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## **Analyzing the Impact of Peak-Shaving on Load Reduction and on Battery Energy Storage System Degradation: A Simulation-Based Study in Husøy**

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# Abstract

The island of Husøy, in Northern Senja, Norway, faces numerous voltage quality difficulties, which arise from the consequent surge in electricity demand by the local growing fishing industry. Collaborating with the local distribution system operator (DSO), Arva, the current study explores the implementation of Battery Energy Storage Systems (BESS) using a peak-shaving strategy to alleviate high-demand periods, aiming to make the grid more robust. Using the open-source tool SimSES as the modeling software, the research examines the strategy's efficiency, focusing on load reduction during peak demand. Four main scenario cases were examined, each with a distinct peak-shaving threshold, to explore the system's performance. Furthermore, this study pioneers a comprehensive degradation analysis of the BESS in Husøy, based on the four scenario cases, shedding light on its long-term lifetime patterns. Furthermore, additional simulation cases were designed to explore the impact of different State of Charge (SOC) levels, temperatures, and Li-ion battery technologies on the system's longevity.



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# Introduction

In today's evolving energy landscape, the importance of efficient energy storage systems cannot be left out. As we move towards a more sustainable and reliable energy future, the need for robust and adaptable energy storage solutions has become increasingly evident. In this context, remote places, like small islands being at the far end of the electrical grid present a unique set of challenges and opportunities in energy storage [1]. With a limited connection to the mainland's grid, usually exposed to bad weather conditions and possessing limited resources, these places suffer from capacity problems, grid breakdowns, and poor voltage [2].

Constructing new transmission lines to support those places requires substantial time and financial expenses. These islands are often in remote or environmentally sensitive locations, making it costly to lay transmission infrastructure, especially when it involves long distances or challenging terrains. Given these challenges and the need to address capacity issues on remote islands, exploring cost-effective alternatives like energy storage becomes a practical and sustainable approach to providing energy stability in those regions.

Energy storage systems have emerged as an essential component in modern electricity grids [3], playing an important role in enhancing grid stability, integrating renewable energy sources, and meeting peak demand. They offer a diverse range of benefits, including load leveling, frequency regulation, and backup power supply, all of which can contribute to the overall grid stability. Moreover, energy storage technologies reduce the reliance on fossil fuels by

allowing excess energy from intermittent renewable sources, such as solar and wind, to be stored for later use.

While the general importance of storage systems in the modern grid is well recognized, their limited lifetime cannot be left out. Battery storage, one of the most common ways to store energy in the last few years [4], suffers from degradation [5]. Generally, the more the battery is being used the quicker it will degrade. More specifically, the various strategic operations of the battery, affect its lifetime. Given the importance of understanding battery degradation and maximizing investments in battery energy storage systems, it is important to use models for simulating battery operations as they provide valuable insights into how batteries degrade and operate, thus allowing for potential optimization of those investments effectively [6].

## 1.1 Scope of the Study

This study is centered on the island of Husøy in Northern Senja, Norway, in cooperation with the local distribution system operator (DSO), Arva, owner of the Smart Senja project [7], where in recent years a significant expansion of the fishing industry has been witnessed [8]. With this developing sector bringing about an increase in electricity consumption, the main challenge in the distribution network at Senja is large voltage variations both in the short and long term. Particularly challenging is low voltage in heavy load periods (winter time and/or high production in the industry) [9]. Husøy is located at the far end of a radial network. This causes a loss of income and costs for local operators linked to the increasing number of interruptions and voltage disturbances. Notably, the equipment used within the fishing industry is greatly sensitive to fluctuations in voltage. Those fluctuations have also negatively impacted the many households on the island. As a result, it has become increasingly important to seek solutions that can effectively mitigate this issue and enhance voltage quality and grid reliability throughout the island.

The industry at Northern Senja is expected to grow in the coming years, and this growth will contribute to further intensifying the problems with voltage quality in the area. Currently, the distribution network is operated by a 22 kV line, very close to its capacity limit, which is connected to a 66 kV line in Silsand. Network upgrades are being planned, for example a new 132 kV line from Finnfjordbotn to Silsand is planned to replace the current 66 kV line, which is thought to improve the distribution's network capabilities. However, for the time being, temporary solutions are being examined until the line is in place.



A battery of 2 MWh has already been installed on the island to help mitigate the problems. The way the battery will operate is still under discussion. However, the decision on how to operate will affect its degradation-dependent lifetime range. This is an important aspect, that requires further investigation, considering that Battery Energy Storage Systems (BESS) are an expensive investment, requiring maintenance, and at the end of its life a potential replacement.

The main objective of this thesis is to gain information on the degradation of the BESS in Husøy. This is done by means of simulating a common battery storage operation strategy, named peak-shaving, a strategy aimed at mitigating the challenges posed by high-demand periods by reducing high loads, making the grid more robust, less prone to voltage drops [10]. This is done with the use of the open-source software SimSES (Simulation Tool for Stationary Energy Storage Systems) [11]. Since this aspect has not been previously explored in Husøy, this thesis attempts a pioneering effort to understand, not only how this operation strategy helps reduce the load in Husøy, but also how it will affect the BESS's lifetime in the long term.

## 1.2 Literature Review

The primary challenge addressed in this thesis is the poor voltage quality within the distribution network of Northern Senja. This issue arises from the rise of the fishing industry in the region, which strains the network's capacity beyond its designed limits. To improve voltage quality, various strategies utilizing BESS have been proposed [12]. One such technique involves reactive power compensation [13]. However, heavy load is one of the main issues for common power quality issues in distribution networks [14]. This insight suggests that an alternative approach to enhancing voltage quality is the reduction of heavy loads in the network.

Previous research carried out under the Smart Senja project and the Renewable Energy research group has explored various ways to enhance the stability of the electrical network. These studies have delved into both the challenges existing within the current distribution network and potential solutions. Master's theses within the project have investigated methods for improvement, such as shunt capacitor reactive compensation and the integration of distributed power production in specific regions [15, 16]. In a previous study [15], a peak-shaving operation strategy was suggested in Husøy and it was analyzed how it can significantly reduce peak load. However, in this same study, the BESS operation was not studied in detail, and it neither included an analysis of different Li-ion chemistries nor a BESS degradation analysis under this operation.

Furthermore, the research has involved evaluations of the pumped hydro energy storage capacity within the network [17]. Published papers from the project have also focused on forecasting electricity demand in the area and predicting electrical faults within the distribution network [18, 2, 19]. Modeling results show that implementing basic distributed power generation alongside electrical energy storage significantly enhances both network capacity and opportunities for industrial expansion [20].

Regarding peak-shaving operation, a review on peak-shaving has been conducted [10], discussing the main strategies for peak-shaving and how they can significantly reduce peak load, as well as challenges and future research in each of those. There are also publications focusing on optimal sizing and optimal peak-shaving operation of a BESS [21, 22, 23].

The open-source software SimSES which was used for the operation and degradation simulations of this thesis has been used in similar cases [24, 25, 26]. In those, a techno-economic study was carried out, on a PV-BESS system installed at a Norwegian stadium, with the aim to analyze the installation's performance by studying a variety of cases involving operation strategies for peak-shaving, self-consumption maximization, energy arbitrage, and feed-in limitation. Also, it was used to simulate the degradation of the BESS, on which the overall financial cost is heavily dependent.

### 1.3 Thesis Contribution

After evaluating the existing efforts made to enhance the stability of the electrical network in Husøy and identifying the research gaps essential for expanding the theoretical understanding of this real-world case study, as well as guiding industry professionals in the right direction, this thesis was developed.

In this context, this thesis attempts to simulate the BESS in Husøy as realistically as possible. With the use of the open-source tool SimSES, which has been previously used in real-world case studies, the aim is to conduct an in-depth analysis of the peak-shaving operation, which could contribute to reducing stress on the grid and make it more robust and less prone to voltage drops. More significantly, this study attempts to pioneer a detailed degradation analysis of the BESS, a topic that has not been previously explored in Husøy. Apart from contributing valuable insights into enhancing the stability of Husøy's electrical network, this thesis also aims to provide information for potential future investment planning research. It aims to offer industry professionals data to make informed decisions, for stable energy solutions in Husøy. It also aims to recognize the abilities and potential of the open-source tool SimSES

for future research.

