Analysis of Battery Integrated Fast-Charging Station for Electric Vehicles

Optimized Battery Utilization

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Thesis submitted for the degree of
Master of Science in
Renewable Energy Systems
30 credits

Department of Technology Systems
The Faculty of Mathematics and Natural Sciences

UNIVERSITY OF OSLO

May 2022

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http://www.duo.uio.no/

Trykk: Reprosentralen, Universitetet i Oslo

Preface

The Master thesis is the final part of the Renewable Energy System Master's degree program at the Department of Technology Systems (ITS), University of Oslo (UiO).

This thesis is in collaboration with Glitre Energi. The goal of this project is to develop a model and analyse the battery supported EV fast charging station at Kongsbergporten with the main focus on optimal battery utilization.

I would like to extend my thanks to my internal supervisor Josef Noll for guidance and insight throughout this project. I also wish to thank my external supervisor from Glitre Energi, Anniken Borgen, for providing information and answering my questions for the realization of this project. Thanks to Alexander Kristensen at Glitre Energi for helping me find an interesting and relevant thesis project. I am also grateful to ITS PhD Guillermo Valenzuela for helping with implementation of the model in GAMS.

Lastly, i want to thank my colleagues at UiO ITS for support throughout this project.

Kasper Strindberg

May 24, 2022

Abstract

The amount of electric vehicles (EV) in Norway is rapidly increasing, leading to the need for more EV charging infrastructure. Modern EVs are able to charge at a capacity up to 250 kW. EV charging demand, therefore, creates high, rapid load peaks in the electricity grid. Circle K and Glitre Energi have collaborated on a pilot project with support from Enova to address these challenges. A fast-charging station named Kongsbergporten is developed with an integrated li-ion battery energy storage system (ESS) to increase energy flexibility and reduce the variability of EV charging.

This thesis is a collaboration between Glitre Energi and UiO and is an analysis of a hybrid fast-charging station based on Kongsbergporten. An LP model of a hybrid fast-charging station is developed, and historical data from Kongsbergporten is used to conduct an analysis of the system with a focus on battery utilization. The model calculates the optimal size for the ESS as well as the flow of electric power from the distribution grid to charging EVs. A sensitivity analysis is conducted on the most influential parameters: investment cost of ESS, electricity prices, grid tariff power fee, size of ESS, peak shaving and EV charging demand shape.

The results show that the integration of a battery ESS in an energy station is economically beneficial if the system is designed with a proper ESS capacity. Due to flexibility introduced with ESS, the system is resilient against changes in electricity prices and the power fee in the grid tariff. The system is most sensitive to high demand peaks to the extent where a few hours have significant impact on the operational costs of a full month. Furthermore, 62% of the battery capacity is used to meet demand 90% of the simulated time. It is, however, during periods of high demand the battery is most valuable and thus dimensioned for. Therefore, the operational strategy is highly influential for optimal ESS size and operation of a hybrid energy station.

The analysis of the model created in this thesis indicates that the system at Kongsbergporten is adequately designed for its intended purpose. The optimal size of the ESS is modelled to be 174 kWh and the installed ESS at Kongsbergporten is 180 kWh.

Keywords: EV fast-charging, energy station, energy storage system, LP optimization

Contents

List of Terms and Abbreviations

Terms

Kongsbergporten	Name of fast-charging station operated by Glitre Energi
Grid	Electricity distribution grid
Hybrid energy system	Energy system consisting of multiple energy sources or energy storage
Energy Station	Vehicle service station with both combustion fuel pumps and EV chargers
Energy flexibility	The capacity of an energy system to adapt to inherent variability and uncertainty of supply and demand
Peak shaving	Levelling out peaks in electricity consumption
C-rate	Discharge rate compared to battery capacity
ESS size	Capacity of battery ESS to store energy (kWh)
Grid tariff	Cost of utilizing the electricity grid
Power fee	Part of grid tariff. Cost of maximum power supplied from grid.
Peak shaving threshold	Grid power consumption limit in which the battery starts peak shaving
System costs	Operational costs including annuitised cost of investment

Abbreviations

EV	Electric Vehicle
ESS	Energy Storage System
PV	Photovoltaic
V2B	Vehicle to building
V2G	Vehicle to grid
IEC	International Electrotechnical Committee
LIB	Lithium-Ion Battery
LCO	Lithium Cobalt Oxide
NCA	Lithium Nickel Cobalt Aluminium
NMC	Lithium Nickel Manganese Cobalt
LFP	Lithium Iron Phosphate
LMO	Lithium Manganese Oxide
SoC	State of charge
LP	Linear Programming
SLP	Stochastic Linear Programming
MILP	Mixed-Integer Linear Programming
MMPP	Markov-Modulated Poisson Process
GAMS	General Algebraic Modeling System
EVCS	Electric Vehicle Charging Station
RoI	Return on Investment
DSO	Distribution System Operator
NOK	Norwegian Krone

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I Introduction and Theoretical Background

1 Introduction

This is a 30 ECTS Master thesis that elaborates the use of stationary energy storage to increase energy flexibility at fast-charging stations for electric vehicles. The work is a collaboration bewteen Glitre Energi Energiløsninger and UiO. A mathematical optimization model of an EV charging station based on an existing station is created and used to conduct an analysis on the system.

In recent years, the effects of climate change have become increasingly apparent around the world. Global warming as a result of human activity is threatening the Earth as we know it today. In order to slow down this process, we must reduce the emission of greenhouse gases into our atmosphere. Countries around the world have committed to reducing emissions through agreements such as the Paris Agreement as well as national or local measures. One measure is to decrease the use of fossil fuels and substitute to other zero-emission alternatives. This can be realized both in the generation of energy and at the end-use of energy. Renewable energy sources such as wind and photovoltaic energy have become the most prominent technologies for zero-emission energy generation. These technologies are variable due to being dependent on weather, which creates a need for flexibility in the energy system. Also, at the end-use of energy, electricity has become the most popular energy carrier in many sectors. Coupling the electricity sector with sectors that historically have been dependent on fossil fuels presents new challenges. Energy storage systems are one solution to many of these challenges. In road transport, batteries are utilized to store electric energy which can be used as the energy source in vehicles.

1.1 Background

Electric energy generation in Norway is highly renewable, mostly dependent on hydroelectric and wind power. In 2020 the energy mix in the electricity sector in Norway consisted of 90% hydroelectric and 7% wind power [10]. Therefore, Norway is in a special position in the transition to a net-zero society. Instead of investing in renewable generation, Norway is creating measures to reduce emissions from other sectors than electricity generation. One sector in which the Norwegian government has turned to is road transportation. In the past decade, measures have been taken to increase the market share of electric vehicles which has resulted in a significant increase in electric vehicles on Norwegian roads.

The process of electrifying the road transport sector in Norway is accelerating, especially for personal vehicles. In 2021 65% of new cars registered in Norway were fully electric, which is a 25% increase compared to 2020 [11]. The Norwegian Environmental Agency's goal is 100% of new vehicles to be zero-emission in 2025 [12]. This transition introduces new demand for electricity and the electricity consumption of electric vehicles (EV) is expected to increase from 2 TWh in 2021 to 8 TWh by 2030 [13].

In the 2010s the popularity of EVs skyrocketed in Norway. As a result of Klimakur 2020 [14], the Norwegian government introduced economic incentives in favour of EVs in 2011. At this time EVs alone could not compete technologically with combustion vehicles. Driving range and charging time was limiting the competitiveness of EVs. Today, however, new EVs can drive over 500 km and are able to charge to about 80% in a matter of minutes which means that EVs are competing head-on with combustion cars in both price and comfort for the vehicle owners. The most recent EV models from Tesla, Hyundai, BMW and KIA hold battery packages between 70 and 100 kWh and support charging capacity above 200 kW [15]. The amount of EVs on Norwegian roads is growing, creating a need for more charging infrastructure. EV's increasing number and performance present new loads to the electrical grid which have never been present, which is one of the main challenges of electrification.

As of December 2021, there are 19 268 public charging points in Norway of which about 6 400 are fast chargers [16]. Although 20k charging points are many, there are 455 271 personal EVs on Norwegian roads [1]. This means that there are more than 20 cars per

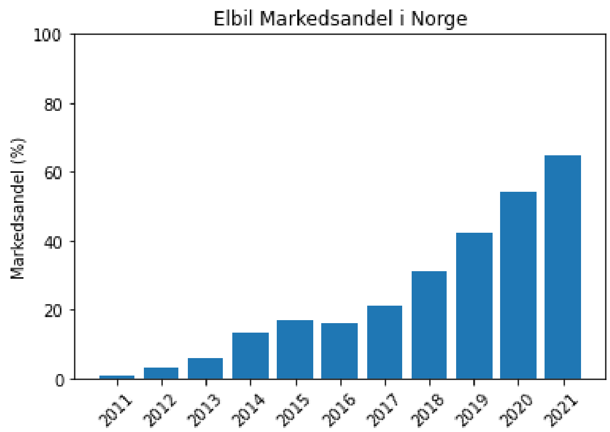

Figure 1.1: *Market share of EVs in Norway 2011-2021 [1]*

charger and even more per fast charger. Most EV owners normally charge their vehicles at home [17], but for those who don't have access to home charging as well as for long drives to vacation homes, fast chargers are necessary. Fast charging requires a high (>22 kW) charging capacity for short periods of time, creating short, high peaks in the electricity demand. High, short peaks are undesired as they can overload the electricity grid as well as significantly reduce profit for charger operators dependent on the grid tariff scheme.

1.2 Motivation

The increasing market share of EV's leads to an increase in charging demand. To be able to support the electrification of the road transport system more EV fast-chargers must be installed around the country. More than 40 companies in Europe are working to expand the domestic EV fast-charging infrastructure [18]. In order to ensure economic feasibility of fast-chargers, demand peaks and flexibility must be accounted for. One solution is to install energy storage systems (ESS) together with fast chargers. An ESS can supply peak-shaving and load-shifts to the grid, decreasing the chance of overloading the grid and having to pay grid operators high grid fees.

Circle K and Glitre Energi have collaborated on a pilot project with the goal of addressing the aforementioned challenges of EV fast-charging. Circle K and Glitre Energi opened a fast-charging station with a supporting battery ESS as well as local solar photovoltaic

(PV) generation in the summer of 2021 called Kongsbergporten. Roadside service stations have historically been called gas or petrol stations. However, with the introduction of EV charging facilities, energy stations has become the normal term for service stations with both fuel and charging facilities. The project is a part of the larger NorFlex project and is partly funded by Enova. The charging station is equipped with four 300 kW fast-chargers which are capable of charging most modern EV's from 20% to 80% in 10 to 20 minutes. Apart from supplying EV owners with fast-charging opportunities, this station is meant to test and research the operation of a hybrid EV fast-charging system.

The ESS and PV supported system at Kongsbergporten is designed to be able to fully supply all fast-chargers with 300 kW simultaneously for a period of time without using grid power. Furthermore, the hybrid electricity system should increase flexibility and avoid drawing power from the grid above a set threshold, also called peak-shaving. The system has proven to be able to meet the requirements. However, Circle K and Glitre Energi believe that there is room for improvement and further optimization of the system.

This thesis is a collaboration between Glitre Energi and UiO and will analyse the system at Kongsbergporten using historical data. The aim of the project is to investigate to which extent the capacity of the installed ESS can be reduced while still meeting system requirements. This is to examine if the pilot project at Kongsbergporten, and other similar projects, can be economically optimized without sacrificing the experience of the customers at the station. A model of the power system is to be created in order to explore the capacity requirement of the battery ESS.

1.3 Scope of Work

The objective of this thesis is to develop a mathematical model of a battery integrated EV fast charging station. The model is to be used to analyse the sensitivity of the energy system on its most relevant parameters: investment cost of ESS, electricity prices, grid tariff power fee, size of ESS, peak shaving and EV charging demand shape. This thesis will take the example of an existing charging station to assess the capabilities of the integrated ESS with respect to peak shaving. This is a 30 ECTS thesis completed in 18 weeks. Therefore, the work done in the thesis is highly focused on specific aspects.

The process of the thesis is done by completing specific tasks. Theoretical background sets the foundation on which the requirements for the model are based and defined. A literature review on hybrid EV charging station modelling is conducted to support model selection. The model is thereafter developed with basis on the existing hybrid energy system at Kongsbergporten. To ensure the validity of the model, results are then compared with system parameters and historical data from Kongsbergporten. Lastly, the model is used to conduct an analysis on battery integrated charging stations to provide insight into which factors the system is sensitive to and to explore possibilities of further optimizing the design and operation on a hybrid energy station with focus on the battery ESS.

The structure of this thesis is as follows. It is divided into four main parts. Part I Introduction and Theoretical Background introduces the thesis work, the objectives of the thesis and the theory behind the thesis work. Part II Methodology covers the full model development process, from defining system requirements and literature review to model validation and intended use. In part III Results the results from the sensitivity analysis are presented. Lastly, in part IV Discussion and Conclusion, the model and analysis results are discussed, an assessment of the system at Kongsbergporten is made, and lastly the thesis is concluded.

2 Energy Flexibility

This section covers the concept of energy flexibility which is a core motive of the ESS installed at Kongsbergporten. Firstly, energy flexibility is explained, then methods used to realize energy flexibility are described.

Energy flexibility is the capacity of an energy system to adapt to inherent variability and uncertainty of supply and demand [2]. Energy systems can be subject to rapid changes in either supply and demand, and the ability to meet these changes is defined as the flexibility of energy systems. This has always been an issue to be addressed in energy systems but it is becoming more prioritised today. Historically, energy generation has been through thermal power plants or hydropower. These generation technologies can rapidly vary their output to adapt supply to varying demand. Today, however, variable renewable generation technology is increasing in market share and energy sectors are coupled, resulting in an increased variation on both supply and demand side. Electrification of the transport sector contributes to increasing variations in electricity demand. Therefore, energy flexibility is an increasing requirement to ensure that energy service demand is met.

Energy flexibility can be categorised into four main types: flexible energy supply, flexible energy demand, electricity trade and energy storage. All of these provide flexibility to an energy system. The following chapter will assess each of the four areas and address to what degree they are of relevance of this thesis.

2.1 Flexible Energy Supply

Flexible energy supply refers to the capability of energy generation technology to adapt to variations in the system. Examples of this are hydroelectric generation with water readily accumulated in reservoirs or natural gas power plants. As mentioned earlier, these generation technologies are able to ramp generation over a short period of time to meet a change in demand. Power plants like these are often referred to as peaker plants, as they vary their output to meet demand peaks and valleys.

2.2 Flexible Energy Demand

Flexible energy demand refers to an energy consumer's ability to vary energy consumption. This is more difficult to implement on a large scale because consumers usually need energy to perform certain tasks at certain times. A factory, for example, consumes most of its energy during working hours when staff is on location, or that most people make dinner using their kitchen appliances after they come home from work. Similarly, EV charging stations need to meet charging demand as soon as an EV connects to a charger. Therefore, incentives are needed to manage the demand side of energy systems. Figure 2.1 shows the different results of demand side management. Peak shaving, load shifting and energy conservation are the most desired results of flexible energy demand.

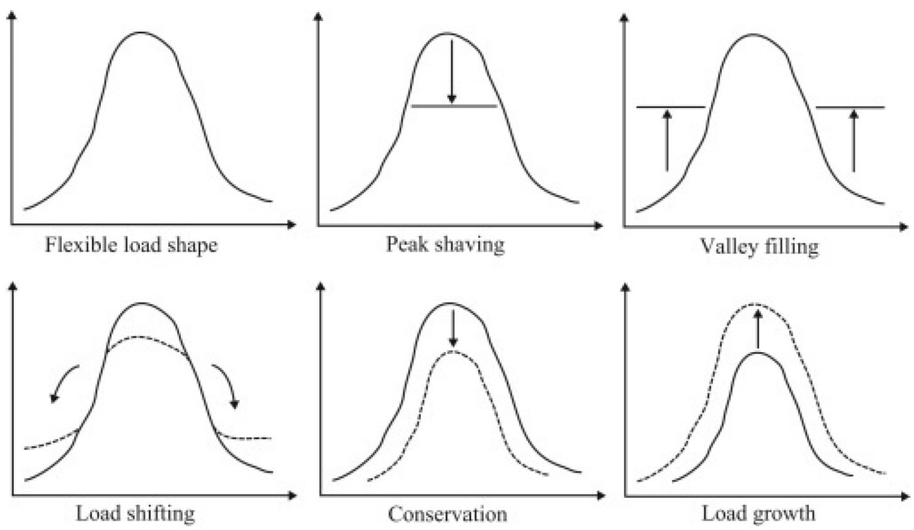

Figure 2.1: *Goals of demand-side management. Cutout from [2]*

Flexible demand is realised through changes in the behaviour of energy consumers. This can be charging EVs at night when general energy demand is low, leading to load shifting, or by installing better building insulation to reduce energy consumption on heating resulting in energy conservation. Consumers often need economic incentives to change their behaviour. Therefore, demand-side management is often done through energy pricing schemes. Examples of this are power fees, time-of-use fees or subsidies.

For energy stations such as Kongsbergporten, the battery ESS is installed for peak shaving. Due to unpredictable demand throughout a day, a battery is able to supply power when

EV charging demand is high in order to minimize peaks and fluctuations in the energy grid. This is economically feasible due to a power fee in the grid tariff.

2.3 Electricity Trade

Energy or electricity trade refers to the movement of excess energy from one place to another. Electricity is traded at all scales, from international networks to consumer electronics. The Norwegian electric energy system is interconnected with Sweden, Denmark, Netherlands, Great Britain and Germany. These interconnectors allow electricity trade between large energy systems, which increases flexibility. For example, when there is little to no solar or wind generation in Germany, Norway can increase hydroelectric generation and sell electricity directly to Germany. Likewise, when there is abundant wind and solar generation in Germany, excess energy can be sold to Norway.

Electric vehicles can be used for small scale electricity trade. EVs with two-way compatibility of energy flow can supply a house with electricity when electricity prices are high. When electricity prices fall, the EV can be recharged. This concept is called vehicle to building (V2B). Similarly, EVs can supply the distribution grid to meet demand peaks, a concept called vehicle to grid (V2G). As a result, EVs can contribute to increased flexibility in an energy system. As mentioned earlier, batteries in modern EVs are in the range of 70-100 kWh. A typical Norwegian household consumes roughly 16000 kWh a year [19], averaging about 45 kWh per day. Thus, by utilizing 10% of EV battery capacity, V2B can meet household energy demand for 4-6 hours each day. However, bidirectional usage of EV batteries has implications with respect to the availability of a fully charged EV, EV battery lifetime and the cost of required infrastructure.

