This thesis has developed and implemented an optimization tool, which can be used to determine how batteries can be utilized to support a low-voltage electric grid with the increase in EVs and PV production.

From the results and analyses presented in Chapter 4, it can be concluded that smart charging of EV batteries can reduce peak loads and smoothen the load profile of an individual household. Furthermore, smart charging can reduce voltage variations for the households in the residential area, when PV power production exists. Additionally, the more controllable batteries that are available for smart charging, the greater the reduction of voltage variations becomes for the grid. For the entire grid, the greatest overall improvement in voltage variation reduction is achieved during the summer and is explained by the high PV production of the households. This is true for both the EV and SBS.

It can also be concluded that SBSs can reduce peak loads and voltage variations as well, and to a greater extent than an EV with the same battery capacity. Also, a smaller battery capacity for a SBS can generate better results than an EV with a larger capacity, due to the fact that a SBS is available to use throughout the day.

The maximum integration of non-controllable EVs depends on several factors, such as where the EV is placed in the grid, the SoC of the EV's battery when it arrives home, and the charging power. With the assumptions that were made in this thesis regarding the maximum EV integration capability in Section 4.4, 97 % of the households in the residential area can charge simultaneously with a charging power of 3.7 kW. Whenever the charging power is increased, the maximum integration level is decreased. For instance, with a charging power of 11 kW, 18 % of the households can have an EV and charge simultaneously.

6.1 Future Work

This section brings up thoughts on how this work could be continued in the future.

Driving Pattern

To have a better representation of the reality, a more realistic driving pattern for the EVs could be applied. This would enable vehicles to depart and arrive home at separate occasions. The implemented driving pattern in this thesis is the same for all EVs, regarding if its controllable or not. One specific driving pattern can for instance be if one EV is always at home and available for control, and several others are away for different hours of the day. This scenario would basically represent a controllable SBS and multiple controllable EVs that exist in the residential area.

Consumption Estimation

This thesis uses known power consumption data, and an optimization tool to investigate the potential EVs and SBSs have when it comes to supporting the electrical grid. In order to implement this in reality, a model for estimating future power consumption of households will most likely be needed, as well as different control strategies which ensure that multiple controllable batteries cooperate to support the grid.

Electric Vehicle Placement

The placement of both the controllable and non-controllable EVs should be more thoroughly investigated. For the controllable EVs, it would be interesting to find the best placements which support the electrical grid the most. For the non-controllable EVs, it would be interesting to find where the EVs should be placed and in what order, to minimize the number of EVs that makes the grid collapse.

Battery State of Health

A consideration for the state of health of the battery should be implemented, to circumvent excessive wear of the battery. This could be done by including stricter limitations on the battery power flow, or by introducing a new term in the objective function which solely considers changes in battery power. Another thing that could be implemented regarding the battery health is information of the battery usage after each optimization, such as the number of cycles the battery has experienced over the course of one optimization. The health of the battery is of interest for the owner of the EV. Thus, if the EV is intended to be used to support the grid, an appropriate business model to compensate the EV owner will be needed.

Appendix

A

Appendix A

A.1 Future Grid Survey

The entire survey brought up in Section 1.1 is found here.

- What solutions do you currently investigate, related to reinforcement and support of the existing electrical grid when more people own an EV or produce their own electricity by RES?
- What is your prediction of how the electrical grid is affected when more people acquire an EV? Do you have a suggestive strategy to solve the issue of e.g. voltage variations and increase in peak loads?
- What is your prediction of how the electrical grid is affected when more people acquire PV-modules? Do you have a suggestive strategy to solve the issue of e.g. voltage variations and increase in peak loads?
- Do you investigate how a SBS can be used to support the electrical grid at high load demand? For instance, if they are positioned at an individual household or a transformer.
- What do you think about the idea of using EV batteries to support the electrical grid?
- How can the seasonal (winter/summer) difference in production and consumption be solved? What are your ideas about this if only RES are to be used for electric power production?
- What challenges regarding maintenance and extension of the electrical grid do you have in the next 20-40 years? What is the largest difficulty?

- What problems related to this matter might appear?

The questions of the survey were altered to suit the company Nilar AB, since it is not an EDC. The questions to Nilar AB are listed below.

- Do you currently have stationary battery packs located at EDCs in Sweden to deal with voltage variations and peak loads?
- Are battery packs for households or industry your most common product?
- Where do you consider the best placement for stationary battery packs is? Close to the customer or at the transformer?
- What do you think about the use of EV batteries to support the electrical grid? Are there any associated problems thereby?
- What challenges are there for stationary battery packs to be used to support the existing electrical grid, both for the customer and an EDC? What challenges are there to you as a company and the system in full?

The organization and its corresponding person(s) that the survey was sent out to are found in Table A.1.

Table A.1: *People that replied to the survey questions and their respective organization.*

Association	**Person(s)**
Gävle Energi AB	David Jakobsson, Power Grid Development Engineer
Jämtkraft AB	Hampus Halvarsson, Power Grid Engineer
Linköping University	Tomas Uno Jonsson, Adjunct Assistant Lecturer
Mälarenergi AB	Anders Malmquist, Power Grid Development Engineer
Nilar AB	Marcus Wigren, CEO
Skellefteå Kraft	Johan Andersson, Plant Engineer
Svenska kraftnät	Ulf Moberg, Technical Director
Öresundskraft AB	Pierre Andersson Ek, Power Grid Strategist
	Andreas Feurst, Projection Engineer
	Bo-Göran Johansson, Customer Engineer

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