Summarising this, the key aims of this thesis are:

- An **Operational Analysis**, which investigates the impact of the peak-shaving strategy on load reduction in Husøy, providing practical insights into its effectiveness in reducing heavy loads, answering the question, *how does the peak-shaving strategy influence load reduction in Husøy, specifically in mitigating high-demand periods?*
- A **BESS Degradation Analysis**, which explores the effects of the peak-shaving strategy on the BESS, offering valuable information on BESS degradation patterns, answering the question, *what are the degradation patterns of the BESS in response to the peak-shaving strategy, and how do these patterns influence its long-term lifetime?*

Furthermore, it's crucial to emphasize that the insights gathered from this thesis are relevant to other places other than just Husøy. Although the main focus remains on enhancing Husøy's electrical stability, the methods and findings in this study are relevant for other places dealing with similar challenges. Communities globally, especially the ones at the far ends of the electrical grids, struggling with high-demand periods and searching for sustainable energy solutions, can learn from the operational strategy analysis performed in this research. Understanding how the peak-shaving strategy impacts load reduction in Husøy, can work as a starting point for other regions facing comparable issues.

Additionally, the BESS degradation analysis conducted here isn't limited to Husøy; it offers a valuable method for evaluating energy storage systems in diverse settings. Understanding BESS degradation patterns is important for the long-term viability of energy storage solutions universally.

## 1.4 Outline of the Thesis

The thesis will be structured into the following sections:

- In **Chapter 2**, the theoretical background related to the study will be given. Information about the power system, energy storage; specifically battery storage, and the mechanism of battery degradation will be discussed. The modeling software that was used will also be presented in this chapter.
- In **Chapter 3**, the data and the methodology of the study will be presented.

It will contain information regarding the location in the study, like the local power grid, and consumption data but also the formulation of the simulation cases regarding the BESS operation.

- In **Chapter 4**, the results of the simulations regarding BESS operation and its degradation will be presented.
- In **Chapter 5**, a discussion of the findings in relation to the research objectives and questions will be carried out.
- **Chapter 6**, will contain a summary of the key findings and their significance and suggestions for future work.

# /2

## Theoretical Background

### 2.1 Power Grid System

#### 2.1.1 Transmission, Regional and Distribution Networks

In Norway, the electricity system operates on three levels: the transmission grid, managed by Statnett, the regional grid, and the distribution grid [27]. Responsible for the high-voltage transmission network are the transmission system operators (TSOs), while for the distribution network, responsible are the distribution system operators (DSOs).

- The **transmission grid** links producers and consumers across the country. Statnett is Norway's designated transmission system operator, managing high voltage lines of 300 to 420 kV, with some parts at 132 kV.
- The **regional grid** connects the distribution grid to the transmission grid, connecting production and consumption radials with voltages ranging from 33 to 132 kV.
- The **distribution grid** contains local electricity networks supplying power to smaller users. It operates at voltages up to 22 kV, divided into high-voltage and low-voltage segments.

Different types of electricity producers and consumers are connected to these grids based on their scale, with large producers linked to transmission or re-

gional grids, major consumers to transmission or regional grids, and smaller consumers, like households and small-scale industries, connected to the distribution grid.

The connection between the above networks is being done with the help of transformers. Transformers are used to step up the voltage from generation to transmission and step down the voltage from transmission to distribution [28].

## 2.2 Energy Storage

Nowadays, where everything from households to industries relies on a constant supply of energy, the issue of storing this energy efficiently has become a hot topic [3]. There are various types of energy storage methods designed for different applications, but in recent years, electrochemical energy storage has gained significant attention, thanks to a substantial decrease in its prices [29]. This reduction in costs has led to its widespread adoption in various sectors. In this section, the diverse array of energy storage options available will be presented, with a particular emphasis on electrochemical energy storage, specifically focusing on the widely used Lithium-ion (Li-ion) technology, which is also used in this study.

### 2.2.1 Energy Storage Technologies

Currently, various energy storage technologies are available, and the choice of which one to use depends on the specific application. Some of the most common energy storage technologies are [30]:

- **Pumped hydro energy storage (PHES):** PHES is the most common form of mechanical energy storage with big capacity, long storage period and high efficiency. A typical PHES system consists of two large reservoirs at different elevations, a unit to pump water from one reservoir to the other, and a turbine to generate electricity from the higher reservoir to the lower, taking advantage of the potential energy of the water on the highest reservoir.
- **Flywheel energy storage (FES):** FES is also a mechanical energy system device that saves the rotational kinetic energy of a massive cylinder. Their response is very rapid making them them useful for frequency regulation.
- **Compressed air energy storage (CAES):** CAES, also part of mechanical

energy storage, is a method of storing energy by compressing air and storing it in a container. The stored energy is determined by the container's volume, as well as the pressure and temperature at which the air is stored.

- **Battery energy storage system (BESS):** BESS are systems that use batteries, which are electrochemical devices, to convert chemical energy to electrical energy, using different chemical compositions. Battery energy storage will be discussed further in Subsection 2.2.2 since it's the main subject of this thesis.

### 2.2.2 Battery Energy Storage

To dive into the upcoming chapters about battery degradation, it's essential to present the basics of electrochemical cells. Batteries are essentially a chain of interconnected cells [31]. These cells can be linked together in series or parallel to achieve a specific voltage and energy capacity for the whole battery. There are two main types: primary cells, which can't be recharged, and secondary cells, which are rechargeable. To grasp how batteries function, it's crucial to understand the workings of a single cell.

Electrochemical cells operate by converting electrical energy into chemical energy through a process called oxidation-reduction [31]. In this method, electrons move from one substance to another. During oxidation, electrons are lost, while during reduction, electrons are gained. The three main components of an electrochemical cell are the negative electrode (anode), the positive electrode (cathode), and the electrolyte, which acts as a medium for electron transfer between the electrodes.

When a battery is being charged or used (discharged) with the help of connected devices, ions, both positive and negative, travel between its inner components, creating a complete electric flow. This ion movement is vital for the battery's operation, allowing it to convert chemical energy into electrical energy when required.

During discharge, when the battery powers a device, electrons travel from the negative end to the positive end through the external device. Simultaneously, inside the battery, negatively charged particles move toward the negative end, while positively charged particles move toward the positive end, completing the energy circuit. Conversely, during charging, this process reverses. Negatively charged particles move toward the positive end inside the battery, and positively charged particles move toward the negative end, replenishing the battery's energy stores. Figure 2.1 visually illustrates this charging and discharging

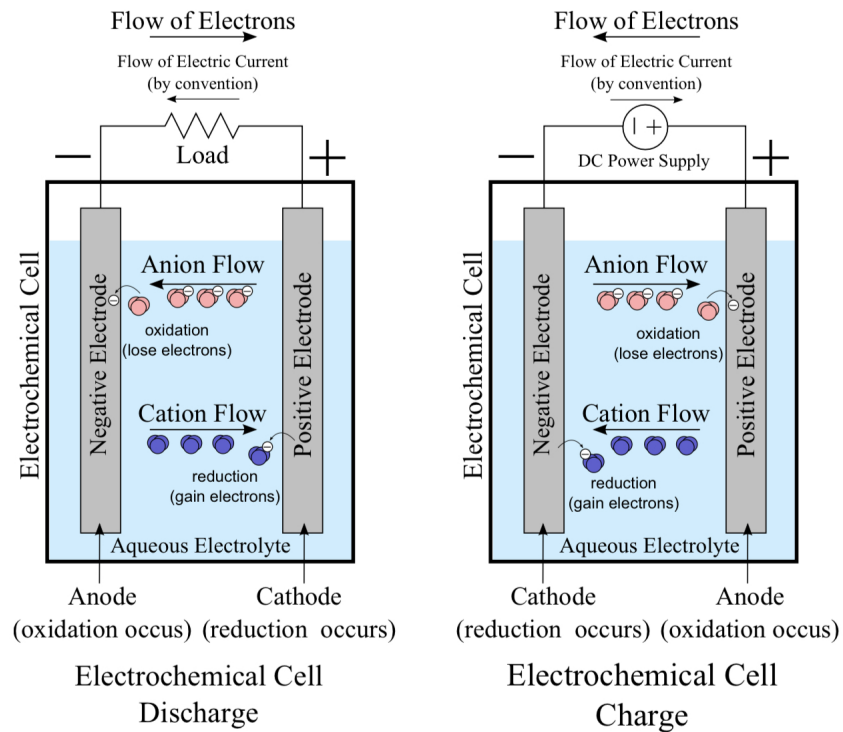


Figure 2.1: Charge and discharge of an electrochemical cell [32]

cycle.

A battery, often on a large scale, is essentially a cluster of numerous electrochemical cells working together to supply the necessary energy. These cells, as described earlier, undergo various electrochemical processes to store and release energy, and when combined into a battery, they can power a wide range of devices and systems.

Some key parameters regarding the battery's state, that are gonna be used further during this thesis are [33]:

- **State of Charge (SOC) (%)**: SOC represents the current battery capacity as a percentage of its maximum capacity.
- **Depth of Discharge (DOD) (%)**: DOD refers to the percentage of battery capacity that has been discharged, expressed as a percentage of its maximum capacity. For example, a discharge down to at least 80% DOD is considered a deep discharge.