2.4 Energy Storage

Energy storage refers to the act of storing excess energy with the intention to use it at a later time. Many energy storage technologies exist, including batteries, thermal storage and hydrogen storage. Reservoirs connected to hydroelectric power plants are considered a type of energy storage. Stored energy can contribute to increasing flexibility in energy supply, energy demand and electricity trade. Energy storage introduces flexibility by allowing excess energy to be stored when generation is high and to be discharged when generation is low. An example of this is coupling an energy storage system (ESS) with PV generation. Solar energy is abundant in the daytime, and non-existent at night. Thus, an ESS can be charged during the daytime and discharged at night, distributing the supply evenly.

The focus of this thesis is the use of ESS for peak shaving and load shifting in order to increase the flexibility of energy stations. Peak shaving is desired at EV fast charging stations due to a power fee in the grid tariff, which is defined by peak power consumption. From the energy assessment the focus on this thesis is on energy shaping where ESS batteries are in the size of 10-20% of max demand are used.

3 EV Charging Technology

This section covers the basics of EV charging technologies. An overview of different types of EV charging methods, European EV charging standards and the influence on this thesis is presented in the section.

Similarly to consumer electronics, EVs can be charged in different ways, using different technologies. This section will explain the basic principles of EV charging and the different modes and methods EV charging is classified into. An EV charger is a device which is designed and used to transfer energy from a source to the battery system in an EV. The energy source is conventionally the electric distribution grid. In recent years, local renewable energy generation and energy storage systems have been introduced to EV charging stations just like Kongsbergporten. This section is focused on EV charging systems downstream from the energy source.

For the typical EV driver, an EV charger should be as easy to use as a fuel pump. This means that the user should only have to plug their vehicle into the charger and wait, just like one does with their cellphone. There are many factors that must be considered while designing an EV charging system including cost, safety, power and communication. Overall, an EV charging system has three key functions:

- Charging: Transferring energy from source to battery
- Stabilising: Optimising the charging rate
- Terminating: Avoiding overcharge of the battery

This requires control units in both the charger and on board the vehicle. In figure 3.1 a block diagram of an EV charging system is given. The main parts of an EV charging system are the control units and the energy transfer unit which is usually a cable [20]. For charging at high capacity, communication between the control units is required, this data transfer is to ensure stability, safety and to avoid damaging the EV battery.

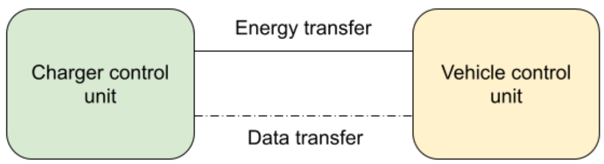

Figure 3.1: *EV charging block diagram*

3.1 Charging Methods

As mentioned earlier, EVs can be charged in different ways. These methods are separated by how electrical energy is transferred into the EV battery. Today, there are three methods to charge an EV: conductive, inductive and battery swap.

3.1.1 Conductive charging

Conductive systems require a physical connection between the source and the battery. A cable connects the vehicle to either a socket or a charger which conducts electrical energy from the source to the battery. This is the most common charging system today because it is cheap and efficient. Another advantage is that conductive charging can be applied with both AC and DC supply. An EV user can charge their vehicle at home with AC supply without installing expensive equipment and also charge on public stations with DC supply for fast charging.

3.1.2 Inductive Charging

Inductive charging systems are also known as wireless charging systems. Inductive chargers create an electromagnetic field to allow energy transfer. This requires that the EV is in proximity of the charger, but physical contact is not required. The electromagnetic field is created by a wire spool conducting an AC current. When an EV is parked close to the charging point, the electromagnetic field induces an electric current in an on board wire spool and delivers electric energy to the battery. Inductive charging only requires the EV to be parked at a charging point in order to start charging making it easy to use.

3.1.3 Battery Swap

Battery swap systems physically changes the battery of the EV. The main advantage of battery swap is the charging time experienced by the driver because a battery can be changed in the matter of seconds. Another advantage is that batteries can be charged in optimal conditions, increasing their lifetime. There are some drawbacks however. The batteries and chargers must be compatible with each other. This system also requires that there are more batteries than vehicles, which can be expensive.

The focus on this thesis is on conductive charging. Therefore, the following chapters are concentrated on conductive charging.

3.2 EV Charging Standards

The International Electrotechnical Committee (IEC) has developed an international standard for EV charging systems, IEC 61851 [21]. The increasing diffusion of EVs on European roads has an impact on a large amount of actors such as EV manufacturers, charging station manufacturers, grid operators, EV drivers, service providers etc. The standard is developed to promote open, secure systems and to provide interoperability between all actors. The standard also defines safety requirements for EV charging technology to ensure robustness, safety and security [22].

EV charging is in IEC 61851 categorised into three types based on the function of charging, depending on the rated power of charging. These three types of charging are:

- Slow charging ($< 3,7\ kW$)
- Quick charging ($< 22\ kW$)
- Fast charging ($> 22\ kW$)

A summary of the electrical ratings of these three charging types can be found in table 3.1

Table 3.1: *IEC 61851 Charging types and electrical ratings [9]*

Charging type	Power [kW]	Connection	Max current [A]	Location
Slow charging	$< 3,7$	1-phase AC	10-16	Domestic
Quick charging	$3,7 - 22$	1- or 3-phase AC	16-32	Semi-public
Fast Charging AC	> 22	3-phase AC	> 32	Public
Fast Charging DC	> 22	DC	> 3225	Public

Furthermore, the IEC (IEC 61851-1) has defined four modes of conductive charging systems. These modes are defined by the type of power supplied (AC or DC), the level of voltage, electric grounding, data transfer between charger and EV and the presence and location of device protection [9].

3.2.1 Charging Modes

Figure 3.2 illustrates the four charging modes. Mode 1 is the simplest charging mode, applying a standard wall socket and cable for charging at home. Charging mode 1 does not require any additional equipment and is therefore limited to very slow charging. The rated voltage and current cannot exceed 16A and 250V 1-phase or 480V 3-phase and there is no communication between the source and the EV. Modern EVs do not support Mode 1 due to lack of safety and control. Mode 2 is what most EV drivers considers as home charging. Power is supplied from a standard wall socket and the charging cable is equipped with a

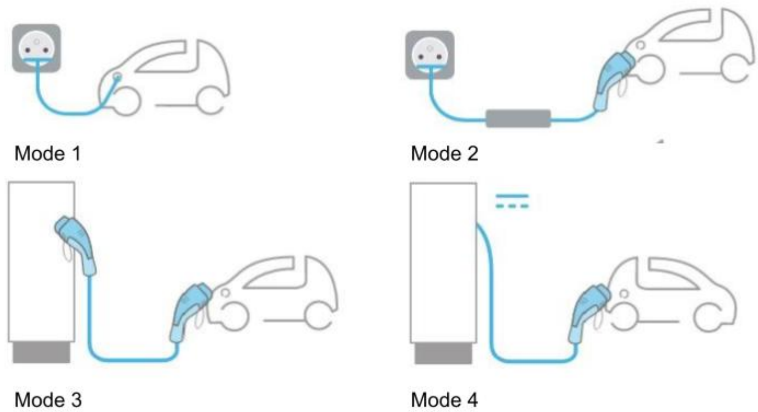

Figure 3.2: *Illustrations of charging modes. From [3]*

control unit. The control unit ensures protection for both the user and the EV battery through one-way communication from the control unit to the EV. According to IEC, the rated voltage and current cannot exceed 32A and 250V 1-phase or 480V 3-phase. Therefore, mode 2 is also considered slow charging. Mode 3 is charging at a dedicated charging station. In mode 3, stationary equipment is required at the charging station with integrated control and protection units. Charging stations also have specific charging sockets and connections to ensure security and safety. The supply side is permanently connected to an AC source, usually the electricity grid, and limited to 22 kW. Mode 3 is mostly public charging but can also be installed domestically with the correct equipment. Mode 4 is DC fast charging. Like mode 3, specific equipment is used to enable mode 4 charging. In mode 4, DC power is supplied directly to the battery, allowing fast charging up to 350 kW. For charging mode 3 and 4, two-way communication between the EV control unit and the charger control unit is required. The chargers at Kongsbergporten are able to charge in both Mode 3 and 4.

Table 3.2: *Classification of charging modes.*

	Mode 1	Mode 2	Mode 3	Mode 4
Type	Slow	Slow/Quick	Quick	Fast
Data Transfer	No	One-Way	Two-Way	Two-Way
Source	AC	AC	AC	DC

The charging station at Kongsbergporten which is used as data source in this thesis is able to charge in both mode 3 and mode 4. This thesis focuses on mode 4, DC fast charging, and this is the charging mode to be considered from this point.

3.3 Typical EV fast charging profile

While in charging mode 4, EVs are not charged with constant power. This is because charging at high power over long periods of time can damage the EV battery. The vehicle control unit and the charger control unit shown in figure 3.1 communicate and determine the optimal power delivery at all times while charging. The usual charging profile of EVs can be seen in figure 3.3. As the figure shows, for that specific EV charging cycle, charging starts at ca. 95 kW and declines throughout the charging cycle to around 30 kW over a period of on hour. This is seen in the majority of charging cycles at Kongsbergporten.

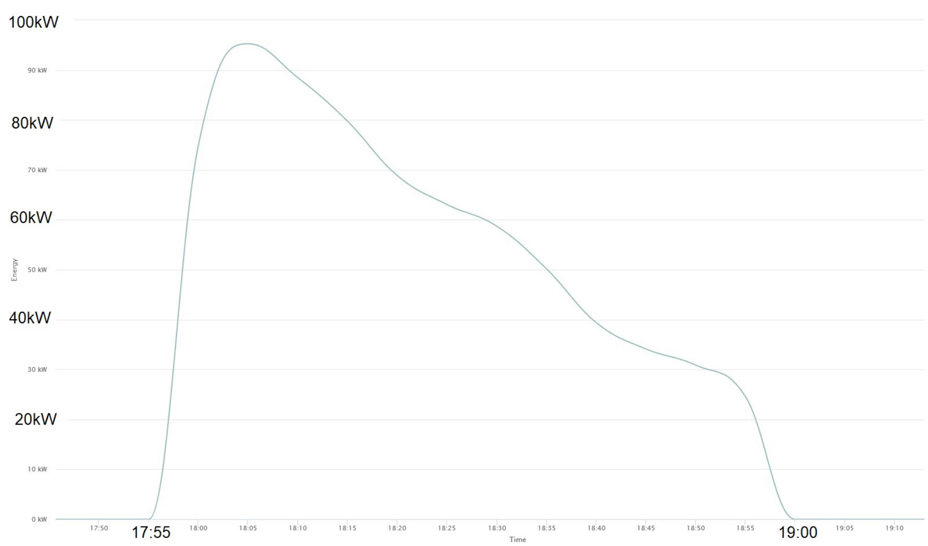

Figure 3.3: *Typical 100 kW fast charging profile of an EV. Screenshot from data portal for Kongberg-porten 25.04.22 17:55-19:00*

4 Lithium-Ion Batteries

The battery ESS at Kongsbergporten is a li-ion battery and in this section, basic chemistry, commercialized materials used in li-ion batteries and the impacts on the battery choice for stationary ESS is presented. The theory in this chapter is collected from the UiO course TEK5320 Battery Technology [23].

Lithium-ion batteries (LIB) store electrochemical energy and is a common type of rechargeable electrochemical energy storage technology. LIBs are mainly used for power electronics such as cellphones, laptop computers and handheld power tools. However, due to its properties, the applications of LIBs are increasing and the storage technology is increasingly used in transportation and utility-scale energy storage. Most hybrid electric and fully electric vehicles today are fitted with LIBs. With the increasing market share of variable renewable energy generation technologies LIBs have also been applied to utility-scale energy storage systems such as the 300 MW Victorian Big Battery system in Australia [24]. These fairly new markets have led to an acceleration in research and development in the technology which in turn has led to decreasing costs which can be seen in the graph in figure 4.1.

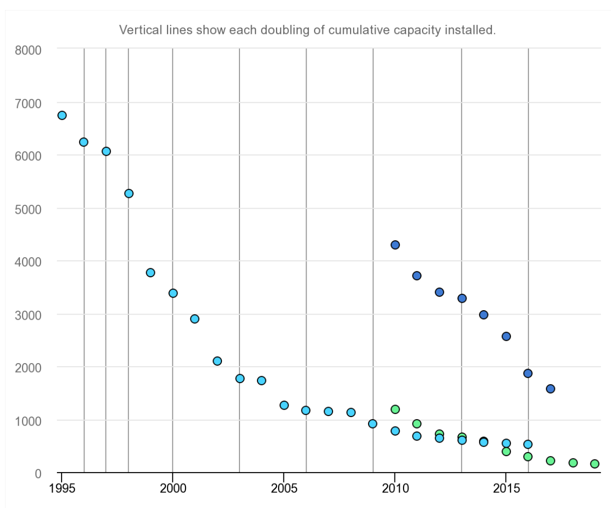

Figure 4.1: *Evolution of Li-Ion battery price 1995-2019. Light blue represents consumer electronics cells, dark blue represents utility-scale projects and green represents automotive battery packs. [4]*

The properties of LIBs are the reason why it is becoming a preferred energy storage technology for many applications. Batteries have the advantage of being mobile and scalable, making them suitable for mobile applications. Many types of batteries exist such as lead-acid and nickel-metal hydride and each technology has its advantages. The specific energy density and the volumetric energy density of the different battery technologies can be seen in figure 4.2. Out of all commercialized battery technologies, LIBs have the highest specific and volumetric energy density. LIBs are thus the smallest and most lightweight batteries, which is why they are great for mobile applications. Compared to other battery cell technologies, LIBs are highly flexible meaning that partial charging or discharging does not affect the battery capacity as much as it does for other batteries. The self-discharge rate of LIBs is also low.

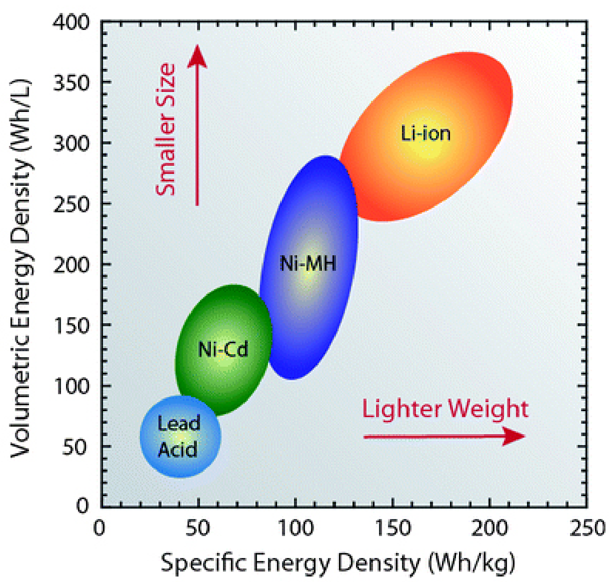

Figure 4.2: *Energy density of battery cell technologies [5]*

4.1 How Lithium-Ion Batteries Store Energy

An illustration of the basic working principle of LIBs is shown in figure 4.3. LIBs store and discharge energy by limiting and allowing the movement of electrons and ions. Batteries consist of a positive electrode (cathode), a negative electrode (anode) and an electrolyte, a chemical solution between the electrodes. The electrodes are connected by a metal conductor which allows electrons to travel between them. The electrolyte is a liquid solution containing molecules that allow positively charged lithium ions to flow between the electrodes. Between the electrodes there is a microporous separator wall that allows lithium transport but blocks electron transport, forcing electrons to flow through the metal conductor. In a fully charged LIB, lithium is accumulated in the anode. The positively charged lithium ions are electrochemically attracted to the cathode side. As a battery is discharging energy, lithium ions are released from the anode material and flow to the cathode material. As the ion is released from an electrode it releases an electron which travels through the metal conductor to the opposite electrode. This electron transport creates an electric current which results in the electrical energy we can use to power electronic devices.

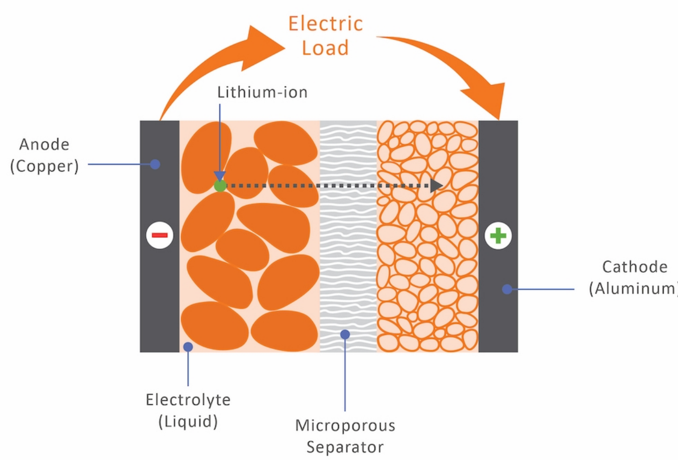

Figure 4.3: *Lithium-Ion battery cell design [6]*

The working principle of LIBs is based on the transport of lithium ions between the electrodes, and this can be achieved using many different materials. Several types of LIBs exist with varying chemistry and properties. A single lithium-ion battery cell creates between three to five volts depending on its chemistry. Most battery systems consist of multiple cells connected together which delivers higher voltages. The battery packs in EVs for example, consist of several thousand cells, to be able to deliver the desired power to run a car. In a Tesla, there are 2976 li-ion cells that make up the 100 kWh battery pack [25].

4.2 Types of Lithium-Ion Batteries

The working principle of LIBs can be achieved using several materials. On the anode side, graphite is the most common and widespread material used in LIBs. Materials to use as the cathode however is more diverse. Therefore, the different types of LIBs are named by the cathode material of choice. Figure 4.4 is a representation of six types of LIB applicable for EVs and large scale energy storage as well as their main properties. All of the presented types of LIBs contain lithium alloyed with a metal oxide on the cathode side.

$LiCoO_2$ (LCO) batteries were introduced in 1980 by John B. Goodenough for which he won a Nobel Price in chemistry in 2019 [26]. They were the first commercialized LIBs and accounted for 30% of the global revenue share of LIBs in 2021 [27]. LCO batteries have high theoretical specific and volumetric capacity, high discharge voltage, little self-discharge and good cycling performance [28]. Disadvantages of LCO batteries include the use of toxic materials, low thermal stability and capacity fade at deep cycling.