- **Nominal Energy capacity(Wh):** Refers to the total amount of energy it can provide, measured in Watt-hours (Wh) when discharged at a specific current level.
- **State of Health (SOH) (%)**: Refers to the overall condition or health of a battery relative to its original capacity. It indicates how much of the battery's original energy storage capacity remains after a certain amount of usage and aging. SOH is expressed as a percentage, with 100% indicating a battery in perfect condition and lower percentages indicating degradation or wear over time.
- **Cycle Life:** The number of charge-discharge cycles the battery can experience before it fails to meet performance criteria.
- **Specific Energy (Wh/kg):** The nominal battery energy per unit mass.
- **Energy Density (Wh/L):** The nominal battery energy per unit volume.
- **Open-circuit voltage (V):** The voltage between the battery terminals with no load applied. Depends on the state of charge, increasing with the state of charge.
- **Internal Resistance:** The resistance within the battery. As internal resistance in a battery rises, efficiency drops and thermal stability decreases, converting more charging energy into heat.
- **C-rate:** The rate at which a battery is discharged relative to its maximum capacity.

### 2.2.3 Li-ion Battery Energy Storage

In this thesis, the BESS system that will be studied is based on Li-ion battery technology. In the last few years, Li-ion batteries have been on the rise because they offer several benefits for energy storage [34]. These include a long lifespan, minimal self-discharge, compact and lightweight design, fast charging, and suitability for a wide range of temperatures, as supported by [35][36][37].

The energy storage mechanism of lithium-ion batteries follows the same logic as any electrochemical cell, as explained in Section 2.2.2. Li-ion batteries store electrical energy in electrodes made of lithium-intercalation compounds with oxidation and reduction occurring at the two electrodes [38]. Generally, they consist of a graphite negative electrode (anode), a nonaqueous liquid electrolyte, and a layered  $LiCOO_2$  positive electrode (cathode). During charg-

ing,  $\text{Li}^+$  ions leave the  $\text{LiCOO}_2$  cathode and through the electrolyte move towards the graphite layers in the anode. During discharging the opposite happens.

### Li-ion battery chemistries

Li-ion batteries come in various types based on the structures of their anodes and cathodes, as well as the materials used in them [34]. Specifically, the cathode can have three different structures: layered, spinel, and olivine. These differences in cathode materials impact the battery's energy density and cost-effectiveness.

In general, and also within the context of this thesis, several main chemistries are utilized, each with distinct material compositions. These include Lithium Iron Phosphate (LFP), Lithium Nickel Manganese Cobalt Oxide (NMC), and Lithium Nickel Cobalt Aluminum Oxide (NCA). Each of these chemistries has its unique properties, making them suitable for specific applications and influencing factors like capacity, stability, cycle life and operation temperature range.

- **LFP:** Among the phosphate cathode materials, it has the highest capacity and stability, though a much lower open circuit voltage.
- **NMC:** The cathode of NMC consists of Lithium Nickel, Manganese and Cobalt Oxide. It offers improved cycle life, thermal stability and energy density [39]
- **NCA:** NCA batteries are similar to NMC (both have a layered cathode structure), but in this case, the Manganese is replaced by Aluminum, improving specific energy and lifespan when compared to NMC

## 2.3 Battery Storage for the Grid

For the electricity system to work reliably, a balance between the energy that is used and that's available is needed. This balance is becoming destabilized as more renewable sources like wind and solar power are incorporated into our grid [40] or as more load is added, for example, due to sudden industry expansion. This is especially true in remote places like the area discussed in this thesis, where the energy options are limited, and there's no easy backup plan [41].

Battery storage systems have the ability to balance out fluctuations in power supply and demand. They can manage situations where power generation and consumption don't align by storing excess energy and supplying it when needed. It acts as a smart system that ensures there's a steady supply of power, even when the production and usage of energy don't perfectly match up.

In this part, we'll explore the most common applications used for aiding the power grid. We'll also focus on the specific topic of peak-shaving, which is the primary area of study in this thesis.

### 2.3.1 Application Categories

Many functions can be performed by a BESS to support the grid. It's important to categorize these applications based on their specific uses to better understand their significance. The authors in [42] have classified Li-ion battery storage applications into four categories; *Ancillary Service*, *Behind-the-Meter*, *Energy Trade and Investment Deferral* and *Local Grid Support* applications.

#### Ancillary Service

BESS excels in responding rapidly to grid fluctuations, which is increasingly important due to the intermittent nature of renewable energy sources and evolving power grid dynamics. In various regions, the demand for frequency control reserve is managed through auction systems overseen by Independent System Operators (ISOs) [43]. BESS, particularly for addressing short-term fluctuations (milliseconds to a few seconds), addressed as **Primary Control Reserve (PCR)**, have shown technical maturity and potential economic advantages over traditional power plants [44]. However, successful BESS operation in this context depends on complying with regulatory constraints, profit schemes, and strategic operation planning. Also, **black-start** capability is another option for the grid with the use of BESS. In case of a supply or grid failure, a BESS can supply the needed energy due to the batteries' high nominal power and capacity.

#### Behind-the-meter

It refers to the combination of a local generation and a battery system, usually for residential customers but also for industrial customers. One of the most common behind-the-meter applications is **PV-BESS** [45], the use of a photovoltaic system connected with a BESS to increase self-consumption and reduce monthly bill costs. On the other hand, when it comes to industrial customers,

they often have to pay for their energy usage and peak demand separately. For them, one of the most common behind-the-meter applications is using BESS for **Peak-Shaving**, through which they can effectively cut down their peak electricity demand. As a result, this can lead to substantial savings on their electricity bills. Peak-shaving is the operation strategy used in this thesis, so it will be discussed further in the next section.

## Energy Trade

Due to the variation in energy production and energy demand, electricity prices vary as well. Storage **arbitrage**, is a BESS application aiming to take advantage of these fluctuations in prices, charging up the battery when prices are low and discharging it when prices are high, to avoid buying energy when it's expensive to buy.

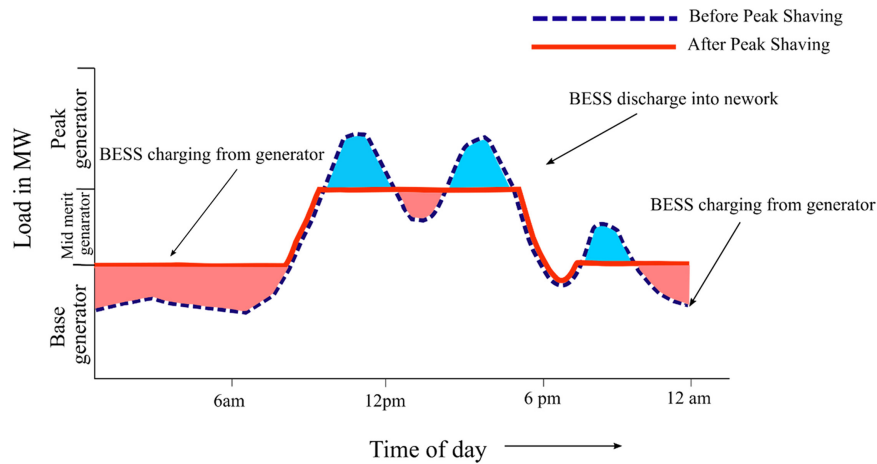
## Investment Deferral and Local Grid Support

BESS can act as an alternative or delay the need for traditional grid upgrades. Power grids have to be adaptable to handle changes in electricity flow from both consumers and suppliers, which happen constantly. Typically, the power grid's infrastructure, like transformers, is designed to manage peak power loads. When demand rises or renewable energy sources vary, the cables carrying power can experience resistance, causing voltage fluctuations. BESS, with the right control, can actively manage these fluctuations by supplying power as needed, both locally and for entire communities [46]. This can prevent overloads and enhance the stability of the grid without the immediate need for extensive upgrades.

### 2.3.2 Peak-Shaving

Peak-shaving is a strategic operation used in the energy sector to manage the highest points of electricity demand effectively [10]. During specific periods, typically when the demand for electricity is at its peak, the power grid experiences extensive stress. This increase in demand often exceeds the regular capacity of the grid, leading to challenges such as increased costs, potential blackouts, poor voltage quality and stress on the existing infrastructure [47]. The main logic behind peak-shaving is illustrated in Figure 2.2

Peak-shaving operation addresses this issue by using BESS, but also other types of energy storage, to smooth out these demand peaks. The primary goal is to reduce the stress on the grid during these high-demand periods. By storing



**Figure 2.2:** Peak-shaving using a BESS. Red areas indicate the charging of the BESS from the grid or a generator and blue areas indicate the discharging of the BESS by supplying energy to the grid [10].

excess energy during periods of low demand and releasing it during peak times, this technique helps balance supply and demand [48].

In this context, the implementation of peak-shaving operation could help establish a more reliable, resilient, and sustainable energy grid [10]. This approach not only benefits utility providers by enhancing grid stability but also brings important advantages to consumers by potentially lowering costs and ensuring uninterrupted access to electricity, even during periods of high demand. The benefits of peak-shaving could be grouped into three categories [10]:

- Benefits for the Grid Operator
- Benefits for the End-User
- Carbon Emission Reduction

### Benefits for the Grid Operator

Some of the most important benefits for the grid operator are:

- **Power quality:** When the generation system fails to match the electricity demand, problems such as instability, voltage fluctuation, and total blackout can possibly occur [47]. Studies have shown that peak-shaving can help mitigate those problems [49].

- **Efficient energy utilization:** Peak-shaving can help reduce the peak electrical load and as a result can improve the load factor, Equation 2.1 which determines how efficient the energy is being used [50].

$$LF(\%) = \frac{P_{AVG}}{P_{Peak}} \quad (2.1)$$

LF is the load factor,  $P_{AVG}$  is the average power demand, and  $P_{Peak}$  is the peak power demand.

- **System efficiency:** During periods of peak load, the supplying current needs to increase. This will increase the power losses which can be calculated through Equation 2.2, where  $I$  is the current through a transmission line and  $R$  is the ohmic resistance in the transmission line.

$$P_{LOSS} = I^2 * R \quad (2.2)$$

Since power loss is proportional to the square of the current, by reducing the peak load, the power losses can be reduced significantly [51].

- **Cost reduction:** Peak-shaving can help reduce certain costs in some cases. For example, it can help minimize the waste of excess electricity produced saving it for later periods. It can help expand the lifetime of the transmission and distribution system, further reducing costs of maintenance and upgrades [52][53].
- **Renewable energy integration** can be achieved more easily with the help of peak-shaving. The intermittence of most renewable energy sources can be mitigated by storing this energy in low-demand periods and releasing it in high-demand periods.

### Benefits for the End-User

Peak-shaving is important for end-users like residential and industrial customers as well. They can cut down on their electricity expenses by using less power during peak hours when electricity costs more and shifting their usage to off-peak hours when energy prices are lower [54][55]. Apart from the economic benefits, end-users can also benefit from the improved power quality and reliability that peak-shaving offers, as it was discussed earlier.

### Carbon Emission Reduction

Peak-shaving can contribute to avoiding using any kind of fossil fuel-generated electricity, leading to overall carbon emission reduction of a system.

## 2.4 Battery Degradation

A significant challenge that battery storage faces is battery degradation. As batteries operate, they undergo physical and chemical changes that affect how they perform and how long they last. It's essential to understand these degradation processes in detail. Doing so is key to improving battery technologies, making them last longer, and ensuring they are economically viable for energy storage applications. In the upcoming sections, battery degradation will be explored and the key factors that influence Li-ion battery degradation will be highlighted.

In essence, when referring to battery lifetime, it could be broken down into two main aspects: calendar life and cycle life [56]. Calendar life describes the degradation a battery experiences while stored without undergoing charge and discharge cycles. In contrast, cycle life revolves around the wear and tear a battery undergoes from repeated charging and discharging.

In real scenarios, for example, electric vehicles, batteries are active during driving or at charging stations, involving continuous charge and discharge cycles, leading to cyclic degradation. However, when the vehicle is parked and not in use, the battery remains idle and this leads to calendric degradation. So, it's crucial to consider both calendar and cycle life, recognizing that the battery can be affected both by usage and by periods of being inactive.

### 2.4.1 Mechanisms of Battery Degradation

Although it is not the work of this thesis to delve deep into the mechanisms of battery degradation, it is considered necessary to present some of the most important degradation mechanisms. The direct observable effects of degradation are capacity and power fade [57]. Between degradation mechanisms and observable effects, lie the degradation modes, a method of grouping degradation mechanisms based on the overall impact on the cell's behavior. The authors in [57] highlight four of those modes:

- **Loss of active material (LAM)** in both anode and cathode. This mode groups mechanisms that lead to a reduction in the material available for electrochemical activity.
- **Loss of lithium inventory (LLI)**. This mode groups mechanisms that result in a reduction of the amount of cyclable lithium available for transport between the electrodes.
- **Stoichiometric drift**, where electrodes become imbalanced to each other.

- **Impedance change or internal resistance increase** where the cell's kinetic behavior is affected. Some of the causes of impedance change are related to SEI (solid electrolyte interface) formation, high voltages, high temperatures, etc [57].

### 2.4.2 Factors Influencing Battery Degradation

In this thesis, the focus is on the operational side aspects of BESS and examine the resulting degradation. To do this, understanding the key factors affecting battery degradation is vital. The factors that significantly impact the lifespan of batteries are [56]:

- High temperature [58][59]
- Low temperature [60]
- High SOC or overcharge [61]
- Low SOC or over-discharge [62]
- High charge and discharge rate [63]

#### Influence of temperature

Temperature is one of the main factors affecting battery life [56]. Both high and low temperatures can contribute to accelerated degradation [64]. Many reactions happening inside the battery are temperature-related. If the temperature is too high then the side reaction rate is also higher. Low temperature may lead to polarization increase due to internal resistance increase, leading to more side reactions. The temperature in the battery is affected by factors like environment temperature, battery heat capacity, battery thermal conductivity, battery heat generation, heating and cooling system.

#### Influence of SOC

Higher SOC means higher terminal voltage which further means lower anode potential and higher cathode potential. In this case, SEI thickening will be higher resulting in a higher degradation rate [65]. When SOC is low, the anode potential is higher, and the cathode potential is lower, which is generally good for the battery's longevity. However, if the SOC becomes too low, it can lead to problems like corrosion of the anode copper current collector and disordering



of the cathode's active material structure, significantly impacting the battery's overall lifespan [62].

### Influence of current

Current flow has also an obvious impact on battery life. One of the main results of current flowing is Joule heat, and especially large charge and discharge rates can increase the battery temperature a lot, which leads to a higher degradation rate as was already stated. Current flow also affects the battery terminal voltage and internal potential resulting in side reactions that reduce battery life.

### 2.4.3 Battery Degradation Modelling

Modeling the battery's operation with the scope of modeling its degradation is proven to be a valuable tool that can help optimize the use of batteries and prolong their lifetime [66][67]. Generally, there are two types of modeling: empirical and physics-based [57]. The first method applies equations and parameters to match real-world data, while the second method models degradation behavior based on equations that represent physical and electrochemical phenomena, which are hard to measure. In empirical models, the equations might not reflect reality but are used to mimic the battery's behavior. The simulation tool used for this thesis uses an empirical model, the **equivalent-circuit model (ECM)**, which describes the electrical behavior of the battery using a set of circuit elements, such as resistors and capacitors. Those elements might not have a direct relevance to the device but simulate its overall behavior. It cannot provide details about the electrochemical interactions happening inside the battery.

## 2.5 Modelling Software

As power grids face new challenges and the costs of BESS continue to drop, there's an ongoing discussion about whether these technologies are a good fit for various stationary applications. However, designing storage systems involves many technical choices, like the type of energy storage to use, the size, and the operation strategy, among other factors. There are several software tools, many of them open-source, that have been developed to study the energy flows in a system containing a BESS. Some of them are StorageVET [68], SimSES [69], Blast [70], HOMER [71]. In this thesis, the open-source tool SimSES was used for its holistic approach and its degradation model with a special focus on Li-ion batteries, which suits this study.

In the upcoming paragraphs, SimSES's simulation framework will be presented. The main goal is to grasp how SimSES models BESS, the specific battery cells that are available for use and the degradation models. Overall, the aim is to showcase its capabilities as an open-source tool, showing how it effectively simulates BESS functionalities. All the information regarding the software is based on [11].

### **2.5.1 Simulation Framework of SimSES**

SimSES is an open-source tool that allows both technical and economic simulation framework, allowing multiple technologies comparison, allowing to model their thermal behavior, the corresponding power electronics and the impact of different operational strategies. Its main task is to determine the effect of the target power given by the Energy Management System (EMS), with regard to efficiency, temperature and degradation when applied to the energy storage system (ESS). It is divided into two parts; a simulation part, for modeling the physical representation of the ESS, and the analysis part which gives technical and economic results.

Its basic working principle is a time-series-based simulation that allocates the AC power target given by the EMS to the storage system. After each step the models are updated, regarding variables such as SOC, temperature, SOH and the available power, and a new target power is calculated for the next time step. Also, it takes into account various important components in order to simulate the storage system as a whole. To be more specific, apart from the power electronics, like AC and DC converters, it also includes a housing that covers the ESS, allowing for thermal-controlled simulation.