The drawbacks of LCO led to research into better compositions for cathode materials. One alternative is NCA, where nickel and aluminium is introduced in the alloy. NCA batteries have great specific capacity and power and possess many properties desirable for EV application. They are however not as safe to use as other options and require extensive monitoring and safety measures for safe operation [7]. Therefore, Tesla is the only EV manufacturer to use NCA batteries [28]. Another alternative is $LiNi_xMn_yCo_zO_2$ (NMC), which is a mix of lithium, nickel, manganese and cobalt. Manufacturers vary the mix of the alloy materials for the intended use for the battery, which is mostly for high specific energy or power. NMC batteries have similar properties to LCO with less safety issues. This combination of properties make NMC batteries the dominant choice for applications such as EVs [7].

$LiFePO_4$ (LFP) batteries are known to be safe to use in addition to being composed of environmentally friendly materials. Therefore, LFP batteries are increasingly used as an energy storage technology. Compared to NCA and NMC, LFP has low volumetric and specific capacity as well as low operating voltage. LFPs are therefore competing in the market that is dominated by lead-acid batteries as well as long-term stationary storage. $Li_2Mn_2O_2$ (LMO) batteries are very safe and have high thermal stability. LMO batteries have a rel-

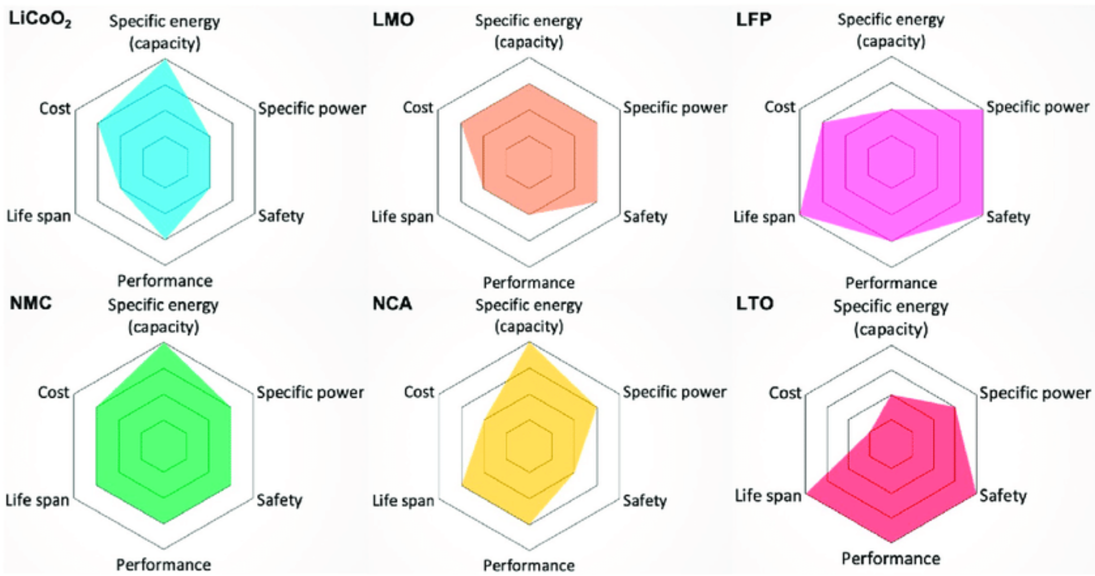

Figure 4.4: *Properties of LIBs used in EVs [7]*

atively low volumetric and specific capacity which limits their applications. However, due to the high safety of LMO, the technology is widely used in medical equipment. LMO can also be applied to small EVs and power electronics.

4.3 Electric Vehicles and Energy Stations

The requirements for EV batteries are good safety, small size, low weight and high power, which is why most EVs are fitted with NMC batteries. At an energy station such as Kongsbergporten, the requirements are similar. The battery needs to be safe in operation, and deliver power at a high rate in order to meet EV fast-charging demand. NMC batteries meet these requirements and are therefore the LIB of choice for the system at Kongsbergporten. However, the high volumetric capacity of NMC batteries is not required for stationary storage systems.

The voltage and power a LIB can deliver is dependent on the battery state of charge (SoC). The relationship between SoC and voltage for a LIB cell is shown in figure 4.5. A battery pack with multiple cells follow the same curve with higher voltage. The figure shows that a LIB has highest capacity at full SoC. Therefore, for a system designed for peak shaving, it is favorable to ensure adequate SoC at all times to be able to meet unforeseen demand peaks.

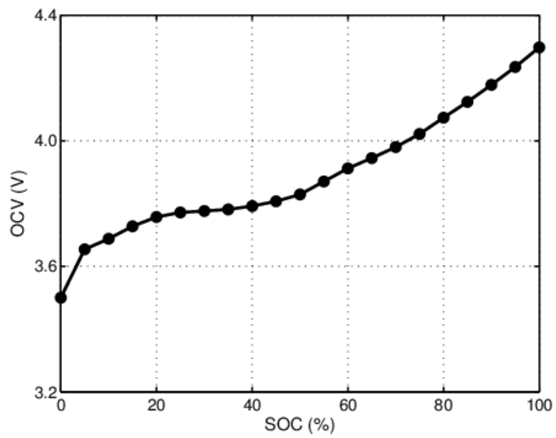

Figure 4.5: *Open circuit voltage vs. state of charge for a LIB cell [8]*

LIBs are also prone to degradation which affects the capacity of the battery. There are three factors related to degradation which should be taken into account when deciding battery for a system; cycle life, shelf life and self discharge. Each time a battery is cycled, it loses a tiny amount of capacity. Also the deeper the cycle, the more harmful it is. The battery ESS at Kongsbergporten has a cycle life of 6000-8000 cycles [29, 30]. The shelf life of a battery refers to how long a battery can be idle without being used. The capacity of batteries fade over time and LIBs shelf life varies from 2-3 years to 10-12 years based on the type of battery and how it is stored. Lastly, self discharge is due to electrons leaking from anode to cathode when the battery is not used. LIBs typically have self discharge rate of 1.5-2% per month.

Because this thesis is focused on the utilization of LIBs with a foundation in an existing installation, alternative battery technologies such as thermal batteries or salt batteries are not considered.

5 Linear Optimization Modelling

This section introduces the main principles and application of linear optimization models. The model developed in this thesis is a linear optimization model. In section 7.2 the reason for this choice is explained.

Linear optimization modelling is a type of mathematical modelling. Mathematical modelling is a tool used to translate real-world systems into mathematical formulations that provide insights and supports decisions. Mathematical modelling can be divided into three major categories: optimization models, dynamic models and probability models [31]. The application of each type of mathematical modelling depends on the system or problem being modelled. An overview of the application of the different model types is presented in table 5.1. In this thesis an energy system is modelled with a linear optimization model, also called linear programming (LP). Therefore, in this section linear optimization modelling will be defined.

Table 5.1: *Mathematical modelling methods*

Model type	Application	System Examples
Optimization models	Maximize a good or product while minimizing the related cost or consequences	Production of consumer goods, minimize calculation time of software, profit maximization and distribution of products
Dynamic models	Represent the changing behaviour of systems that evolve over time.	Population growth, chemical reactions and military conflicts
Probability models	Represent systems of a random nature with associated outcome probability	Raffles and lotteries, betting odds or human behaviour

Optimization models are mathematical models that minimize or maximize an objective function that is subject to a set of constraints. The purpose of an LP is to identify the optimal values for a set of decision variables which results in the optimal value of the objective function. The model is an LP if the objection function and constraints are represented by linear equations. Constraint equations are categorized into equality constraints and inequality constraints and define the limits within which the decision variables have to be to give an allowable solution. Decision variables are the quantities that are to be determined. The general formulation of an LP can be expressed as:

$$
\begin{aligned}
\text{max/min} \quad & f(\underline{x_i}) \\
\text{subject to} \quad & h(\underline{x_i}) = \underline{c}, \quad i = 1, \dots, n \\
& g(\underline{x_i}) \geq \underline{b}, \quad i = 1, \dots, n
\end{aligned}
$$

where $f(\underline{x_i})$ is the objective function, $h(\underline{x_i})$ are the equality constraints, $g(\underline{x_i})$ are the inequality constraints and $\underline{x_i}$ are the decision variables. Typically in LP models, the objective function represents the total costs of operating a system and is to be minimized.

Optimization models can be created to represent many problems. Non-linear optimization models often represent a real system or problem more realistically. However, linear programming models require significantly less computing power and do in many cases create an applicable model. Another advantage of linear models is that there is only one optimal solution.

6 Kongsbergporten

In this section the energy station on which the model in this thesis is based, Kongbergporten, is described.

Kongsbergporten is an energy station with two fuel pumps for combustion vehicles and eight charging points for electric vehicles. This thesis is focused on the electric power and charging facilities of the energy station. In this section, the system at Kongsbergporten is introduced. The information in this section has been provided by Glitre Energi [29].

Kongsbergporten is a Circle K energy station located along highway E134 by Kongsberg in the province of Buskerud in Norway. The station is owned by Circle K and the fast charging infrastructure is designed and operated by Glitre Energi Energiløsninger. A large amount of the population in the urban areas from Oslo to Drammen frequently visit mountain towns west of Oslo. Highway E134 is the main road to the city of Kongsberg and many of the

Figure 6.1: *Photograph of Kongsbergporten energy station*

roads to mountain towns start there. Therefore, Kongsbergporten is strategically placed to service both the population of Kongsberg as well as holiday traffic from Oslo and its surrounding area.

The energy system at Kongsbergporten is separated in two parts, one to supply a restaurant and shop, and the other to supply the EV charging infrastructure. Because of the possibility of autonomous operation of the EV charging grid, this is considered a microgrid. This thesis is focused on the EV charging system which is the system operated by Glitre Energi Energiløsninger. This microgrid is connected to the distribution grid through a transformer and is additionally supplied by local solar PV generation. The PV system is installed on the roof over the charging points and has an installed capacity of 50 kW. The microgrid is also equipped with a stationary battery ESS. The installed battery is a 180 kWh NMC lithium-ion battery which is used mainly for peak shaving. The power fee in the grid tariff at Kongsbergporten is a significant monthly cost for Circle K and is the motivation to increase flexibility with the ESS. Furthermore, four 300 kW fast chargers are connected to the microgrid and make up the demand side of the microgrid. These chargers are designed to either supply two EVs in charging mode 3 or one EV in charging mode 4 each.

This thesis focuses on the utilization of battery ESS at an energy station. The technical specifications and system limits at Kongsbergporten are used in the model to have practical relevance and to assess the model using real-world values. The theory presented in the previous sections is applied to develop a model of a battery integrated EV charging station. The following part presents the process of developing the model, model validation and the application of the model with sensitivity analysis.

II Methodology

This part covers the modelling methodology for this thesis. One of the primary objectives of the thesis is to generate a mathematical model of the energy system of a battery integrated EV fast charging station based on the existing energy station at Kongsbergporten. In this part of the thesis the process of creating this model is described. Beginning with defining the requirements of the model, to model description and ending with creating analysis scenarios, the full process of model generation is covered in the following sections.

7 Model Approach and Selection

This section covers the process of defining the framework for the model. This includes system requirement definition and how and why the model type was selected.

Energy systems, microgirds and EV charging stations can be modelled in multiple ways. In order to create a suitable model of Kongsbergporten for this thesis, a survey of literature on EV charging station modelling has been conducted. As well as a literature review, the requirements and targets for the model of Kongbergporten were mapped and weighted on importance. This preparation work laid the foundation for selecting the best model method for this thesis.

7.1 Review of Hybrid Energy Station Modelling

This is a non-comprehensive overview of literature on modelling hybrid EV charging stations and models used for energy monitoring. A range of models used for hybrid energy station have been reviewed in order to provide an assessment of which model types and parameters to select for the model developed in this thesis.

In Yan et al. (2019) a four-stage optimization and control algorithm was used with the aim of minimizing operational costs of an EV charging station with integrated battery energy storage and local PV generation [32]. The algorithm applies forecast data and day-ahead prices to optimize energy consumption versus PV generation. The model of the energy system is a linear programming model that minimizes the total operation cost per day. Mehrjerdi and Hemmati (2019) employed an optimization model of an EV charging station equipped with battery ESS, diesel generator and solar panels to optimize the rated power of EV charging facilities, power and capacity of the battery ESS as well as hourly operation of the ESS and diesel generator [33]. The load demand and PV generation are modelled by probability distribution functions and stochastic programming. Bryden et al. (2019) modelled an EV charging station with integrated battery ESS to investigate the relationship between the size of the ESS and customer waiting times [34]. The model is a two-stage algorithm that produces the best size of the ESS based on acceptable waiting times. The demand and consumption data is based on random number generation weighted to a normal distribution as well as a charging profile similar to figure 3.3. Haupt et al. (2020) researched the impact of EV charging strategies on the sizing of battery ESS in microgrids. In the paper, a Mixed-Integer Linear Programming (MILP) model was created to separate the strategies in order to address the research. Three charging strategies were used in the model; immediate, controlled and bidirectional. Their study found that charging strategy significantly influences the optimal ESS size [35]. Bayram et al. (2020) use a stochastic model for EV charging with on-site ESS [36]. Based on Poisson arrival, departure and demand statistics, a Markov-modulated Poisson process (MMPP) model is developed, and storage sizing is solved by computing the model's probability distributions. The model considers one vehicle waiting as an outage, and determines the battery size according to the probability of an outage. They can also size the battery using maximum power from the grid to avoid a power fee from the grid, reducing operation costs by peak shaving similar to the motivation behind the system at Kongsbergporten. Negarestani et al. (2016) used an optimization-based method to determine the optimal size of ESS and the optimal energy flow in a battery integrated EV charging station [37]. In the model, the researchers have also separated demand on weekdays and weekends as well as investigated the impact of different electricity pricing schemes. Hussain et al. (2020) used an optimization model on an EV charging station to find the resilience of EVs in the case of a power outage using the distance to the nearest working charging station and the range of EVs [38]. Their model considers three factors; cost minimisation, peak load and resiliency to find which of these factors has the highest impact on ESS size. Results show that resiliency has the lowest impact on the sizing of the ESS but state that it should not be neglected. Longo (2021) is an M.Sc. Thesis from KTH Royal Institute of Technology in Stockholm [39]. The thesis is a study on the economic and technical feasibility of an EV fast-charging station coupled with ESS in the Stockholm area using a MILP model of an EV charging station. Yi et al. (2020) is a study on how the charging pattern of EVs affects a microgrid with PV and wind generation as well as an ESS [40]. The microgrid is modelled as an optimization model using a simulated annealing algorithm. The research includes demand-side management by lowering EV charging prices when total demand is low, which greatly affects the total costs as well as the required ESS size in the microgrid. Chowdhury et al. (2020) is an analysis of battery ESS for grid-level services [41]. Using historical data, an optimization model is used to decide the size of the battery ESS. Chowdhury et al. discuss that installing an ESS larger than optimal size may be beneficial due to increased lifetime of the system as battery degradation will impact the system later in the system lifetime.

EV charging stations are thus modelled to create insight in specific factors. For this thesis the focus is on the utilization of an integrated battery ESS. The following sections on model development are based on observations made in this review as well as the existing system at Kongsbergporten.

7.2 Model Requirements and Selection

The model of Kongsbergporten is intended to represent the existing energy system of the charging infrastructure already existing at the energy station. In order to select a suitable model method for this thesis, the primary requirements for the model were determined. Following the primary requirements, secondary requirements were determined and used as a tool to select the methodology of the analysis. The main purpose of the model is to realistically represent the energy system and through this representation, calculate the optimal size of the ESS. Because the demand of the real charging infrastructure is to deliver power to charging EVs it was decided that the model should primarily represent the power flow from the distribution grid and/or the battery ESS to the chargers based on historical demand data from Kongsbergporten.

The secondary requirements were determined as the additional parameters that should be calculated by the model. Therefore, a list of feasible parameters to include in the model was produced based on the existing system at Kongsbergporten, discussions with Glitre Energi, similar models in literature and brainstorming. The parameters are weighted on the significance and presumed influence on the results of the model. The proposed model parameters and their assumed importance in the model are seen in table 7.1.

Table 7.1: *Proposed model parameters*

Parameter	Unit	Weight
Electricity price	NOK/kWh	++
Grid Tariff (peak load)	kW	++
BESS charge curve/behaviour	V/SoC	+
BESS discharge curve/behaviour	V/SoC	+
BESS min/max SoC	%	++
BESS C-Rate		0
BESS efficiency	%	+
BESS degradation	%/year	0
PV capacity	kW	+
PV capacity factor		++
PV weather forecast		-
Charger amount	#	+
Charger power	kW	++
Charger maximum waiting time	min	0
Charger price per kWh for customer	NOK/kWh	+
Traffic forecast		-
Historical traffic data		++
EV charging efficiency	%	0
EV battery size	kWh	+
EV battery charging profile	V/SoC	-
EV initial SoC	%	++
Annualised investment cost BESS	NOK/year	+
Annualised investment cost per charger	NOK/year	+
Annualised investment cost on PV system	NOK/year	0
Discount rate	%	+
Expected lifetime	years	+
Grid load at time t (peak/max load)	kW	++
Duration of time interval	min	+

The primary requirement of the model is to calculate the optimal size of the ESS in the microgrid. Comparing the model types presented in section 5, an optimization model is most applicable for the model in this thesis. Furthermore, most of the models presented in the literature applied an optimization model to represent the energy system being researched. Optimization models are used to calculate defined parameters of a system, decision variables, in order to reach the optimal value of an objective function. Therefore, the model of Kongsbergporten is decided to be an optimization model. The objective of the model is to minimize operational costs and ESS size based on the parameters mentioned in table 7.1. Input parameters are power demand and costs, and the model should calculate the optimal values of the rest of the parameters in order to minimize operational costs and ESS size. Three types of optimization models were considered:

- Linear Programming (LP)
- Stochastic Linear Programming (SLP)
- Mixed-Integer Linear Programming (MILP)

Compared to the research mentioned in section 7.1, the work done in this thesis is based on an existing system. This means that historical data on charging demand and power flow is available. The probability of EV charging traffic and demand is therefore not needed to be included in the model, eliminating stochastic linear programming as an option. MILP is used when binary variables are included in the model. In Longo (2021) binary variables are used to distinguish if the integrated ESS is charging or discharging [39] and in Haupt et al. (2020) binary variables were used to distinguish different charging strategies [35]. LP and MILP models are very similar and converting an LP to a MILP is possible with only a few constraints.

As a reult of the requirement analysis, the model is selected to be a LP optimization model. An LP will provide a realistic representation of the power flow of the system without requiring time-demanding computation while also providing a single optimal solution for the program.

8 Electric Vehicle Charging Station (EVCS) Model

This section covers the primary product of the thesis work, the EVCS model. The model will be used to conduct the sensitivity analysis on the energy station.

The model presented in this section is a linear programming optimization model. Input data includes historical output data from chargers at Kongsbergporten, investment cost of the battery ESS, spot prices of electricity as well as other operation costs. These make up the total system costs of the time period in which the data represents and is minimized in the model. The output data is the power flow, represented as power delivered or consumed by components, as well as the size, rated power and the SoC of the battery ESS.