### **2.5.2 Storage Technology Modelling**

Models of various technologies are available through SimSES, each of them with specific applications regarding their physical behavior. Namely, some of them are lithium-ion (Li-ion), redox flow (RFB), and hydrogen energy. The subject of this thesis is lithium-ion battery technology, so this is where the focus will be.

#### **Lithium-ion battery**

The modeling of Li-ion in SimSES is done with four components [11]. Firstly, the electrical behavior of each cell type is described by an Equivalent Circuit Model (ECM) (see Subsection 2.4.3 on degradation modeling), giving terminal voltage

based on operational input data. Secondly, the Battery Management System (BMS) monitors the cell operation and updates current values. Thirdly, the different degradation models, depending on the different cell chemistries that come with predefined manufacturer-specific datasets. Lastly, the cycle detector (half-cycle detector) allows the aging calculation of the system.

### Lithium-ion cell types

SimSES incorporates advanced technologies utilizing a Carbon-Graphite (CG) anode and different cathode materials. Specifically, it features two cells with Nickel-Manganese-Cobalt-Oxide (NMC) cathodes and one cell each with Lithium-Iron-Phosphate (LFP) and Nickel-Cobalt-Aluminum-Oxide (NCA) cathodes. These variations in cathode materials highlight the diverse capabilities of SimSES in simulating various battery configurations.

### Lithium-ion degradation models

In SimSES, degradation is simulated using a semi-empirical approach that combines cyclic and calendar aging, as detailed in Equations 2.3 and 2.4. This method calculates the loss in capacity and the rise in resistance by considering both calendar aging ( $C_{loss}^{cal}, R_{inc}^{cal}$ ) and cyclic aging factors ( $C_{loss}^{cyc}, R_{inc}^{cyc}$ ). SimSES offers a range of primary Li-ion degradation models, each with specific dependencies on simulation time, SOC, cell terminal voltage, and cell temperature. Additionally, factors like the delta in the depth of discharge for a cycle, the number of equivalent full cycles (EFC), charge throughput, and the average cell terminal voltage over one equivalent cycle are taken into account.

$$C_{loss}^{total} = C_{loss}^{cal} + C_{loss}^{cyc} \quad (2.3)$$

$$R_{inc}^{total} = R_{inc}^{cal} + R_{inc}^{cyc} \quad (2.4)$$

Calendar aging is computed at every simulation step, while the routine to calculate cyclic aging increase is activated after detecting half an equivalent cycle of charge throughput. This approach optimizes calculation time, allowing for the determination of DOD for that specific half-equivalent cycle. In Figure 2.3, the process of degradation modelling on SimSES is shown.

### 2.5.3 Thermal Modelling

In Subsection 2.4.2, it was discussed how temperature affects battery lifetime. Both high and low temperatures can contribute to the acceleration of the mech-

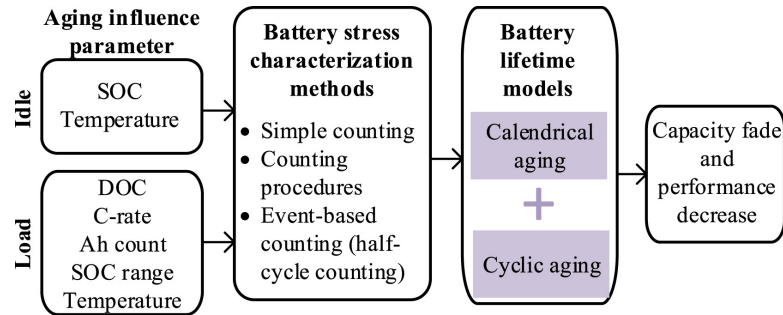


Figure 2.3: Representation of the SimSES degradation model [72]

anisms contributing to battery degradation. For this reason, across all applications, the regulation of temperature within the BESS is vital. SimSES has thermal modeling as an option across four stages.

- An **ambient thermal model**, which accounts for the temperature of the environment in which the BESS is installed. The two options available for this stage are; a **constant ambient temperature model**, that the user decides and a **location-specific model** based on temperature data from the location where the application takes place.
- A **housing model**, which models the housing that hosts the battery. It is being simulated as a 20-foot shipping container with three material layer walls.
- A **heating, ventilation and air conditioning model** that is used to maintain the temperature inside the housing.
- A **system thermal model**, that mimics the heat transfer across the different components and the environment.

#### 2.5.4 Operation Strategies

Depending on the applications and the needs of the BESS user, there are different operation strategies that one can follow. SimSES provides a limited amount of operation strategies, that can be adjusted to the user's needs since its code is open source. Some of those are:

- **Power follower.** A basic strategy that aims to replicate a given power profile with the storage system.
- **SOC follower.** A strategy that given a SOC profile attempts to make the

storage system fulfill the calculated demand.

- **Residential PV greedy / Residential PV feed in.** Strategies to include Photovoltaic (PV) units in the operation.
- **Simple Peak Shaving.** Under this strategy, when the demand is above a specified threshold, the extra required power is supplied by the BESS. The BESS is recharging itself when the demand value is below the specified threshold.
- **Peak Shaving perfect foresight.** Under this operation, the load profile is assumed to be perfectly known and the BESS will charge itself up right before the next load peak. This is a strategy to reduce calendar aging.
- **Frequency Containment Reserve (FCR).** The BESS charging and discharging are dependent on the frequency deviation.
- **Intraday Continuous Market (IDM).** A strategy to trade energy by charging and discharging the BESS when it is economically beneficial, taking advantage of the hourly electricity prices.



# /3

## Data and Methodology

### 3.1 Existing Network

Until today, the grid in Senja is supplied via a 132 kV connection from Bardufoss to Finnfjordbotn, where the voltage is transformed down to 66 kV connection from Finnfjordbotn to Silsand [8]. On Senja there are four regional grid stations, Silsand, Svanelvmoen, Straumsnes, and Stonglandseidet at which the voltage is stepped down for distribution at 22kV. The northern part of Senja, which includes the island of Husøy, is supplied from the three stations Silsand, Svanelvmoen and Straumsnes.

The distribution network is operated with a 66 kV line and approximately 666 km of 22 kV network distributed over 15 areas. Some parts of this network have a limited capacity and are exposed to frequent power supply failures. Based on the current and future scenario demand, the 66 kV connection from Finnfjordbotn to Silsand is not sufficiently strong to handle the growth in demand in the next few years and there are plans for it to be replaced by a 132 kV connection.

#### 3.1.1 The SVAN22LY1 Power Grid

The SVAN22LY1 grid is a 60-kilometer line from the south in Svanelvmoen to the northernmost point of northern Senja with several branches to many communities towards the north.

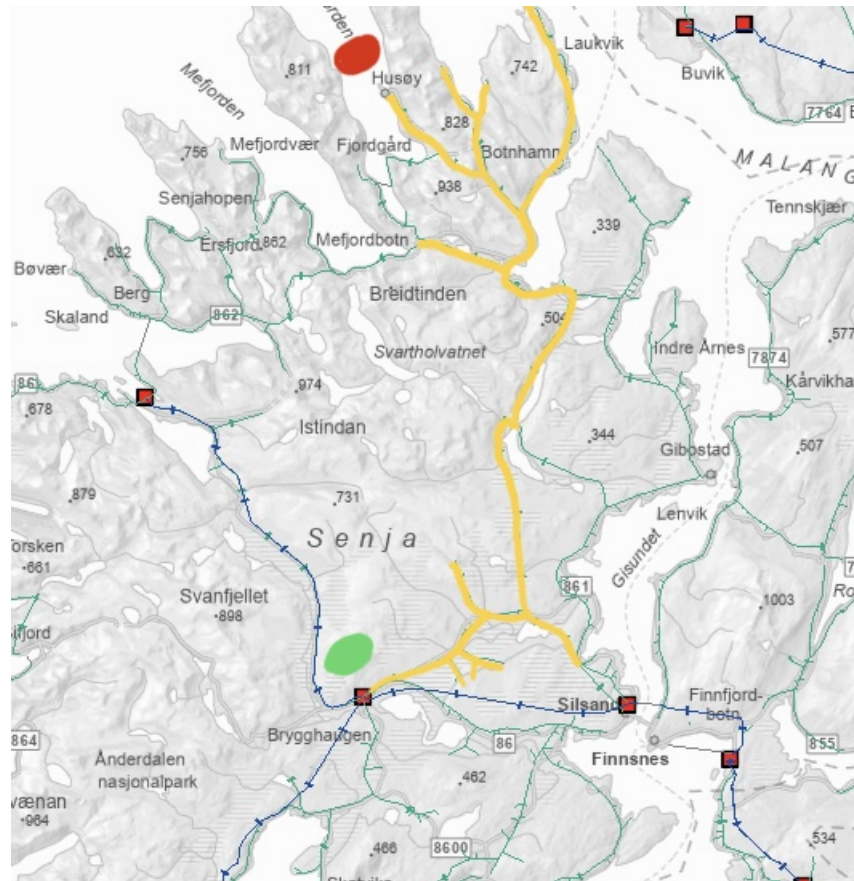


Figure 3.1: The SVAN22LY1 power grid. [NVE, 2023]

The largest customers connected to the SVAN22LY1 line, are located at the end of the northernmost point. This is also where Husøy, the island that is being studied in this thesis, is located.

It has a capacity of 22 kV and it is operating very close to its maximum due to the increase of electricity demand in the last few years. The total demand in the area is a combination of both household and industry load profiles, although the industry accounts for more than 50% (see Subsection 3.2.1).

### 3.1.2 Power Grid Failures

The local industry is expanding, with ambitions beyond grid capacity. The installed equipment is very sensitive to changes in voltage and therefore depends on a stable power supply. When the industry is operating at a heavy load, there is a high risk of voltage drops and therefore a high risk of power interruption.



All the communities connected to the SVAN22LY1 have no alternative that can provide backup when the voltage decreases or when there is an interruption in power.

On top of that, the location of this grid is characterized by typical Arctic conditions exposed to strong winds for a big part of the year making the risk of power grid failures higher. There have been some previous studies that studied the connection between power grid failures and harsh weather conditions [2] [73]. This thesis' objective is to approach the problem from the high-demand point of view and study a way to handle this with the use of energy storage.

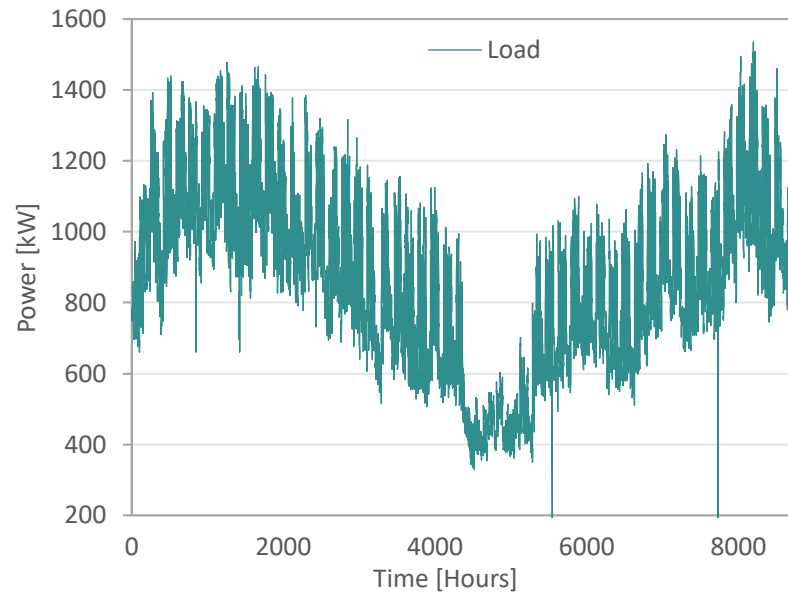
## 3.2 Husøy Load

As discussed in Section 3.1, Husøy is situated at the end of the SVAN22LY1 grid, making the area vulnerable to voltage drops caused by an upsurge in electricity demand witnessed in recent years. To comprehensively assess how a BESS could effectively address this issue, it is essential to analyze this demand.

The dataset employed for this thesis consists of hourly load data collected from a single node on the island, including both residential and industrial activities. The simulations in SimSES were based on the year 2021, starting on January 1st and concluding on December 31st. This dataset includes 8760 data points, corresponding to the 8760 hours within a year. Additionally, data from the previous year, 2020, was utilized for comparative purposes. This comparison aimed to show any shifts or fluctuations in industrial and residential activities between the two years.

Figure 3.2 presents the hourly load for Husøy in 2021, revealing a clear seasonal pattern. The load peaks during the winter months, particularly at the start and end of the year. This surge in demand is attributed to increased industrial activity and lower temperatures, which drive up electricity usage for heating purposes. Conversely, there is a substantial decline in load during the summer months. This drop is associated with reduced industrial operations, warmer weather, and many locals being on vacation. In Table 3.1, the maximum and the minimum load of every month are shown. It can be seen that the highest load of the year was in December, specifically on 08/12/2021 at 15:00 UTC, with a value of **1534.85 kW**.

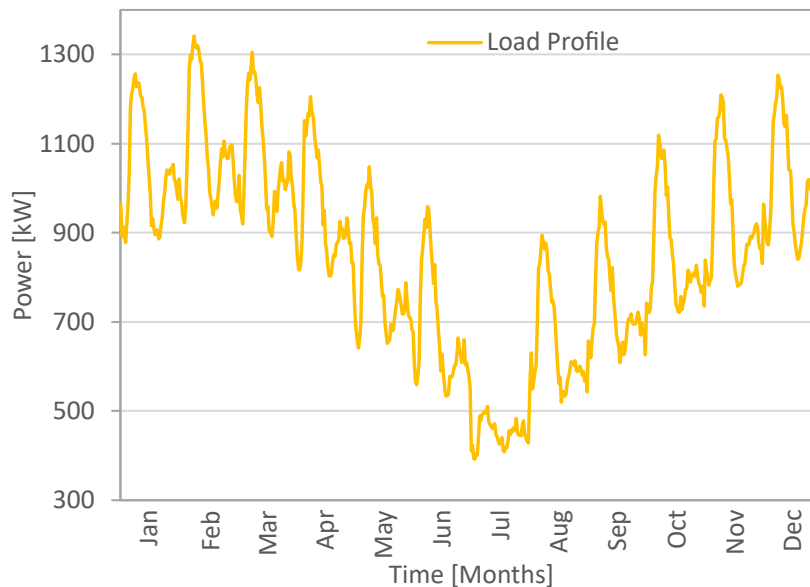
Upon analyzing the 2021 data, an additional load variation was discerned based on the type of day, distinguishing between weekdays and weekends. To visualize this variation, a new load curve was generated by averaging the hourly load for each month separately for weekdays and weekends, resulting in 12\*24



**Figure 3.2:** Hourly load on the node in Husøy in 2021 [Arva].

**Table 3.1:** Maximum and minimum load of every month, based on 2021 dataset.

Month	Maximum Load (kW)	Minimum Load (kW)
Jan	1439.32	661.57
Feb	1476.09	660.23
Mar	1465.05	660.41
Apr	1383.83	687.47
May	1265.62	515.04
Jun	1123.95	506.59
Jul	857.32	329.86
Aug	1059.84	24.08
Sep	1099.38	540.01
Oct	1274.39	510.84
Nov	1404.83	25.06
Dec	<b>1534.85</b>	746.21



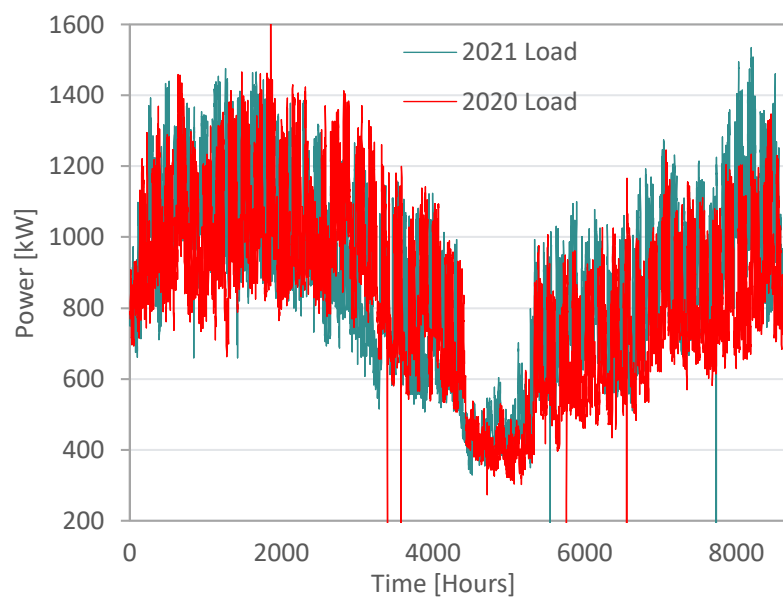
**Figure 3.3:** Yearly load profile for Husøy in 2021. This graph shows how an average weekday and weekend day changes throughout the different months of the year

data points for each category (weekday/weekend day) throughout the year. This was done by using the software LEAP [74]. This is depicted in Figure 3.3. The key insight from Figure 3.3 is that it retains the same annual load fluctuation observed in Figure 3.2, with higher loads during winter and lower loads in summer. However, the primary purpose of this curve is to illustrate the difference between an average weekday and an average weekend day in each specific month. This load profile in Figure 3.3 reveals that every month exhibits two distinctive spikes: the first and taller spike represents the average load on a weekday for that month, while the second, and shorter spike represents the average load on a weekend day in that same month. This indicates that the highest loads are achieved mostly during weekdays. The highest values from every month in Figure 3.3 will later be used for setting the monthly peak shaving limit in one of the simulation cases.