The optimization model is mathematically formulated and solved in General Algebraic Modeling System (GAMS). GAMS is a modeling system for mathematical programming and optimization [42]. The GAMS software is designed for mathematical modelling, and is excellent for linear optimization, which makes it a good choice for the EVCS model. GAMS was chosen instead of other options like Python or HOMER because it is specifically designed for mathematical modelling, which is beneficial in model generation and solving. Solving time is less than 20 seconds on a Microsoft Surface Pro 6 with Intel Core i5-8250U processor. Results from GAMS are stored in databases and post processing work is done in Python.

8.1 System Definition and Description

The EVCS model is created to represent a realistic and applicable version of the existing system at the energy station. EV chargers are the demand end of the microgrid, and the primary requirement of EV chargers is power in kW. Therefore, the system is modelled as a power system with components that either discharge or consume power in the system. The system boundary is defined from grid power to the power delivered to EVs through chargers. An illustration of the system which is modelled is seen in figure 8.1 and include the following components:

- Control Unit
- Lithium-Ion Battery ESS
- Chargers (represented as a single load)

The control unit is a fictional component representing the optimization model which calculates the optimal power flow from grid to load. The distribution grid is the sole power source to the system and the ESS is able to store energy. Historical demand data is the main model input, and the model calculates optimal power supplied to the load from either the grid and/or ESS for every timestep. The ESS is modelled as either a source of power as it is discharging, or as a load as it is charging. For every timestep the ESS is used, the discharge or charge power is stored and the state of charge (SoC) of the battery is updated.

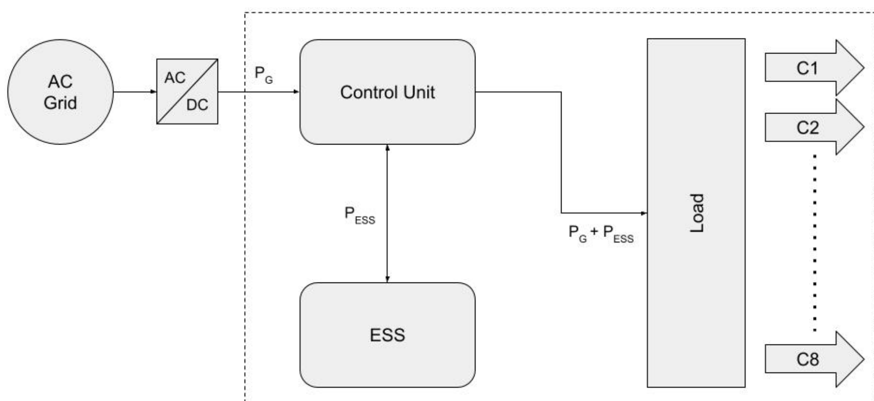

Figure 8.1: *Schematic functional illustration of the EVCS model.*

This is a simplification of the actual energy system at Kongsbergporten which in reality from the physical implementation is much more complex. Therefore, some components are not included in the model and assumptions have been made. The roof-mounted PV system at Kongsbergporten is not included in this model. Although PV generation will supply the system with "free" power, it has been excluded from the model used in this thesis as the main focus is on the ESS. Transformers, converters, inverters and other power electric components are not represented in the model. This in essence means that the efficiency of all unrepresented components is 100%. Losses are thus not included in the model, resulting in a supply equal to demand. This includes battery efficiency as well, which will be further discussed in the section on future work 15. Another simplification is that the microgrid is modelled as a DC grid to be able to focus on power supply and demand in kW. Given simplifications, the model represents the main purpose and principles of the hybrid energy system and it allows analysis on the system, which is the aim of this thesis.

8.2 Acquisition of Data for EVCS Model

Historical operational data from Kongsbergporten is provided by Glitre Energi. An advantage of the fact that Kongsbergporten is a modern and recently opened energy station is the amount of data gathering and the tools used for operation of the station. Glitre Energi provided access to their online data gathering portal with both live and historical data accessible online. This has been a helpful tool to both acquire data for the model as well as understanding the system and its operation. At Kongsbergporten, data is stored every five minutes, giving historical data 5 minute resolution. Through the portal all required data for operation and analysis of the system is provided. The necessary data from Kongsbergporten to the EVCS model is the charging output from each charger to charge EVs.

A disadvantage of the fact that Kongsbergporten is a recently opened energy station is the short time span of available data. This means that the results of the optimization model is based on less than a year of historical data. The energy station was operational in the summer of 2021, but the official opening was not until October 1st 2021 [43]. It was therefore decided that data to be used in this analysis is for the four winter months from November through February. This is a period with high electricity prices, high grid tariff rates and presumably frequent traffic, which is what the energy station should be designed for. In the future, when more data is produced, this can easily be used in the model.

Power output data from all chargers is downloaded from the data portal. Data cleaning and conditioning for GAMS applicability is done in Python using mostly the Pandas data analysis and manipulation package [44]. The input power demand file used in the model includes the historical power output for all chargers for each five minute timestep. The total power demand of an arbitrary winter day can be seen in figure 8.2, an indication of the typical EV charging demand profile at Kongsbergporten. The graph shows that power

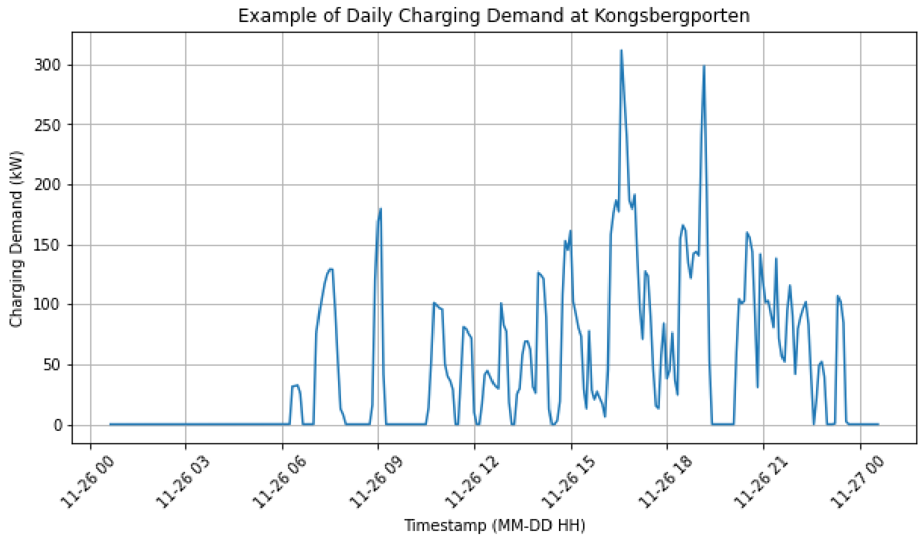

Figure 8.2: *Total EV charging demand at Kongsbergporten Nov. 26. 2021*

consumption is unpredictable and characterized by short, high power peaks. The demand for EV charging does not follow a clear pattern and therefore makes it difficult to estimate the need for energy storage. While the majority of consumption peaks around 150-170 kW, the are two incidents of high peaks exceeding 250 kW. The maximum demand for the simulated period is 418 kW.

8.3 System Costs for EVCS Model

The main incentive to install a battery ESS at an energy station such as Kongsbergporten is to reduce operational costs. It is therefore imperative for the model and analysis that costs are correctly represented in the calculation. The optimization model is created to minimize costs by balancing power supply with grid power and battery power. As mentioned earlier, energy storage also provides energy flexibility which is required for adequate energy service from the distribution grid. Grid operators therefore design grid tariffs to create incentive to increase energy flexibility on the demand end of the grid.

System costs used in the model are the costs which affect the operational costs with respect to the battery ESS. The main contributing costs for this system are investment cost of the ESS, grid tariff costs, cost of electricity purchase and taxes.

8.3.1 Operational Costs for Electricity

Since the PV system at Kongsbergporten is not included in the model, all energy supply is from the grid. Electricity is purchased at spot price. Historical, hourly spot prices is therefore acquired from Entso-E Transparency Platform [45]. The data is formatted for the GAMS model using Pandas in Python. Spot prices are given on hourly basis, but the EVCS model is on five minute resolution. To overcome the resolution difference, the hourly spot prices are extrapolated to 5 minute resolution. The electricity price for all time steps throughout one hour is the same as the spot price for that hour. The downloaded data is also given in EUR/MWh. The unit is converted to NOK/kWh in which one Euro is assumed to be 10 NOK.

8.3.2 Costs of Battery ESS

Utility scale lithium-ion battery technology is considerably costly. Return on investment (RoI) is dependent on proper design and operation of the hybrid system. As seen in figure 4.1 in section 4, the price of battery cells have drastically decreased in the last decade. However, utility scale battery systems are three to four times more expensive. This is not because different battery cells are used, but it is because of all the equipment required to install battery ESS on this scale. For battery technology to be compatible with energy systems at this scale, transformers, inverters and rectifiers, safety systems and housing is required, which drives up the costs. In this thesis, the investment cost of ESS therefore is meant to include the whole ESS system with equipment. Glitre Energi shared that the investment cost of the ESS at Kongsbergporten was roughly 5000 NOK/kWh. Thus, it was decided that this is the cost which is used as investment cost of ESS.

The cost of ESS is in this thesis regarded as linear, meaning that any size ESS costs 5000 NOK/kWh. In reality however, ESS costs are not as simple due to the required associated equipment. At low capacity ESS systems, the cost of required infrastructure is higher compared to the cost of the actual battery cells. ESS costs can therefore not be considered linear in reality. Economies of scale applies to the investment cost of utility scale li-ion battery ESS.

Due to the short simulation time in this thesis, it does not cohere to use capital investment cost of ESS in the system cost calculation. Therefore, annuitised costs are calculated to be used in the model. Annuitised costs refer to the yearly cost of investment, based on lifetime and the discount rate. The ESS at Kongsbergporten is assumed to have a lifetime of 10 years, and the discount rate of investment is assumed at 5%, partly due to expected decrease in battery cell costs. The cost of ESS used in the model is calculated with equation 8.1. The annuitised cost is divided by three because the model represents four months of the year.

$$X_{ESS} = \frac{X_{invest,ESS}}{\sum_T \left(\frac{1}{(1+r)^T}\right)} = \frac{5000 \text{ NOK/kWh}}{\sum_{10} \left(\frac{1}{(1+0.05)^{10}}\right)} = 650 \text{ NOK/kWh/year} \tag{8.1}$$

The input cost of ESS in the battery is 650 NOK/kWh/year converted to 54 NOK/kWh/month, resulting in 216 NOK/kWh/4 months.

8.3.3 Grid Tariff and Taxes

The grid tariff and taxes are costs defined by grid operators and the national government. They are unavoidable costs, and the rates cannot be affected by consumers. A grid tariff represents the cost of using the distribution grid and covers operational and maintenance costs for the grid operator [46]. In Norway, taxes are included in the grid tariff with a yearly fixed fee and an energy fee. The grid tariff for companies in Norway vary between provinces and includes monthly fixed fee, energy fee and power fee. Energy fees are fees on the amount of energy used, given in NOK/kWh. The power fee is a fee based on the maximum power drawn from the grid at any point throughout the month. It is the power fee that created an incentive to install battery ESS, which can greatly reduce the maximum power by peak shaving.

The grid tariff and taxes used in the model are based on rates in Oslo and Viken provided by Elvia [47] and corrected to rates in Buskerud provided by Glitre Energi [29]. Rates from Elvia are used mainly because they are almost identical to Buskerud as well as being easily accessible online. The main difference is the power fee, which is bimonthly adjusted in Oslo and Viken, but seasonal (summer and winter) in Buskerud. The model is generic and based

Table 8.1: *Operational costs of EVCS model*

Cost	Value	Unit
ESS Cost	5000	NOK/kWh
Annuitised ESS Cost	650	NOK/kWh/year
Monthly ESS Cost	56	NOK/kWh/month
Tax Fixed Fee	159	NOK/month
Tax Energy Fee	0.018	NOK/kWh
Grid Tariff Fixed Fee	340	NOK/month
Grid Tariff Power Fee	70	NOK/kW/month
Grid Tariff Energy Fee	0.07	NOK/kWh
Cost of Electricity	Spot Prices	NOK/kWh

on the system at Kongsbergporten, making it viable to combine tariff schemes. Costs used in the EVCS model can be seen in table 8.1.

8.4 Operational Strategy

This model is specifically designed for utilizing the ESS for peak shaving because it is the fundamental purpose of the ESS at Kongsbergporten. Although, it was found in Haupt et al. (2020) that operational strategy had great influence on a hybrid energy system [35], operational strategy is not thoroughly analysed in this thesis. Peak-shaving as the operation strategy is the main focus in the analysis. For further insight in the system at Kongsbergporten, additional operational strategies should be analysed, which is discussed in section 15 on future work.

The battery ESS is limited to operate within 20% and 80% SoC. The operational range of the battery is for preservation of battery performance. Operating a battery at the extremes of SoC boosts degradation of cells. Limiting the range of operation therefore increases the lifetime of the battery ESS.

At Kongsbergporten today, the battery ESS is set to discharge and deliver power if the grid power exceeds 180 kW as an initial value. This limit was reached through experimental operation where the threshold was adjusted until it was found that 180 kW was a good option [29]. Therefore, in the model, the ESS is set to supply power if the demand exceeds

180 kW. Peak demand during the simulation period was about 420 kW, and to avoid unnecessarily large ESS, the peak shaving threshold in the model is a soft constraint, meaning that it can be violated. If grid power exceeds the 180 kW limit, the additional power is assumed to be twice the price, encouraging use of ESS.

Because of unpredictability of the EV charging demand, it is desired to recharge the battery ESS back to 80% SoC as soon as possible. This is to ensure the system is prepared to meet demand at all times. Therefore, if the ESS is not at 80% SoC, the system will draw 180 kW from the grid until the ESS is recharged. Through this rule, the battery will be recharged immediately after discharge, as soon as the demand drops below 180 kW. This rule is modelled using a penalty function. The penalty is introduced where SoC below 80% is considered a cost, which makes it cost optimal to recharge the battery. This penalty is subtracted in post processing to attain correct system cost calculations.

The optimal size of the battery ESS is calculated in the model, based on two assumptions. At Kongsbergporten, the C-rate of the battery is 1C, meaning that it discharges from 100% to 0% SoC in one hour. Therefore, the rated power of the ESS is assumed to define the size, where the ESS size in kWh is the rated power in kW multiplied by the C-rate.

8.5 Mathematical Formulation

This subsection describes the mathematical formulation of the LP model. All parameters and variables used in the formulation are defined in tables 8.2 and 8.3. With the equations presented in this section the model can be implemented in any optimization software.

Table 8.2: *Decision Variables*

	Decision Variables	
$P_{dem,t}$	Power Demand of all Chargers	kW
$P_{ESS,r}$	ESS Rated Capacity	kW
P_{ESS_t}	ESS Power	kW
P_{G_t}	Grid Power Within Limit	kW
P_{G,hi_t}	Grid Power Above Limit	kW
P_{G,tot_t}	Total Grid Power	kW
P_{G,max_M}	Maximal Grid Power per Month	kW
E_{G_t}	Grid Energy	kWh
$E_{ESS,max}$	Maximum Energy in ESS (Battery Size)	kWh
E_{ESS_t}	Energy in ESS	kWh
C_{ESS}	Cost of ESS	NOK
C_{el}	Electricity Cost	NOK
C_{gt}	Grid Tariff Costs	NOK
C_{tax}	Energy Taxes	NOK
C_{sys}	Total System Costs	NOK
K	Penalty of Insufficient SOC	NOK
M	Month	

Table 8.3: *Input Parameters*

	Input Parameters	
X_{ESS}	Annuitised Cost of ESS	NOK/kWh
T	Period Length	Minutes
$X_{tax,f}$	Fixed Tax Fee	NOK/year
$X_{tax,e}$	Tax on Energy	NOK/kWh
$X_{gt,f}$	Fixed Tariff Fee	NOK/month
$X_{gt,p,w}$	Power Tariff Winter	NOK/kW
$X_{gt,e,w}$	Energy Tariff Winter	NOK/kW
X_{el_t}	Spot Price of Electricity	NOK/kWh
$P_{G,lim}$	Grid Power Limit	kW
CR	C-Rate	

8.5.1 Objective Function

The objective function is the function which is minimized by the model solver. The motivation behind installing a battery ESS at Kongsbergporten is to lower operational costs by peak shaving with power supplied by the ESS. Therefore the objective function is a function of the total system costs of the system:

$$\text{Min } C_{sys} = C_{el} + C_{tax} + C_{gt} + C_{ESS} + K \cdot 0.2 \tag{8.2}$$

The total system costs are the sum of the cost of taxes, grid tariff, electricity purchase, battery ESS as well as a penalty function for insufficient SoC of the ESS given as K.

8.5.2 Constraints

The constraints define the nature of the model and determine the allowable solutions for the decision variables. Constraint equations represent costs, power flow, energy use, technical limits and the decided penalties.