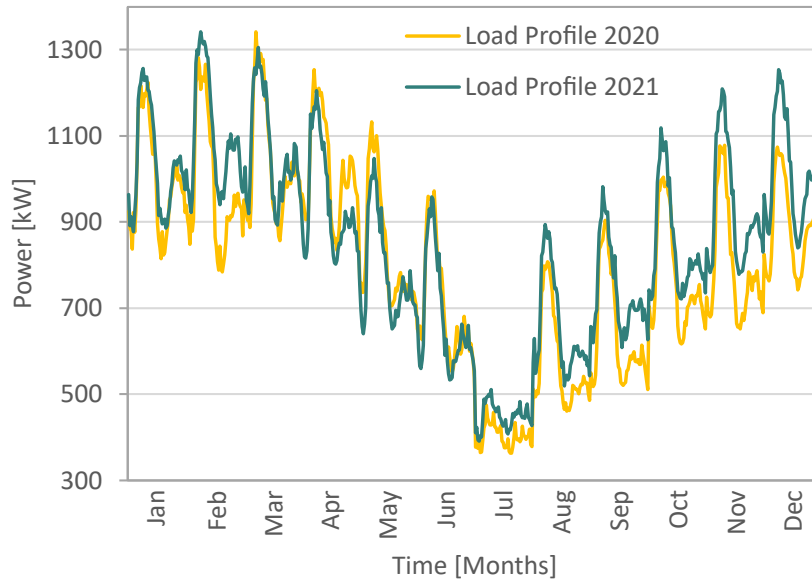
A supplementary analysis was conducted using an hourly load dataset from 2020. The primary objective was to discover variations between the two years (2020 and 2021), with a focus on potential changes in yearly patterns. In Figure 3.4, the load data for 2020 together with that for 2021 are presented. The initial observation reveals a similarity in the seasonal patterns of both years. Both exhibit a pronounced peak in consumption during the winter months and a decline during the summer, with the values of the two datasets being very

**Table 3.2:** Average maximum and minimum load for every month, based on Figure 3.3.

Month	Average Maximum Load (kW)	Average Minimum Load (kW)
Jan	1256.13	877.33
Feb	<b>1341.72</b>	922.52
Mar	1305.60	892.11
Apr	1205.50	802.75
May	1047.97	641.10
Jun	958.29	391.59
Jul	510.30	391.59
Aug	894.57	519.07
Sep	982.01	608.50
Oct	1118.77	719.99
Nov	1208.75	779.08
Dec	1253.50	839.74



**Figure 3.4:** 2020-2021 hourly load comparison for Husøy [Arva].



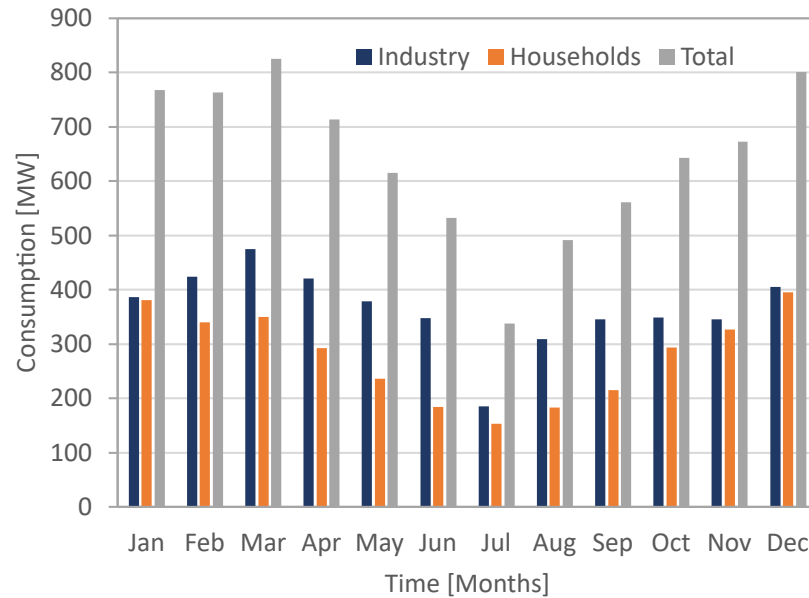
**Figure 3.5:** 2020-2021 profiles comparison [LEAP].

close. However, there is a noticeable increase in demand during 2021, primarily occurring between 0 and 2000 hours, during the summer period, and between 6000 and 8760 hours. During these periods, the load for 2021 surpasses that of 2020 significantly, indicating a trend of escalating electricity demand in Husøy. This is something that the local DSO confirms and it is expected that the demand is set to increase even faster than initially expected. Figure 3.5, which was designed with the same logic as Figure 3.3, shows the two load profiles for the two years, 2020 and 2021, in which is clear that the demand has increased from one year to the other in certain periods, especially from August to December.

### 3.2.1 Difference in Load between Households and Industry

In the previous section, the load analysis primarily addressed seasonal fluctuations and day-type variations. Now, the next step is to investigate how different activities, mainly residential and industrial, contribute to the load in Husøy.

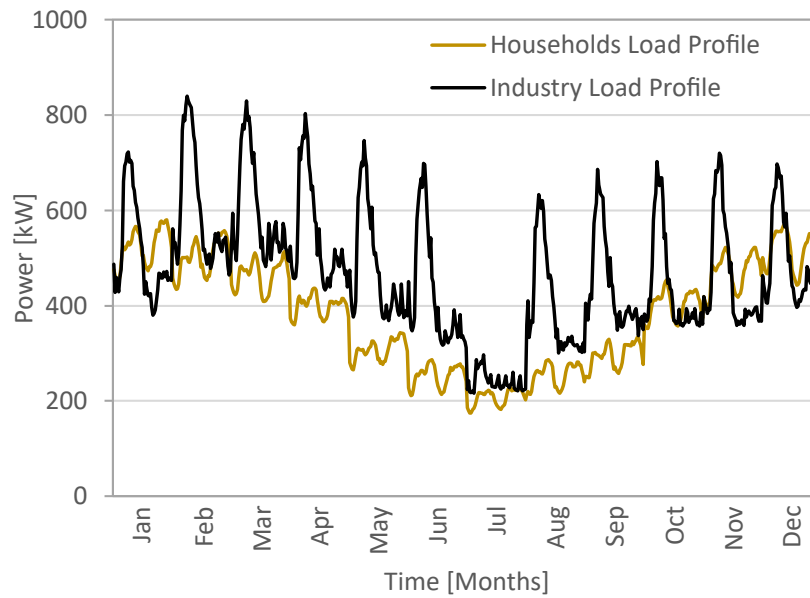
As previously mentioned, the load in Husøy arises from a combination of both residential and industrial activity. To gain a comprehensive understanding of how a BESS might operate effectively, it becomes essential to show the relation of these two contributing factors to the overall load. Figure 3.6 displays the



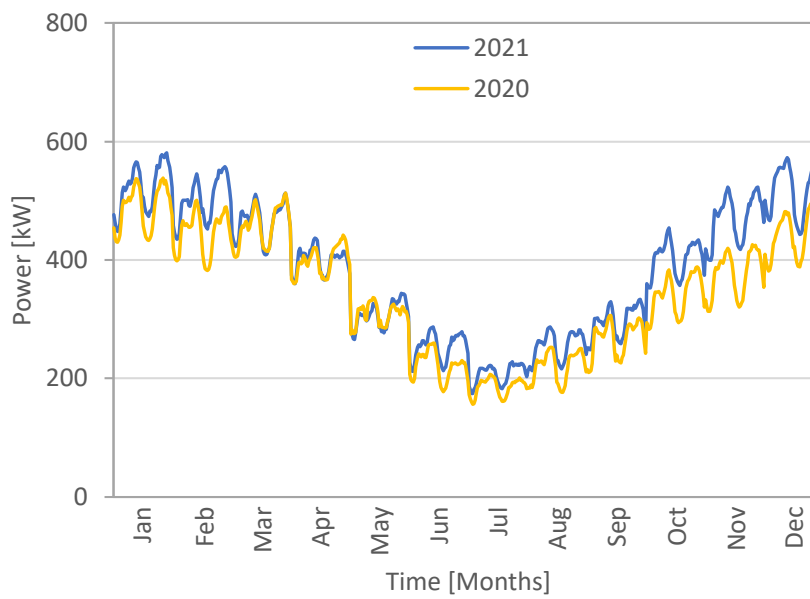
**Figure 3.6:** Households, industry, and the total sum of consumption in MW for the 2021 dataset. Industry accounts for more than 50% of each month's consumption.

monthly consumption patterns for households, industry, and overall consumption based on the 2021 load dataset. It's evident that industry consumption consistently surpasses 50% of the total consumption every month in Husøy. Following the logic introduced in Figure 3.3, load profiles were created for households and industry, as demonstrated in Figure 3.7. Interestingly, there are occasional weekends where household activity exceeds that of the industry. Generally, however, industry consumption dominates. The household profile reveals minimal differences between weekdays and weekends, except for certain weekends with notably higher consumption than weekdays. Conversely, the industry profile indicates significantly higher consumption on weekdays compared to weekends, shedding light on the source of the high load in Husøy.