Equation 8.3 represents the cost of electricity purchase. This is the sum of energy purchased per timestep multiplied by the price of electricity of the timestep. Additionally, if more power than the set system limit is purchased, the excess power is modelled to have twice the price. This is to promote battery use.

$$C_{el} = \sum_{t=0}^{t} (E_{G_t} \cdot X_{el_t}) + \sum_{t=0}^{t} (E_{G,hi_t} \cdot X_{el_t} \cdot 2) \tag{8.3}$$

Equation 8.4 is the calculation of the grid tariff over the total period. The right hand side of the equation is divided into two parts depending on the time period defining the tariff cost. The energy use is priced per kWh, which is calculated per timestep. The fixed fee and the power fee are calculated per month.

$$C_{gt} = \sum_{t=0}^{t}(E_{G_t} \cdot X_{gt,e,w}) + \sum_{M}(X_{gt,p,w} \cdot P_{G,max_M} + X_{gt,e,w}) \tag{8.4}$$

Equation 8.5 represents the cost of energy taxes with a yearly fixed tax and an energy tax.

$$C_{tax} = X_{tax,f} + \sum_{t=0}^{t} E_{G_t} \cdot X_{tax,e} \tag{8.5}$$

The cost of ESS is represented in equation 8.6. This cost is the monthly cost of the investment cost, which is the resulting size of the ESS multiplied by the monthly investment cost described by equation 8.1.

$$C_{ESS} = E_{ESS,max} \cdot X_{ESS} \tag{8.6}$$

Equation 8.7, 8.8, 8.10, 8.11 and 8.9 constitute the power flow and energy use of the system. Equation 8.7 converts the power usage to energy for cost calculations. The demand balance is controlled in equation 8.10 which defines that the sum of grid power and ESS power should always be equal to or greater than the demand power. The peak shaving limit at 180 kW which is the cut-in demand power for the ESS is defined in equation 8.9. P_{G,hi_t} is what makes this constraint soft, all grid power above 180 kW is defined in this variable. P_{ESS_t} is a free variable, meaning that it can be positive and negative. If the ESS is discharging power to EV charging P_{ESS_t} is positive and if the ESS is being charged by grid power, P_{ESS_t} is negative. The battery SoC is updated per timestep in equation 8.11. The SoC is defined in the model as energy in the battery in kWh.

$$E_{G_t} = P_{G,tot_t} \cdot T/60 \tag{8.7}$$

$$P_{G,tot_t} = P_{G_t} + P_{G,hi_t} \tag{8.8}$$

$$P_{G_t} \leq 180 \tag{8.9}$$

$$P_{dem,t} \leq P_{G_t} + P_{ESS_t} + P_{G,hi_t} \tag{8.10}$$

$$E_{ESS_t} = E_{ESS_{t-1}} - P_{ESS_t} \cdot T/60 \tag{8.11}$$

Equation 8.12 through 8.15 define constraints on the battery ESS. In 8.12, the penalty coefficient K which is in the objective function is defined as unavailable energy in the battery. Because the primary purpose of the ESS is peak shaving, it should have sufficient SoC to meet peaks at all time. Therefore, the ESS is recharged as soon as the demand is below the limit defined in 8.4. Equations 8.13 and 8.14 define the initial and allowed operational SoC of the ESS. The rated power capacity of the battery ESS is defined in equation 8.15. The rated power of the battery is defined as the C-rate multiplied by the ESS size.

$$K = E_{ESS,max} - E_{ESS_t} \tag{8.12}$$

$$E_{ESS_{t=0}} = E_{ESS,max} \tag{8.13}$$

$$E_{ESS,max} \cdot 0.2 \leq E_{ESS_t} \leq E_{ESS,max} \tag{8.14}$$

$$P_{ESS_t} \leq P_{ESS,r} \leq CR \cdot E_{ESS,max} \tag{8.15}$$

The maximum grid power used for calculating the power fee in the grid tariff is defined in equation 8.16. In GAMS, if a scalar variable is defined as greater than another variable, it will be the maximum value of the other variable. Thus, the maximum power per month is the highest power delivered by the grid throughout the period.

$$P_{G,max_m} \geq P_{G,tot_{t,M}} \tag{8.16}$$

The resulting ESS size from model simulation is the optimal ESS with an operational range of 100% to 20%. In reality, the operational range is 80% to 20% and this is corrected in post processing. Thus, in the model, a fully charged ESS is in fact 80%. The model was implemented and tested as described in this chapter. The upcoming chapters describe the model validation and the analysis conducted with the model.

9 Model Validation

Validation of the model is required to ensure that the analysis is feasible. Therefore, in this section, results from the base model are shown and described.

The results of the base model set the foundation in which the analysis will be conducted and compared to. The goal of the base model is therefore to attain results that cohere with the existing system at Kongsbergporten. Model validation is done by reviewing results from the model simulation and comparing to expected results. This includes calculated size of ESS, operational SoC range of the ESS, demand balance and peak shaving. This is to validate that the model follows the rules and constraints that are defined earlier in this chapter, and that the resulting values of costs and technical dimensions are realistic.

In table 9.1 the resulting key technical values are listed. The model calculates the optimal ESS size as 174 kWh, similar to the actual battery ESS at Kongsbergporten which is 180 kWh. Because battery efficiency and losses are not taken into account in the model, a slightly smaller battery ESS is an acceptable result. The rated power of the ESS is 174 kW, because the ESS is constrained to 1C C-rate. The SoC of the battery drops below 20% three times during the simulation, which is because the actual ESS size is calculated in post processing as mentioned in section 8.5. Monthly maximum power from grid supply is varying due to varying demand. However, it is clear that it is optimized for each month by balancing grid power and ESS size. The high max power in December is due to high demand one week, just before new years eve, presumably because of significant traffic in the Christmas holiday. In January however, the peak shaving threshold is never violated.

Table 9.1: *Key technical values of model results*

Keyword	Value
ESS Size	174 kWh
ESS Rated Power	174 kW
ESS SoC range	80-16%
Max Grid Power November	222 kW
Max Grid Power December	264 kW
Max Grid Power January	180 kW
Max Grid Power February	225 kW

The time series ESS SoC is presented in figure 9.1. As expected, the ESS is recharged to 80% immediately after discharge. Throughout the four month simulation period, the battery is cycled 378 times. The battery discharges more than 20% of the battery capacity, meaning that SoC is below 60% only 26 times. This accounts for roughly 1100 total cycles and 80 significant cycles throughout one year. The conclusion is that the ESS is operated as desired in the model with respect to charging strategy.

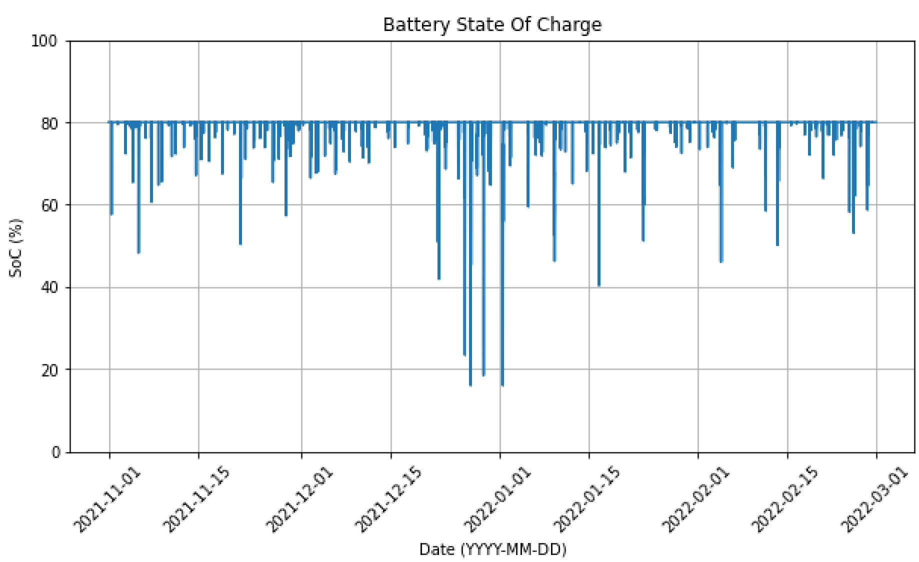

Figure 9.1: *ESS SoC throughout simulation period*

A graphic example of the demand balance in which the ESS is used for peak shaving is shown in figure 9.2. This graph shows that the grid solely supplies power to demand below 180 kW. At demand peaks, the grid supplies 180 kW and the remaining demand is met by battery ESS power. This simulated twice in the period presented in figure 9.2. Furthermore, as soon as the demand power falls below 180 kW after a peak in which the ESS has discharged, the ESS is recharged by grid power.

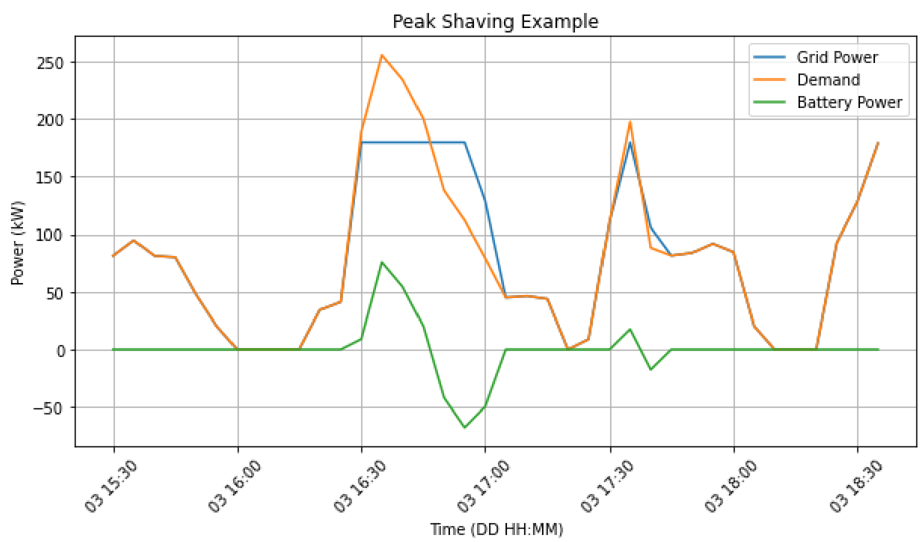

Figure 9.2: *Peak Shaving. Simulated demand balance November 3rd, 3 hour period*

In the model, the limit of grid power at 180 kW is a soft constraint. This is to allow grid power to exceed the limit with extra cost in high demand scenarios. An instance of the grid limit violation is shown in figure 9.3. The figure shows the demand balance of a 3.5 hour period on December 26th, 2021. For periods with extreme EV charging demand, it is more economically favorable to increase grid power than to increase the installed ESS size in order to meet extreme demand. This is seen in figure 9.3 where grid power exceeds 180 kW to meet high demand.

The resulting total system costs is 228000 NOK. This number is not transferable to actual system costs of an energy station like Kongsbergporten due to simplifications made for the model. However, this cost is a reference for the analysis which is conducted, and can illustrate sensitivity. The relation between costs that make up the system cost in the simulation however are realistic, and the cost distribution create an insight for future energy stations. Figure 9.4 shows the cost distribution from the model simulation. Electricity and

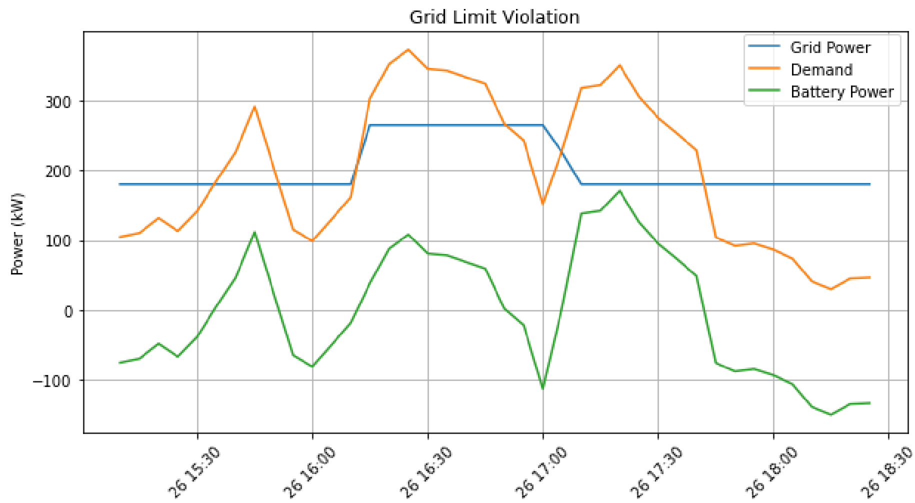

Figure 9.3: *Grid limit violation. Simulated demand balance December 26th, 3.5 hour period*

grid tariff costs account for the majority of the system costs. These costs are the main motivation for the integration of a battery ESS, thus as expected.

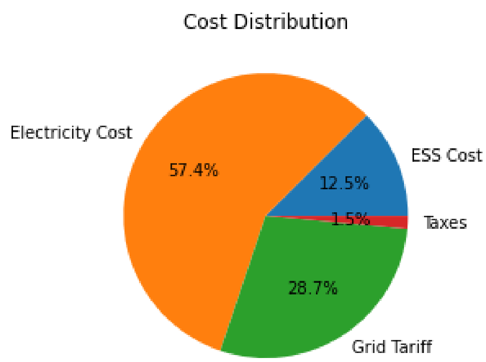

Figure 9.4: *Cost Distribution*

The results presented in this section confirms that the EVCS model is sufficient for its purpose. The technical values are similar to actual values at the energy station at Kongsbergporten and rules and constraints satisfy the desired operational strategy of peak shaving. This base EVCS model will be used for the analysis of battery integrated fast charging energy station and is a simplified, thus adaptable, model for other systems than Kongsbergporten. In the analysis, input parameters altered and results show how the changes affect the optimal system design.

10 Analysis Preparation

In this section, preparatory work for the techno-economic analysis is presented. In order to structure and define the objectives of the analysis, an assessment of the most influential external factors for the model was made. This section thus explains the questions the analysis should answer and why they emerged. Lastly, the methodology of the analysis is described.

The optimization model created in this thesis gives an insight into the relationship between EV charging demand, power flow and system dimensions of an ESS integrated EV fast-charging station. Therefore, the model is used to investigate the impacts changes in external factors have on the operation of the energy station. The motivation for the analysis is founded on two matters, the unpredictability of the EV charging demand and the fact that hybrid energy systems are recently adopted into energy service stations for EVs. The analysis in this thesis is intended to shed light on challenges that may occur for the operators of an energy station like Kongsbergporten.

10.1 Case Definition

Input parameters and constraints presented in section 8.5 define the framework within which the operation of the energy station is limited. The influence and sensitivity of these factors is what the analysis is intended to explain. This includes investment costs, electricity prices, grid tariff schemes as well as technical limits. The most influential factors will be assessed, and the questions to be answered are listed in table 10.1.

Table 10.1: *Questions to be answered in the sensitivity analysis.*

Tag	Motivation
A	What happens if investment costs of battery ESS change in the future?
B	What happens if electricity prices increase or decrease?
C	How does the power tariff affect the model results?
D	What is the impact of a sub-optimally sized ESS?
E	How is the output power of the ESS distributed and what implications does this have for optimal operation?
F	Is the peak-shaving cut-in threshold at 180 kW optimal?
G	To what degree is the highest demand limiting?

The following subsections describe the case scenarios A-G with an assessment done in the chapters thereafter.

10.1.1 Case A: Effects of Battery Costs

In this analysis case, two analyses are done. First, solely the investment cost of battery ESS will be altered and the resulting optimal solution will reveal the impact of changes in ESS costs. Secondly, the ESS size is to be fixed and investment cost altered, together this will show the sensitivity of investment costs of battery ESS.

Even though the costs of batteries have decreased in the last decade, the technology requires a significant investment. In the base case of this model, the capital cost of the battery system is given as 5000 NOK/kWh. The effect a change in the battery costs has on the system is useful insight for the operator. Due to technology learning, the cost of technology is expected to fall in the future, but it is difficult to know to what degree. Also, exogenous factors like laws, geopolitical events, material shortages or natural disasters may lead to increased battery costs. If the charging station operator has insight into how decreased costs affect the system, they may be able to minimize the costs of future projects or upgrading existing stations. It may also indicate how low the cost of the battery system needs to be for it to be profitable to change the existing battery at Kongsbergporten or similar stations. A change in the battery costs may also result in different optimal system dimensions. It is fair to believe that lower battery costs will make it more profitable to increase the battery size, and the model provides the base for assessing to what degree compared to total system costs. A larger battery able to meet higher demand peaks will decrease the maximum power drawn from the grid, decreasing the power tariff costs.

10.1.2 Case B: Effects of Electricity Price

Similarly to Case A, this analysis will investigate the effects different electricity prices have on the optimal solution of the model as well as the model with fixed dimensions from the base model.

Southern Norway has experienced the highest electricity prices in history during the winter of 2021 and 2022 [48]. Figure 9.4 shows that electricity purchase accounts for more than half of the operation costs at Kongsbergporten during this period. The price of electricity has never been constant throughout the year, but now it is at the extreme. In addition, the electricity prices in 2020 were historically low. Therefore, the impact electricity prices have on an energy station like Kongsbergporten is highly relevant for optimal operation. This insight is important for the operator to develop strategies according to changes in the market. The sensitivity of electricity prices is also decisive knowledge for future projects. Electricity prices 1, 5 or 10 years in the future are difficult to estimate, but trends can be used to assess if prices will be high or low in the future. Therefore, the impact and sensitivity of dynamic electricity prices are significant for similar projects in the future or for upgrading and maintaining existing energy stations.

10.1.3 Case C: Effects of Power Fee

For this analysis case, the power tariff fee is increased and decreased compared to the actual fee. The effect of varying the power fee on both the optimal solution and on the base model with fixed battery size will be examined.

The power tariff is a core incentive for the hybridization of the energy system at Kongsberg-porten and is thus believed to be a dimensioning factor. The power tariff is set by the DSO in the Buskerud province [?] which is Glitre Energi Nett, an affiliate of Glitre energi [49]. Knowing the effects the grid tariff has on flexible, renewable systems like Kongsbergporten, may assist lawmakers to create economic incentives for such systems. Furthermore, this insight will help the operators of such energy systems with the effects a change in the power tariff will have on the optimal operation strategy of the system. It is believed that an increase in power tariff will result in a larger optimal ESS size and vice versa.

10.1.4 Case D: Effects of Varying ESS Size

In contrast to case A,B and C, this analysis will be on the effect the battery ESS size will have on costs and power flow. The ESS size is to be fixed in the model and run for different ESS sizes.

The base model is created to calculate the optimal battery size but in this case, the battery size will be fixed and varied. This will give insight in the sensitivity of the battery size and how it will affect grid power, system costs and system operations. The hypothesis is that a larger battery will be more used to meet higher peaks, lowering the power tariff costs. A smaller battery however will result in higher power tariff costs, but lower battery costs. The most interesting is to what degree this difference is. Will increasing/decreasing the battery size by 10% result in much higher costs? In essence, how important is the size of the battery to the system costs?

10.1.5 Case E: Battery Output Distribution

This analysis is on the results of the base model. The resulting data on the battery power is to be thoroughly analysed.

This analysis will be mostly on the base model. The analysis will be on the distribution of battery power output. This will give insight into the utilization of the battery ESS by showing what power output is discharged most. Another interesting result this reveals is the amount of time the maximum output is delivered. An insight into the energy service provided by the energy station and to what degree the operators can meet the required demand. If this analysis shows that the battery delivers 90% to 100% of max capacity for an insignificant amount of cycles, is it feasible to have a smaller ESS and meet most of the demand in order to lower investment and operation costs?

10.1.6 Case F: Effect of Peak Shaving Threshold

Like in case A,B and C, the effect of different cut-in power demand thresholds will be investigated both in relation to the optimal model solution and the base model with fixed battery ESS size.

Glitre Energi Energiløsninger, the operators of Kongsbergporten have through trial and error found that the battery ESS shall cut in for peak shaving if the demand exceeds 180 kW. It is not known if this is the optimal peak shaving strategy at that specific energy station. Therefore, this analysis case is intended to address this cut-in threshold. This will give an indication of how appropriate the existing limit is, the sensitivity of the limit as well as the optimal limit for the time period which is simulated.

10.1.7 Case G: Demand Shape

This case will investigate the effects of different demand profiles. The input demand data is to be altered and the effects on the optimal solution and base model will be examined.

One of the factors that make this model distinct from other models reviewed in the literature is the use of historical demand data from Kongsbergporten. The historical data shows that there were two to three days in the Christmas holiday with significantly higher EV charging demand than the rest of the period. This case will investigate the effect these few days have on the resulting optimal solution of the model. EV charging demand is expected to increase in the holidays, and the effect this has on the system is useful for the operator to be familiar with. Also, with the increasing amount of EVs on Norwegian roads, demand is expected to gradually increase in the following years, which may impact the charging infrastructure. In this case the demand file is altered to represent four scenarios. In one scenario, a demand peak at 1200 kW is introduced. In the next scenario, the demand in the most demanding hours from the historical data is reduced. In two last scenarios, the demand peaks are reduced and distributed over longer periods to represent load-shifting.

10.2 Analysis Methodology

One limitation of the GAMS software is that it does not produce the sensitivity of the model from a single simulation. This means that for the analysis process, the model of Kongsbergporten needs to be run multiple times with different input parameters. Given that the simulation takes up to 20 seconds per run, the process is streamlined using Python. For every run, a database with the resulting data is stored on the computer, giving multiple databases for each analysis case. Model runs thus generate data, which is used to conduct the analysis of the energy station. All work done in the analysis is therefore done in Python, where GAMS is run as a subprocess through Python. Data analysis is also done in Python using mainly the Pandas data analysis and manipulation package.

Data generation for analysis case A, B, C, D and F is done by running the model multiple times with varying input parameters. A Python script is created for each analysis case. In python, the script of the GAMS model is extracted and altered. For case E the data from the base model, which is partly presented in section 9, is thoroughly analysed. For case G, the demand file is altered manually to represent different scenarios, which are then fed into the GAMS model and the simulation is run. Four scenarios are simulated, one in which the peak demand meets the maximum allowed demand at 1200 kW, one where the demand on the most demanding day is reduced and two where demand peaks are lowered and distributed over longer periods at limits of 300 and 350 kW. The system at Kongsbergporten is designed to meet a demand of 1200 kW, and the optimal solution of the model with one instance with this peak is therefore examined. For the case with reduced demand on the most demanding day is to see the influence this one day has on the model. Lastly, the two scenarios with distributed demand are to introduce another operation strategy, load shifting, and see how it affects the optimal solution of the model. The four scenarios are henceforth named "high", "low", "300" and "350" respectively.

The variations of input parameters used for data generation is displayed in table 10.2. In case A, the investment cost of the battery is altered from 1000 NOK/kWh to 10000 NOK/kWh in 21 different simulations. For case B the input electricity price is multiplied by a scalar multiplier ranging from 0.25 to 3 to represent extremely low to extremely high prices. This is done in 12 simulations. For case C the model is run for 11 times with the power fee ranging from 40 to 140 NOK/kW. In case D, the model is changed so that the ESS size is an input parameter instead of a decision variable. The size of the ESS is varied from 0 to 250 in 10 simulations. A reminder that the ESS size in the model represents 80% SoC. Lastly, for case F the grid limit is varied from 100 kW to 300 kW and simulated 21 times.

Table 10.2: *Input parameters used in data generation for analysis*

Case	Variable	Lowest Value	Highest Value	Step	Simulations
A	ESS Cost	1000 NOK/kWh	10000 NOK/kWh	500	21
B	El-Price Scalar	0.25	3	0.25	12
C	Power Fee	40 kW	140 kW	10	11
D	ESS Size	0 kWh	250 kWh	50	10
F	Grid Limit	100 kW	300 kW	10	21

All files created and used for the EVCS model and case analysis are stored on GitHub. These can be accessed by clicking here.

III Results

In this part of the thesis, the quantitative results and insights resulting from the analysis of the model are presented. Thereafter, the main observations made in the analysis are summarized.

11 Case Analysis

This section presents the most important findings from the results of analysis of cases presented in section 10. The results from all cases are presented case by case.

11.1 A: Investment Cost of Battery ESS

In order to obtain the results in this analysis, the input parameters shown in table 10.2 are used and the optimal solution for the model is calculated.

In figure 11.1 a graph of optimal ESS size versus the investment cost of ESS is displayed. The resulting trend is as expected, higher investment costs lead to smaller optimal size of ESS. One result which was not expected however is the step-wise nature of the optimal ESS size. These plateaus occur three times, in the cost range 1000 NOK/kWh to 4500 NOK/kWh, 5000 NOK/kWh to 6500 NOK/kWh and 7000 NOK/kWh to 8000 NOK/kWh. For the model based on Kongsbergporten this means that a 10% decrease in investment cost of ESS leads to a 21% increase in the optimal battery ESS size. This is the case for the base model because it is at the start of a plateau, meaning a 10% increase in investment cost leads to merely 3% decrease in optimal ESS size. The cost of ESS is expected to decrease in the future due to technology learning and maturity, but these results show that cost reduction significantly affects the optimal dimensions of the system at specific values and not linearly.

The calculated costs of the system is shown in figure 11.2. The total system costs increase

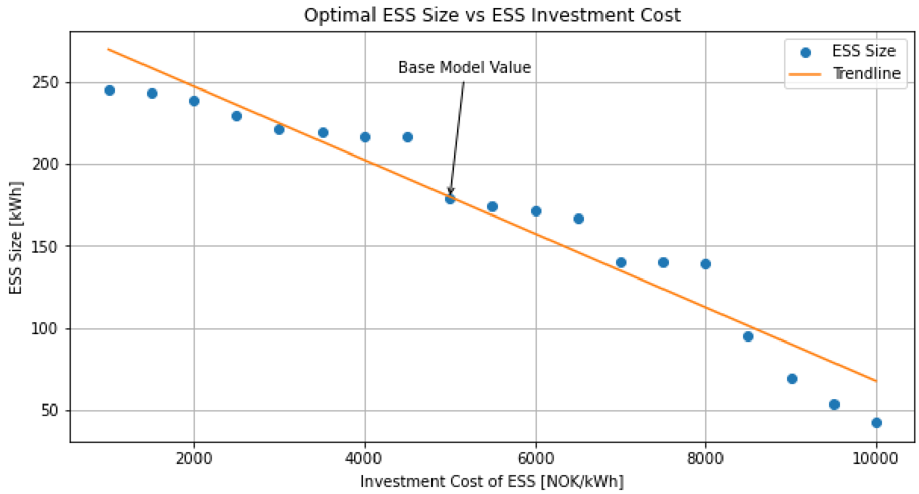

Figure 11.1: *Case A: Optimal size of ESS vs. investment cost of ESS*

with increased investment cost of battery ESS. Due to the grid being the only energy source to the system, the cost of electricity is almost constant for all scenarios. The grid tariff is as expected also lowest in the simulations with largest optimal battery ESS. The base model based on Kongsbergporten is according to this figure in the situation where the highest ESS costs compared to system costs are favorable. If the investment costs were lower, the optimal ESS would be larger, but the investment cost lower.

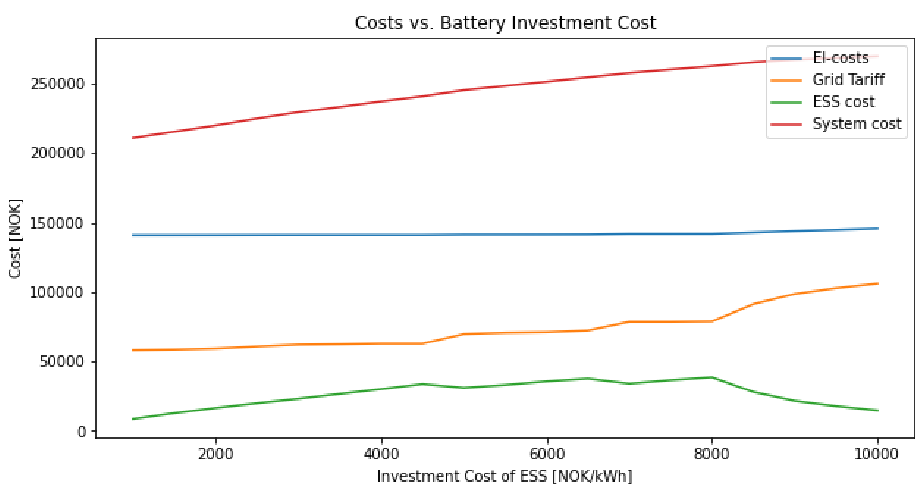

Figure 11.2: *Case A: Costs related to varying ESS size*

The same simulations were run with the ESS size fixed at 174 kWh. This resulted in no changes in optimal operation of the system throughout the period. The only affected factor were the system costs due to increased ESS cost. If the modelled system were to be built, an increase of 1 NOK in investment cost of ESS would lead to 6.3 NOK increase in system cost over the four month period. This is however less relevant as the investment cost is a capital cost and will not change throughout the lifetime of the energy station.

11.2 B: Electricity Prices

For this analysis the model has been altered to have a scalar multiplier for the electricity prices. The resulting optimal ESS size from the simulations is presented in figure 11.3. As expected, the optimal size of the battery ESS increases with increasing electricity prices, but not significantly. The graph shows that a 300% increase in electricity prices results in merely 8.7% larger optimal ESS size.

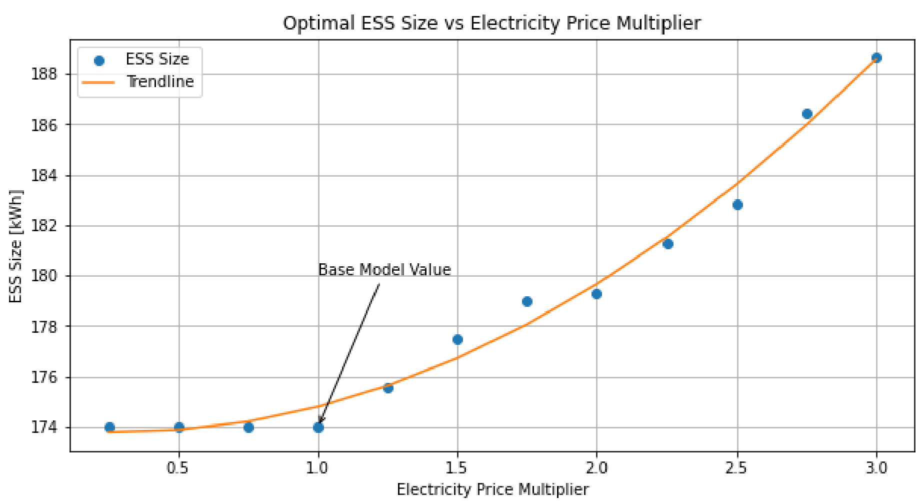

Figure 11.3: *Case B: Optimal ESS size vs. electricity price multiplier.*

The resulting costs from these simulations can be seen in 11.4. This graph shows that increased electricity prices linearly correlates with the system costs. If electricity prices increase by 10%, the system cost increases 5.6%. This correlation is significant relative to the drastic increase in electricity prices the simulated winter.

These simulations were also conducted with the ESS size fixed. Results showed similar

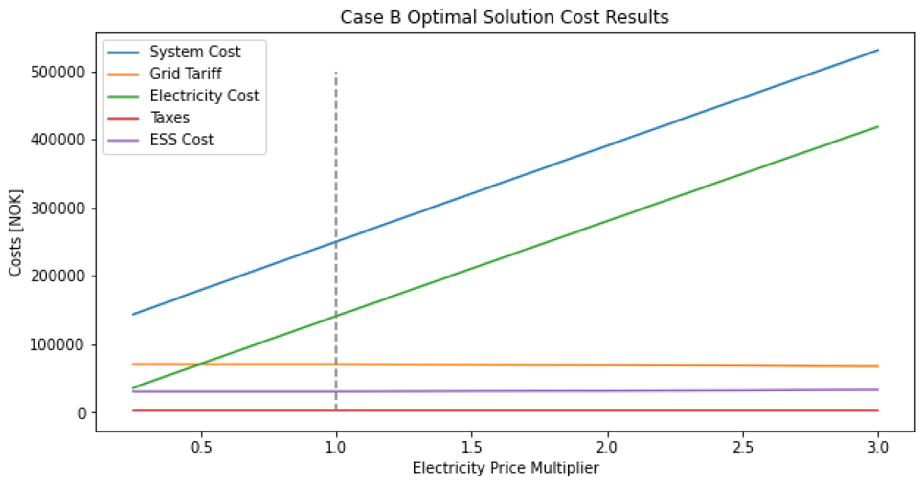

Figure 11.4: *Case B: Costs vs. electricity price multiplier.*

effects, system costs linearly increase with electricity price. However, the system is not as sensitive as the results in figure 11.4. A 10% increase in electricity prices increases system costs by only 1.2%. This indicates that the system at Kongsbergporten is resilient to changes in electricity prices.

11.3 C: Grid Tariff Power Fee

The optimal size of ESS versus the grid tariff power fee is displayed in figure 11.5. The higher the power tariff, the higher the optimal size for ESS. With higher power tariffs, there is an increased incentive for peak shaving, which this graph shows. This relationship is however not linear. Results from simulations with very high power fees show that the optimal ESS size flattens out at around 250 kWh. This is due to the peak-shaving strategy that recharges the battery immediately which limits the use of the ESS to peak-shaving.

The trade-off between investment cost of ESS, grid tariff costs and electricity costs is dependent on the power tariff. This can be seen in figure 11.6. The total system costs increase linearly with increasing power tariff, but the distribution of costs is not constant. With higher power tariff, it is favorable to invest relatively more in ESS because the grid tariff becomes an increasing part of the system costs.

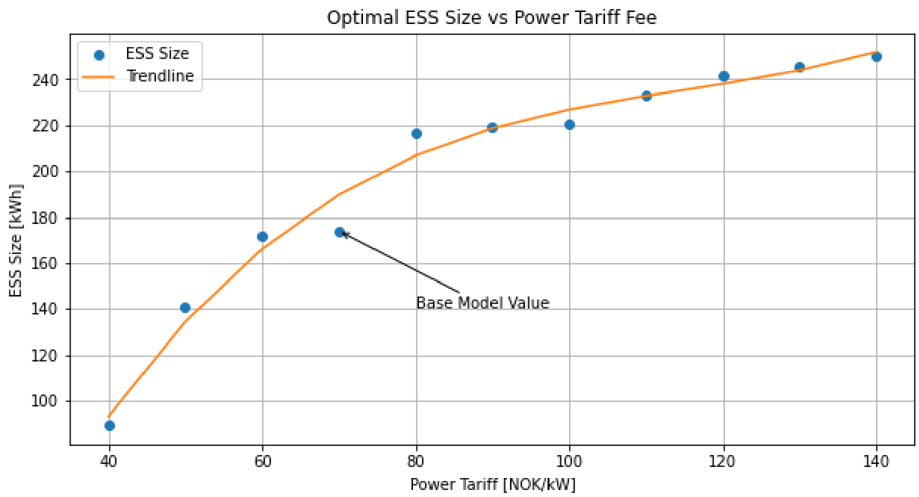

Figure 11.5: *Case C: Optimal ESS size versus power tariff fee*

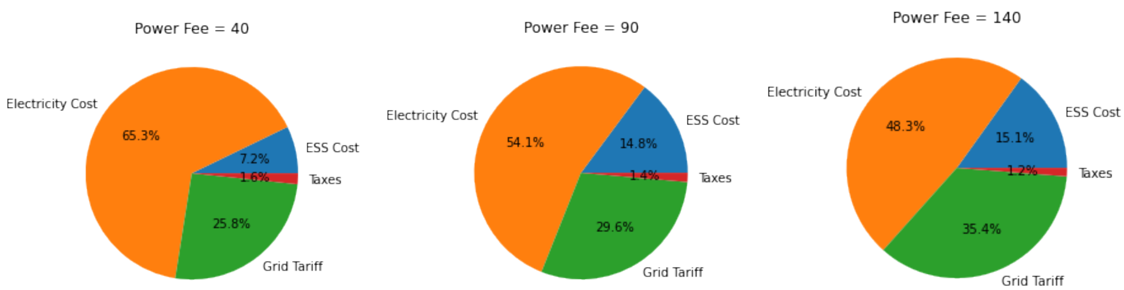

Figure 11.6: *Case C: Cost distribution of low, median and high power tariff simulations*

The same simulations were run with the ESS size fixed. This is to investigate the sensitivity of the existing system at Kongsbergporten. Like in Case A, the relationship between system cost and power tariff is linear. An increase of 1 NOK/kW in the power fee leads to an increase of 890 NOK in operation costs over the four months. This means that for the winter months, based on EV charging demand from the past winter, an increase in the power tariff from 70 NOK/kW to 75 NOK/kW would lead to only 1.8% increase in operation costs.

This is quite significant for the whole year however. In the summer months, the power tariff in the summer months is 12 NOK/kW in Buskerud [29]. If the EV charging demand is similar to the winter demand, this means that operation during the summer months costs approximately 15-20% less per month than during the winter.

11.4 D: Fixed and Varied ESS Size

This analysis is on the base model where the ESS size is fixed and run for various values to understand the affect the choice of ESS size has on the system. Figure 11.7 shows the resulting system costs compared to the size of the ESS. This proves that it is favorable with an integrated ESS. This is a representation of four months, and the model without battery ESS is 5.6% more costly than with the optimal ESS size. Over time, this difference is believed to be significant. The annuitised investment cost of the optimal kWh battery is less than the difference in electricity and grid tariff costs for the simulated winter months. The figure also shows that the system with large battery ESS is more costly than without an ESS. This means that the hybrid system must be properly designed in order to be beneficial. Reminder that this is the case if the ESS is mainly intended for peak shaving.

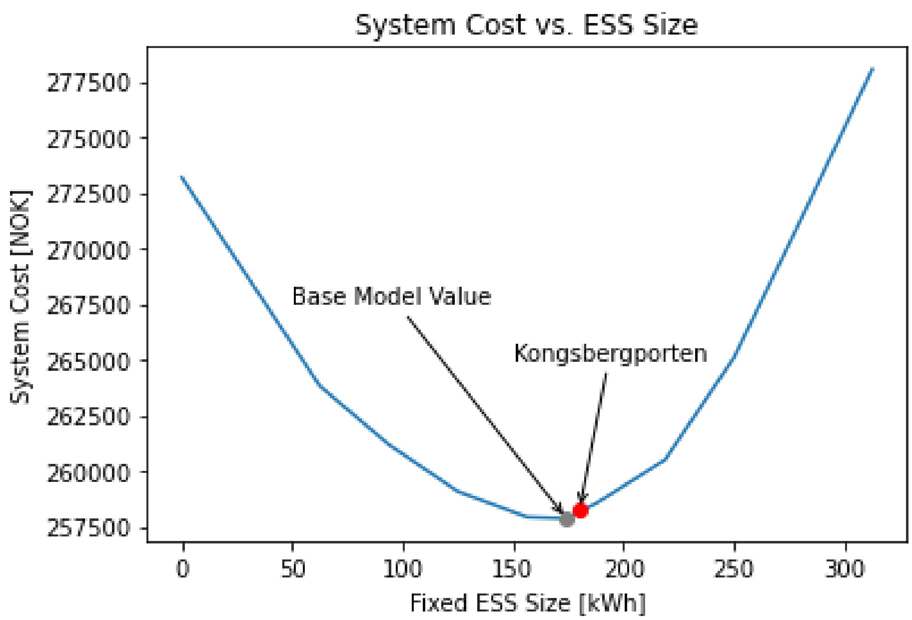

Figure 11.7: *Case D: System Costs vs. Fixed ESS Size*

Table 11.7 shows the calculated costs of the model with zero, optimal and highest battery simulations. It is and indication that the optimal hybrid system leads to reduced grid tariff costs as well as electricity costs. This is a result of load shifting, where the battery ESS supplies power when electricity costs are high.

The amount of battery cycles in the simulations is presented in figure 11.8. It shows that

Table 11.1: *Case D: Costs of model with 0 kWh, 173 kWh and 312 kWh installed ESS*

ESS Size	0 kWh	173 kWh	312 kWh
Electricity Cost	151600	141365	140288
ESS Cost	0	38271	68750
Grid Tariff	117991	74687	55737
System Cost	273194	257880	278050
Cost Difference	0 %	5.6%	-1.6%

at high ESS size, the ESS is cycled about 100 times more during the simulation period. An increase in cycles reduces the lifetime of the battery ESS. This means that this system with large ESS is even less cost effective due to the reduced lifetime of the ESS.

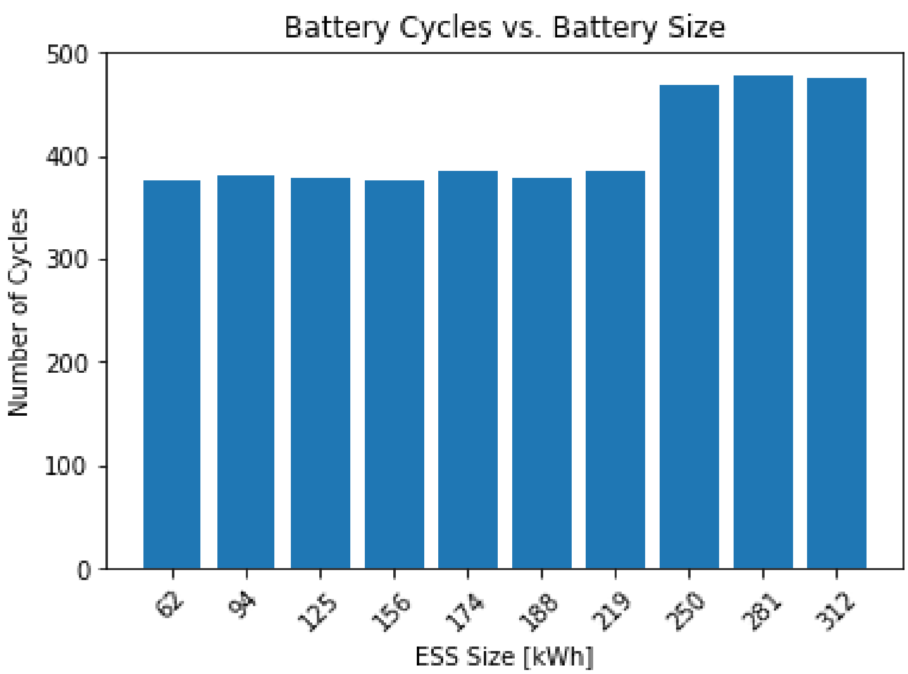

Figure 11.8: *Case D: Battery ESS cycles vs. fixed ESS size*

11.5 E: ESS Power Distribution

The power output distribution of the ESS shows how many times the ESS discharges different power outputs throughout the simulation. The power distribution gives insight into how the battery ESS is used in the model and is displayed in figure 11.9. The figure bar chart is divided into green and red bars where the green bars represents 90% of the discharge occurrences and red represents the final 10%. This means that 90% of the ESS utilization is with discharge power of 108 kW and lower, which is only 62% of the rated capacity of the battery ESS. However, the battery delivers maximum output for a significant amount of times as well. It is at high demand the ESS is most valuable because of the power fee. Although the limits of the ESS is utilized only 10% the time, it does not mean that it contributes to 10% of cost reduction.

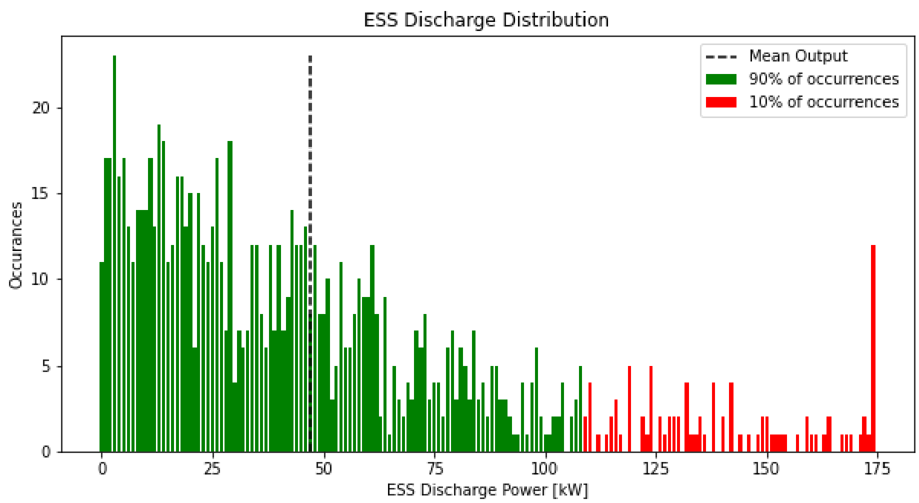

Figure 11.9: *Case E: ESS discharge distribution base model simulation*

11.6 F: Peak Shaving Threshold

The ESS peak shaving threshold is the grid power limit for which the battery starts discharging. In the base model this limit is set at 180 kW. This refers to operational strategy which affects how the battery ESS is used. The optimal ESS size resulting from simulations with various threshold is seen in figure 11.10. A noteworthy result of these simulations is that when the grid limit is 100 kW and 110 kW, the optimal ESS size is relatively small. At higher thresholds, plateaus appear, similarly to the results in Case A. These are results due to the balance between the power tariff, electricity prices and ESS costs.

As this analysis is on the operation strategy for peak shaving, the same simulations were done with the ESS size fixed at the base model value. This is to find the sensitivity of

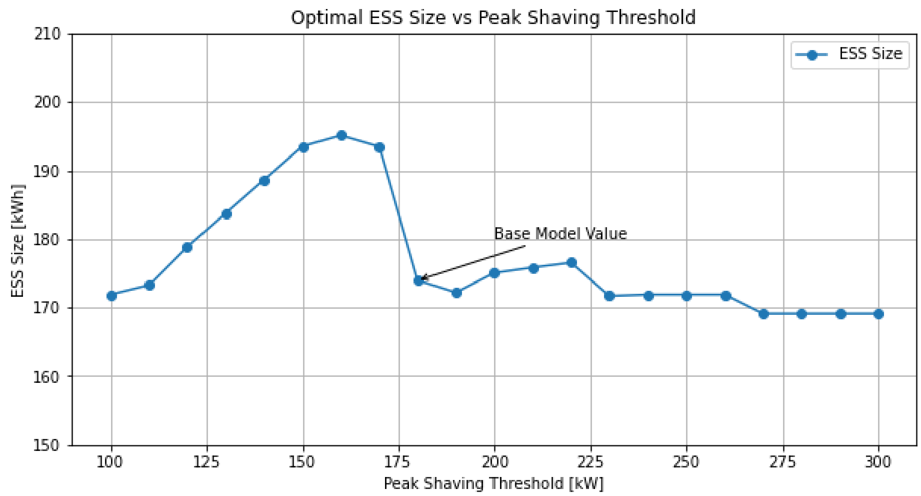

Figure 11.10: *Case F: Optimal ESS size vs. peak shaving threshold*

the grid limit as well as to find the optimal limit for this system. Cut in threshold in this system directly affects the battery use in both power and cycles.

Resulting system costs from simulations with different thresholds are shown in figure 11.11. The system costs correlate perfectly with electricity costs, more specifically cost of energy consumed when the grid supplies more than the limit. Power consumption above the grid limit is twice as expensive as power consumed within the limit in the model. EV charging demand is above 100 kW close to 4000 time steps and above 300 kW only 100 time steps during the simulation. This means that there is significantly more energy consumption which can have twice the price in the simulation with low limit, which explains the graph in figure 11.11.

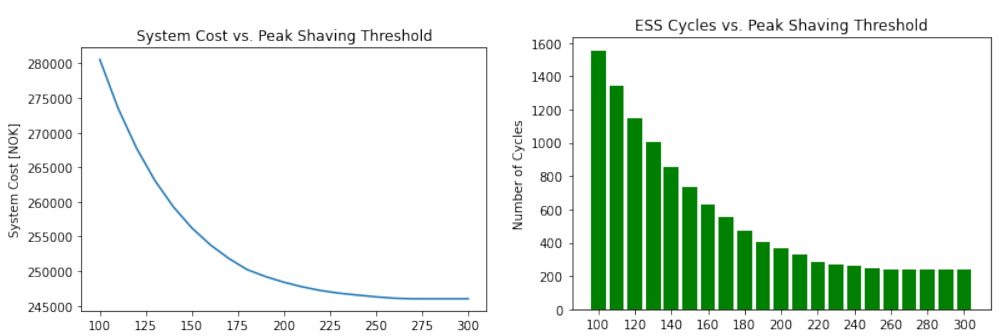

Figure 11.11: *Case F: Fixed ESS size simulated with various peak shaving threshold*

The grid limit also depicts how the battery is used. In the simulation with the limit at 100 kW the battery ESS is cycled 1555 times. With the limit at 300 kW it is only discharged 240 times. Given a cycle life of 6000 cycles, at 100 kW limit one cycle costs 46 NOK/cycle and at 300 kW one cycle costs 84 NOK. The lifetime of the battery and the cost per cycle is thus significantly impacted by the selected peak shaving strategy.

11.7 G: Demand Shape

This case investigates the affect of different demand profiles have on the model results. Four scenarios are compared to the base model and the key results are in table 11.2. The main outlier in cost difference is the scenario named "High" where one time step of 5 minutes had a demand of 1200 kW. In the scenario named "Low", the demand was reduced for a period of 8 hours on the most demanding day. This shows that the optimal solution of the model is sensitive to instances of high demand. Furthermore, the scenarios with distributed demand led to different ESS size even with similar max grid power values. The lower costs are due to lower ESS costs as well as electricity costs because the grid limit is not violated, avoiding double electricity price.

Table 11.2: *Case G: Optimal Solution Key results*

Name	ESS Size	Max Grid Power	Cost Difference
Base Model	173 kWh	265 kW	0%
High	219 kWh	980 kW	-20.8%
Low	173 kWh	223 kW	2.4%
300	120 kWh	259 kW	5.5%
350	170 kWh	265 kW	2.6%

The same scenarios were also simulated with the ESS size fixed. Key results are in table 11.3. Similar results were produced in these simulations. The cost differences in these simulations were however due to the grid tariff costs as contrary to the results in table 11.2.

Table 11.3: *Case G: Fixed ESS Size Key results*

Name	ESS Size	Max Grid Power	Cost Difference
Base Model	173 kWh	265 kW	0%
High	173 kWh	1026 kW	-21.3%
Low	173 kWh	225 kW	2.4%
300	173 kWh	241 kW	3.7%
350	173 kWh	265 kW	0.2%

Similarly to the results in table 11.2, scenario 300 results in lowest system costs. This indicates that if the ESS contributes with load shifting as well as peak shaving operational costs can be further reduced. Load-shifting has implications on the availability of required SoC for peak shaving and may lead to the need for a larger ESS.

12 Summary of Results and Key Observations

This section is a summary of the obtained results from the sensitivity analysis as well as key observations regarding the design and operation of hybrid energy stations.

The investment cost of battery ESS showed to be influential in optimal ESS size. The relation between ESS cost and optimal ESS size is however not linear. It showed a step-wise pattern. The reason for this relation is not clear and is discussed in section 13. Assuming this step-wise relation is true, the design of similar projects in the future should consider a slightly larger battery ESS if the investment costs have been reduced. If the system dimensions are fixed, the investment cost of ESS linearly affects the system costs by 6.3 NOK per 1 NOK. Furthermore, according to the model, the input parameters of the existing system result in an optimal solution with high ESS costs relative to the total system costs. In other words, the investment in ESS is most favourable with the input parameters based on Konsbergporten.

Results from Case B show that the optimal design of a hybrid energy station is sensitive to electricity prices while the existing system at Kongsbergporten is not. Electricity prices linearly affect the total system costs. A 10% increase in prices results in 5.6% increase in total system costs. For the simulations with the ESS size fixed, however, a 10% increase only resulted in 1.2% increase in system costs. This insight shows that when designing similar stations in the future, electricity price forecasts are meaningful and can drastically affect the operating costs of a system. The electricity price does however not affect the optimal size of the ESS to the same degree. For significant changes in the optimal ESS size, the electricity prices must at least be multiplied by 4. Given that the electricity prices used in this simulation are from a period with historically high prices, the possibility of a 4 times increase in the electricity prices is very low.

The total system costs linearly correlate with the power tariff. A 10% increase in the power tariff leads to only 2.5% increase in system costs. This means that the power tariff is not avoidable without local energy generation. The optimal ESS size converges at roughly 250 kWh with a high power tariff. The power tariff affects the total system costs linearly, but the distribution of operational costs varies. Higher power fees lead to relatively more investment in battery ESS. For the DSO, an increase in the power tariff may not lead to as much of an economic profit as expected because it can be answered by increasing flexibility, which is in many cases the intention behind the power fee. It does however directly lead to increased operating costs for the consumer, either through increased grid tariff or increased ESS cost. The existing system at Kongsbergporten however is not very sensitive to small changes in the power tariff. However, as recently as 2019 [50], the power tariff in the winter was at 108 NOK/kW which would make the system costs for the simulated period 13-15% more expensive.

Case D shows that the installation of battery ESS is favourable for the total costs of the EVCS model. It also showed that it is not favourable for any ESS size. The system costs of the simulation with large ESS resulted in an increase in system costs compared to the simulation without ESS, showing that unnecessarily large ESS will counteract its intention. This means that the design of the ESS for this system is imperative for the benefits of hybrid systems. These results cohere with the results in Case A, where low investment costs of ESS resulted in roughly 250 kWh battery. Furthermore, as observed in results from Case C, larger ESS leads to lower grid tariff costs due to increased flexibility.

The battery ESS discharge distribution analysis showed that 90% of the battery use is for peak-shaving with 62% of the ESS capacity or less. This means that 38% of the battery investment is done to meet 10% of the demand. The ESS does however discharge at full power a significant amount of times to minimize the max power drawn from the grid.

The peak shaving threshold shows to affect the optimal ESS size in a strange manner. The resulting system costs are not sensitive to this threshold. The cost difference in the simulations is due to the penalty function linked to the soft constraint on the threshold, which is included in the simulations to favour battery use. However, over the lifetime of the system, this threshold has implications. The battery use is directly affected by the threshold, and the lower the threshold, the battery is more used. This affects the lifetime of the battery ESS due to increased degradation.

The demand shape is also related to operational strategy. The results from this analysis showed that the model is sensitive to demand peaks. Simulations with demand peaks distributed through load shifting yielded the lowest operational costs. These simulations as well as the battery discharge distribution show that unpredictable peaks in demand are responsible for the need for a large battery ESS.

Table 12.1: *Qualitative Sensitivity Results*

Case	Parameter	Sensitivity
A	Cost of ESS	++
B	Cost of Electricity	+
C	Power Fee	+
D	ESS Size	++
F	Peak Shaving Threshold	++
G	Demand Shape	+++

Table 12.1 shows an overview of the qualitative sensitivities of the EVCS model system. Sensitivity is rated from 0 to +++ where 0 is least sensitive. This shows that the system is most resilient to changes in cost of electricity and the grid tariff power fee. On the contrary, the system is most sensitive to the demand shape, especially high demand peaks.

In the following section, the EVCS model and the results from the analysis are discussed. Then an assessment of Kongsbergporten is made based on the analysis done in this thesis.

IV Discussion and Conclusion

In this part, the thesis work, the model and the analysis results are discussed and the thesis is concluded. First, the model's shortcomings and limitations are discussed followed by a discussion of the analysis results. Thereafter, an assessment of the system at Kongsberg-porten with respect to the model results is made. Then recommendations for future work are discussed. Lastly, the thesis is concluded.

13 Discussion

13.1 EVCS Model Limitations

The work done in this thesis is constrained by time limitations due to the thesis being 30 ECTS for a single student. The EVCS model developed is therefore simplified and based on several assumptions and focuses on specific aspects. The EVCS model calculates the optimal power flow and battery ESS size for the system with feasible results. However, results in the analysis of Case A and Case F were not as expected, leading to speculation that the model should be improved to increase credibility. Furthermore, the model is developed to analyse a battery supported EV fast-charging system. Although the optimal battery size is calculated in the model, battery specific properties mentioned in section 4 in the model are limited.

The EVCS model was selected to be an LP optimization model based on the model objective and requirements. This has proven to be a suitable model type for the model developed in this thesis. The limitations discussed in this section are not due to the model type, but due to simplifications and inadequate constraints. The LP model created in this thesis calculates the power flow in the system with optimal solution in less than 20 seconds. The system can be modelled more complex, with less simplifications, as an LP as well. However, limitations in LP is partly the reason for the inadequate constraints. This is because LP does not support soft constraints, which led to the introduction of penalty functions in the EVCS model that are believed to create unexpected results. These limitation can be avoided by creating a MILP model, which are suited to include soft constraints and separate variables by using binary variables.

Different energy storage technologies bring different properties to a hybrid energy system. The EVCS model created in this thesis is based on LIBs as the ESS. For the model to be more focused on this specific technology, properties such as the capacity for specific SoC shown in figure 4.5 as well as battery degradation should be implemented. These properties would lead to more realistic battery ESS behaviour as well as a better indication of battery lifetime from simulations. However, this was considered a secondary priority due to time limitations. In section 15, how these LIB specific properties can be implemented is discussed.

Because the EV charging demand data source for the EVCS model is from Kongsbergporten, which opened for customers relatively recently, the amount of data is believed to be limiting. The winter months were chosen for simulation because in the winter electricity prices are high, the grid tariff is high and EV driving range is low in cold temperatures, leading to more frequent charging for EV drivers. The power tariff is considerably lower in the summer, leading to lower operational costs of an energy station. The impact of simulating the model for a whole year has on the optimal ESS size is not known. The summer power fee is applied for 8 months of the year. This may lead to a smaller simulated optimal ESS size because the winter months account for a smaller share of the simulated period. The type of available data and its resolution of 5 minute time steps is an advantage for model simulation. EVs charge in the span of 20 minutes to one hour for which a 5-minute resolution gives sufficient insight into the demand profile for modelling. Therefore, simulations over the span of several years would improve the model. This can be done by creating demand data using regression or by acquiring data from similar energy stations.

One noticeable simplification of this model is the lack of included infrastructure and the efficiency of the equipment. The energy system of an energy station includes electrical installations such as transformers, inverters and cables which are not included in the model. There are in reality losses throughout the system which are neglected in the EVCS model. The system at Kongsbergporten is however relatively small and simple compared to the distribution grid or other large energy systems. All equipment in the system downstream from the grid connection is installed to supply the EV chargers. It was therefore believed that the efficiency of the infrastructure over a four-month period in this model to be constant. This would be represented by a scalar efficiency from grid source to charger output and is therefore not prioritized.

For the EVCS model to operate the system as desired, two penalty functions are included. One of these is to recharge the battery ESS to 80% SoC as soon as possible after discharge and the other is to encourage battery use. These penalties are represented in the objective function (equation 8.2) and the cost of electricity (equation 8.3). The penalty function of the battery SoC works as intended, resulting in the battery ESS being recharged after discharge. This function is to ensure adequate SoC for unpredictable load peaks but it limits the opportunity for load-shifting. The cost of this penalty is also accounted for in the results presented in section 11. The other penalty, however, is defined as all power consumed from the grid which is above the peak shaving threshold to have double the electricity price. This is to encourage discharging battery power instead of consuming large amounts of electricity from the grid over long periods. This is not how the real system at Kongsbergporten is operated. It is believed that this penalty function is behind some of the strange results in the analysis of Case A and F. The power tariff alone should create incentive enough for the model to use the battery ESS above the peak shaving limit. Also, if PV generation was included, this would supply the system with free energy, which recharges the ESS if EV charging demand is low. This means that the battery ESS would be able to supply this free energy for peak shaving, creating even more incentive to use the battery ESS. This penalty could thus have been avoided, and the model would be more realistic.

In the EVCS model, as mentioned in section 8.5, a fully charged ESS represents 80% of the SoC. This simplification has implications for the cost calculation. The calculated costs of battery ESS in the model results are therefore just 80% of the total ESS costs. This difference is corrected in post-processing and accounted for in the results presented in chapter 10.2. However, because the objective function is the total system costs and the model minimized this function, the optimal solution of the model does not take into account the full ESS size. This means that the optimal solution of the EVCS model is not necessarily the actual optimal solution. Furthermore, equation 8.14 dictates the lowest operational SoC of the ESS at 20%. Due to the calculated size of the ESS being 80%, the resulting operational range is from 16% to 80%. Thus, in the model, the battery ESS can be used with deeper cycles but in the real-world system, this will shorten the lifetime of the ESS. Therefore, if the model calculated the full ESS size, the results would be more credible.

The limitations discussed to this point were discovered while analysing the results from the simulations done for the sensitivity analysis. None of these are unavoidable either. Therefore, the validation process has been insufficient to be able to notice these limitations earlier in the process. Validation of the model was based on the results from model simulation with input parameters as described in section 8. Improving the validation process by running the EVCS model multiple times with varying input parameters as well as a test demand dataset would improve the integrity of the model. Furthermore, the fact that GAMS cannot produce sensitivity reports automatically contributed to this limitation. A sensitivity report might have led to the discovery of these limitations earlier.

In section 7.2 the primary and secondary requirements and objectives of the model were presented. The model calculates the power flow instead of electrical energy flow because it is the power that is the defining parameter for EV charging demand. It is arguable that the EVCS model should model the electrical energy flow to reach more accurate results. However, this was not prioritized for this thesis.

Although the EVCS model has limitations, results from analysis of Case B, C, D, E and G are feasible and close to the expected results. The mathematical formulation and the sensitivities from the analysis are the main products of this thesis. The mathematical formulation can be implemented into any optimisation modelling software to be used for system analysis. This is given that corrections presented in section 15 are made. The sensitivity analysis gives an indication of how sensitive a battery integrated EV charging station is to exogenous factors. The EVCS model is also not limited to being used for hybrid EV charging stations. Because the EV charging demand is modelled as one single load, the model can easily be modified and adapted for other hybrid energy systems with an energy storage system.

These limitations have an impact on the analysis results. In the following section, the results presented in part 10.2 will be discussed with respect to the points made in this section.

13.2 Model Results and Implications

In this section, specific results from the model simulations and analysis are discussed.

The objective of the EVCS model with base case input parameters was to produce similar results for ESS size and power flow as the existing system at Kongsbergporten. The capacity of the battery ESS at Kongsbergporten is 180 kWh. Given that system efficiencies are not included in the model, the result of 174 kWh was acceptable. Furthermore, the power flow observed in the validation process cohered with the operational strategy at the existing energy station. Lastly, the penalty function for recharging the ESS immediately was considered sufficient. Without this penalty function, the resulting optimal solution left the battery at the current SoC after discharge and recharge before an EV charging demand peak. This however is not sufficient because in reality, the operator cannot forecast exactly when EVs come to charge at the station.

The exact reason for the step-wise pattern of the optimal ESS size in analysis cases A and F seen in figures 11.1 and 11.10 is not clear. One theory is that it is due to the penalty function leading to double electricity prices. For Case A, the relationship between the investment cost of ESS and the additional costs of violating the peak shaving threshold at 180 kW may not be linear. With increasing investment costs, the optimal ESS becomes smaller. Simultaneously, this means that the threshold must be violated more often, leading to more electricity purchase at double price. This relationship thus makes it favourable with the ESS at a certain size up until a specific investment cost of ESS. At these limits, it becomes favourable with significantly smaller ESS with the next simulated investment cost. Similarly, in Case F, where the peak shaving threshold is varied, the relationship between costs of ESS and the added costs of violating the threshold is believed to be similar. The peak shaving threshold analysed in Case F is directly connected to the additional costs of electricity, which is seen in the cost calculations with fixed battery size. This results in strange results. For Case A, however, the resulting trends are as expected, indicating that the penalty function is not as influential for this case.

All simulations that were run with optimizing the ESS size resulted in the ESS size converging towards 250 kWh. This is most probably because of the highest demand peak. The highest EV charging demand peak throughout the simulation is 418 kW. With the peak shaving threshold, a battery ESS able to deliver 250 kW in addition to 180 kW from the grid covers the demand in all time steps throughout the simulated period. This is also the reason for the linear increase in system costs in Case D with a fixed ESS size above 250 kWh. Differences in system costs in the simulations with ESS size above 250 kW cohere with the monthly cost of ESS at 56 NOK/kWh/month.

According to the literature reviewed in section 7.1, the operational strategy of an EV fast-charging station has a significant influence on the operational costs of the system. Analysis cases E, F and G in this thesis were performed to provide insight into the operational strategy of the EVCS model and Kongsbergporten. The battery output distribution in Case E showed that 38% of the battery size is needed for 10% of the battery use, which is significant. This is because high load peaks are infrequent, but necessary to meet due to the power tariff. Furthermore, the simulations in Case G showed that load-shifting proved to result in the lowest system costs. These results indicate that investment costs and operational costs can be minimized through a selected operational strategy.

The EV charging profile presented in figure 3.3 shows that the power consumption declines throughout the charging cycle. This can be taken advantage of in the operational strategy of an energy station. It is unlikely that multiple EVs start charging simultaneously. Therefore, as an additional EV connects to a charger, if the power supplied to vehicles that are already charging is reduced for a short period to meet the peak demand for the latest connected EV, the total demand peak would be reduced and the load slightly shifted. After 5-10 minutes the demand for the recently connected EV is reduced so that the rest can be supplied by their optimal demand again. This is believed to significantly reduce the required battery ESS size, leading to reduced investment costs as well. Furthermore, this will lead to a more even distribution of power output of the battery ESS. However, reducing the supply to EVs does have implications for the charging time, the extent of which should be investigated in future work. This is also only recommended on days with normal charging demand because in periods with high traffic, the goal should be to charge vehicles as fast as possible to reduce waiting times. Also, with high traffic comes high demand leading to significant power consumption and power tariff, which should be accounted for.

The analysis on the optimal peak shaving threshold is insufficient to draw conclusions due to the penalty function. However, the threshold does have implications on how the battery

ESS is used and therefore the lifetime of the battery. Results from Case F on battery cycles are as expected. A lower threshold leads to more battery cycles. Therefore, for the operation of Kongsbergporten, this should be further investigated. More cycles lead to longer lifetime, leading to higher annualised costs of the battery ESS. Therefore, in future work, it is recommended to dive deeper into the relationship between the peak shaving threshold, battery cycles and costs per cycle in order to find the optimal limit for which the battery should supply power for peak shaving.

The cost difference between the simulations without an ESS and optimal ESS size in Case D are not necessarily as large as shown in figure 11.7. This is because in the simulation without battery ESS, the peak shaving threshold at 180 kW was not removed. In the system without battery ESS, all power is supplied directly from the grid. As a result, in that simulation, all power consumed above 180 kW cost twice the spot price.

Limitations and shortcomings in the EVCS model discussed in this section affect the credibility of the exact results produced through simulations. It does, however, not imply that the model and analysis is useless. Even though the quantitative results are presumably atypical, the trends and sensitivities discovered in the analysis provide an insight into the system and the influence of changes in certain external factors.

13.3 Assessment of Kongsbergporten

The system at Kongsbergporten is adequately designed with respect to the motivation and operation of the hybrid energy station. The operators of Konsbergporgen at Glitre Energi have reason to believe that the battery ESS installed is too large. Under normal circumstances, the battery ESS does not operate or supply power at its limits which makes it seem unnecessarily large, similar to the results in Case E. It is, however, during periods with high demand that the battery operates at its limits which is also the periods the battery ESS is most valuable for minimizing operational costs. The system modelled in this thesis is most sensitive to peaks in EV charging demand, which is the primary motivation behind the installed battery ESS at Kongsbergporten. Thus, installing smaller battery ESS in similar future projects is feasible, but will not have the same impact in periods with high EV charging demand.

It is stated in section 1.1 that the share of EVs on Norwegian roads will increase in the coming years. Furthermore, the most modern EVs are able to charge at up to 250 kW. This implies that throughout the lifetime of the energy station at Kongsbergporen, EV charging demand peaks will be higher and more frequent. The system is already sensitive to EV charging demand peaks and the exact impact of this development must be analysed through dynamic modelling. However, a hybrid energy station with a smaller battery ESS would be more vulnerable to the developing capacity and frequency of EV charging. It is therefore not recommended to install relatively smaller battery ESS in future projects.

It is recommended that the operational strategy of the system is thoroughly analysed for optimal operation of Kongsbergporten and the design of future projects. It is clear from the analysis that how the battery ESS is used and demand power is distributed has a great influence on the system. However, in normal operation, a peak shaving threshold at 180kW is suitable for Kongsbergporten.

The LIB at Kongsbergporten is an NMC battery which is characterized by high specific and volumetric capacity, which is why they are suitable for mobile applications. The battery ESS installed at an energy station is however stationary, and is rarely constrained with respect to the physical size of the installation. Therefore, it is arguable that other energy storage or battery technologies are more suitable for hybrid energy stations. LFP batteries, for example, are suitable for utility scale storage because they are safe to use, have long lifetime and are as costly as NMC batteries. However, due to the rapid changes in EV charging demand and the high power outputs required from the battery ESS, an LFP battery would require significantly larger capacity than an NMC to meet this demand. The same argument is valid for other ESS technologies such as thermal batteries or hydrogen. Therefore, the installation of NMC LIB at Kongsbergporten is suitable for the intention ESS in energy stations.

For the model to provide more valid and credible quantitative results, imperfections mentioned in this section should be corrected. Furthermore, the model can be further developed to increase its applicability. These corrections, improvements and developments are discussed in section 15.

14 Conclusions

The utilization of energy storage increases energy flexibility and, in many cases, reduces the operational costs of EV charging stations. In this thesis, a model of a battery integrated EV fast-charging station is developed. The model is intended to analyse the utilization of the ESS in the system and to identify sensitivities as well as the optimal size of the ESS. The LP optimization model simulates the optimal flow of power from the energy grid to EV chargers based on historical EV charging demand from an existing energy station. The optimal size of the ESS is calculated with respect to its primary objective; peak shaving. Input parameters in the model are operating costs related to the ESS which can be changed for specific scenarios.

The literature review and the model requirements laid the foundation for the development of the EVCS model. It was chosen to model the system as an LP optimization model based on the defined objective and requirements, as well as previous work. The EVCS model is unique because it takes parameters and data from an existing real-world energy station, rather than predictions or assumptions. Implementation of the model was done in, but not limited to, GAMS.

In this thesis, the optimal ESS size is found and the parameters that the system is most sensitive to are identified. The optimal ESS size is found to be 174 kWh, resulting in a 5.6% reduction in system costs compared to the simulation without ESS. Benefits of the installed battery ESS are limited to the size range up to 250 kWh. An ESS larger than 250 kWh does not introduce additional benefits. It is therefore important to be familiar with the system requirements when designing future projects.

The power fee in the grid tariff linearly affects the system costs, but the distribution of costs is affected. ESS costs and grid tariff costs contribute to a larger share of the system costs with higher power fee. Considering the sensitivity, a 10% increase in the power tariff leads to a 2.5% increase in system costs. This is an indication that the system is insensitive to changes in the power fee due to the integrated ESS. Also, it shows how DSOs can create incentives to increase flexibility in the grid through the grid tariff.

The system proved to be resilient to changes in electricity prices. A 10% increase in electricity prices results in a 1.2% increase in operational costs. Electricity prices are increasing in Norway and in the simulated period were historically high. The integrated ESS contributes to low sensitivity to these changes and thus provides another incentive to increase energy flexibility.

It was found that the system is most vulnerable and sensitive to high demand peaks. A simulation in which demand was reduced for an 8 hour period, accounting for 0.3% of the simulation period, resulted in a 2.4% reduction in system costs. A simulation where demand beyond 300 kW is shifted, resulted in a 3.7% reduction in system costs. Furthermore, the EVCS model showed that 38% of the ESS capacity meets merely 10% of the EV charging demand. These results indicate that the operational strategy of the system is highly influential for the benefits of the integrated ESS and should be further investigated for the optimal operation of Kongsbergporten. However, how the battery is used has implications on its lifetime.

Results from the analysis done in this thesis imply that the system at Kongsbergporten is adequately designed. With regard to the battery ESS, the model analysis shows that the optimal ESS size is similar to the installed battery ESS at Kongsbergporten. If Glitre Energi and Circle K desire to reduce operation costs, it is therefore recommended to study different operational strategies and their implications.

The EVCS model developed in this thesis has limitations which impair the validity of the results. The main impairment is believed to be caused by a faulty penalty function. However, for the objective of the EVCS model and this thesis, the model requirements and selection are suitable. It is therefore for better insight into a battery supported energy system recommended that the corrections discussed for future work are made.

In conclusion, the work done in this thesis proves that the integrated battery ESS provides economic benefits to the energy station at Kongsbergporten. It is also confirmed that the ESS at Kongsbergporten is suitably sized for its intended use and operational strategy is the most effective way to further optimize this specific system.

15 Future Work

In this section, recommendations for future work is presented. Improvements and development of the EVCS model and how they can be implemented is discussed. Analyses and insights that are not made in this thesis but are valuable for the operator of an energy station are also mentioned.

The penalty functions implemented in the EVCS model for desired battery utilization are believed to be the primary source of unexpected results, mainly the penalty function on excess grid power. In future work, this penalty function should be removed. The intention behind the implementation of this penalty function was to encourage the system to use the battery ESS. However, if the PV system which is installed at Kongsbergporten, is included in the model it would supply the system with free energy to either charge EVs or the integrated battery ESS. If power discharged from the battery ESS were free of costs, a cost minimization model would prioritize battery power. Removal of this penalty function would both with and without PV included in the model result in more realistic cost calculations as well. The generation from the PV system is provided in the data portal for Kongsbergporten. A PV system can thus be implemented as an energy source in the model through a single variable.

One clear improvement can be implemented by converting the model to a MILP optimization model. The efficiency of the battery ESS can be modelled using separate variables for charging and discharging. The efficiency of the battery ESS can thus be a scalar multiplier in the relation between charging and discharging. Binary variables and the big M method should be used to ensure that the battery does not charge and discharge simultaneously. The same method can be used to implement efficiency of additional equipment as well.

For the model to give more insight on the battery specific operation of the system, LIB properties presented in section 4 should be implemented. Cyclic degradation of the battery can be modelled by decreasing the capacity of the ESS for each cycle with a minuscule scalar. Also, the discharge capacity for specific SoC can be implemented according to the graph in figure 4.5. This relationship can be an input data set, and the discharge capacity a product of SoC.

To improve the validation process and analysis of the model, it is recommended to create the model in additional software. Although GAMS is exceptional in solving time and ease of use, model sensitivity cannot be produced automatically in GAMS. Therefore, if the model is implemented in another software, results from both can be compared to increase validity. Furthermore, by choosing a software that can produce the sensitivity analysis automatically, for example Excel, the analysis process will be significantly easier.

Because this thesis is a short thesis, the analysis cases chosen are on the presumably most influential aspects of the system. However, to provide further insight in the system, more cases can be analysed. Although the system proved to be insensitive to changes in electricity price in the analysis made in this thesis, the effect of changes in electricity prices should be further analysed. Specifically on daily variations in electricity prices. The electricity prices used in the analysis in this thesis are from a period with irregular prices. Normally, electricity prices vary more throughout the day than they have in the winter of 2021-2022. Therefore, the effects of the daily variation should be analysed.

The analysis indicated that operational strategy has significant influence on the system costs. Therefore, an extensive analysis on different operational strategies will provide the system operator with great insight. The analysis on the peak shaving threshold in this thesis gave indecisive results. A deeper dive into this threshold is therefore recommended. Furthermore, analysis on the effects of load shifting as discussed in section 13.1 and the implications it will have on EV charging time is recommended.

The energy station at Kongsbergporten and the further development of the EVCS model created in this thesis is a suitable project for the UiO course TEK5380 - Project in Renewable Energy [51].

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