Figures 3.8 and 3.9 provide a comparison of household and industry load profiles between the years 2020 and 2021. In Figure 3.8, the household load profile exhibits a slight rise in consumption during 2021, particularly in the latter part of the year, spanning from June to December. Figure 3.9, which illustrates the industry load profile, similarly reflects a modest increase in 2021. This increase is noticeable during weekends and also on weekdays, especially in the latter months of the year, ranging from August to December.



**Figure 3.7:** Household and industry load profile for 2021 [LEAP].



**Figure 3.8:** Household load profile for 2020 and 2021 [LEAP].

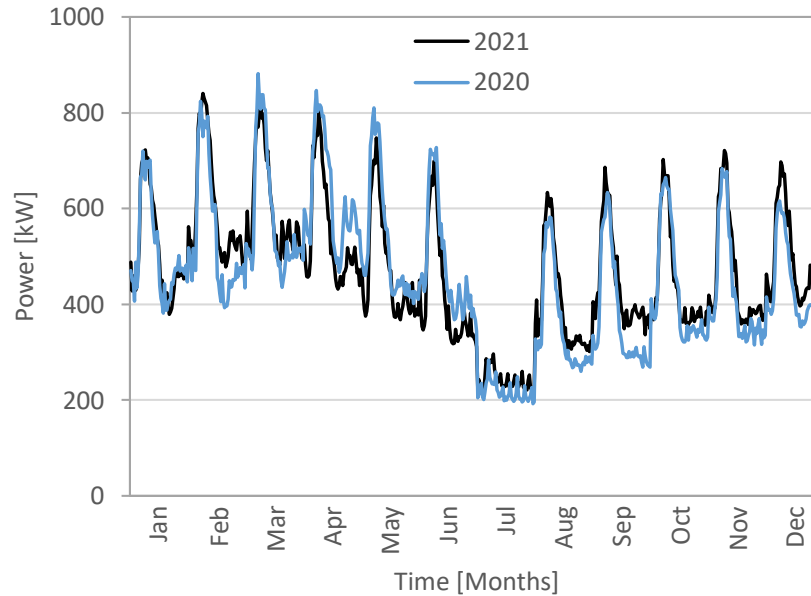


Figure 3.9: Industry load profile for 2020 and 2021 [LEAP].

### 3.3 BESS Simulation with SimSES

In Section 2.5, SimSES was introduced, an open-source tool that will be employed in this study to outline this thesis methodology. SimSES serves as a holistic simulation framework designed for modeling and analyzing stationary energy storage systems. In this section, the methodology employed will be presented, focusing on SimSES's capabilities. Among the multiple operational strategies within SimSES for the BESS, the primary emphasis is on the Simple-PeakShaving strategy that provides peak-shaving (see Section 2.5).

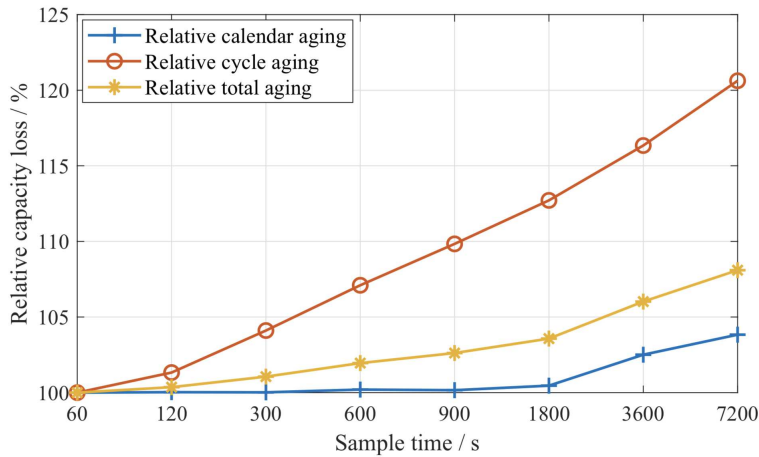
Based upon the 2021 load dataset, SimSES will be used to conduct simulations that will show how peak-shaving can contribute to reducing energy demand in Husøy under various system configurations. Moreover, SimSES will help study the degradation of the BESS under diverse operational configurations to understand how these impact the BESS's lifespan.

#### 3.3.1 Basic Simulation Information

##### Time Resolution

SimSES provides significant flexibility in building simulations to meet specific requirements and accuracy standards. One of the fundamental choices in con-





**Figure 3.10:** Influence of the sample time between 60 to 7200 s on the capacity loss: Deviation of the capacity loss due to calendar aging (blue curve), cycle aging (red curve) and the total aging (yellow curve) in relation to the simulation with a sample time of 60 s. Figure from [75].

figuring a simulation is selecting the temporal resolution, which has a direct impact on how the simulation unfolds. In this thesis, hourly data from the 2021 dataset was utilized (as detailed in Section 3.2), and consequently, the simulation's temporal resolution aligns with this data (3600 seconds or 1 hour), resulting in 8760 discrete steps throughout the year. It's worth noting that SimSES offers the option to use resolutions as fine as 60 seconds (1 minute), but it comes at the cost of increased computational time. This decision regarding resolution has notable implications for simulation outcomes, particularly in terms of the BESS's degradation, as illustrated in Figure 3.10. For example, the choice of 3600 seconds as temporal resolution will lead to about 6% relative total aging higher than the 60-second temporal resolution.

### Maximum/Minimum SOC

Before running the simulations, it is needed to set the maximum and minimum SOC parameters for the BESS. This choice holds significant importance as it directly influences the amount of available energy that the battery can provide to meet the load requirements.

In all the simulation cases conducted, it was assumed that the battery could charge and discharge to its full capacity, meaning the SOC ranged from 0% to 100%. However, it's important to note that this strategy does not optimize degradation minimization, since higher DOD leads to higher degradation.

## Battery size and technology

SimSES offers the flexibility to input precise details about the battery size and its specific cell-type technology. In Section 2.2 of this thesis, a list of various cell-type technologies was presented, including those compatible with SimSES. Based on the information provided by the local electricity supplier, the battery installed in Husøy employs Li-ion NMC (Nickel, Manganese, Cobalt) technology, sourced from Samsung SDI.

SimSES encompasses a range of NMC models from different manufacturers, and for the simulations, the **SanyoNMC** model was selected. The reason for this is that, firstly it is an NMC cell (matching the technology used in Husøy), and secondly after various testing simulations with different cells, the SanyoNMC seemed to be the one having a more detailed description of cyclic degradation compared to other NMC cells. The current nominal energy capacity of the installed BESS in Husøy is 2.6 MWh. However, only 2 MWh of that capacity will be used for operations according to the DSO. So for the simulation, the BESS's nominal energy capacity was set to **2 MWh**. The system's nominal power capacity was set to 1 MW. This selection ensures that the simulations closely describe the real-world conditions and parameters of the Husøy energy system. The end-of-life SOH%, after which the battery needs replacement was assumed to be 70%. This is a valid assumption, considering that most grid-connected Li-ion batteries reach the end of their life when reaching SOH values between 70-80% [76].

## Temperature and thermal simulation

Temperature plays an important role in influencing the battery's performance and its rate of degradation. In this regard, SimSES allows for the account of temperature factors during simulations. This capability extends to both the ambient temperature, representing the local climate, and the temperature inside the housing where the battery resides. The latter is subject to regulation through an HVAC (Heating, Ventilation, and Air Conditioning) system.

During battery operation, the internal temperature of the housing can fluctuate due to the energy exchange, and it falls upon the HVAC system to maintain a stable environment. In Husøy, in 2021, based on information from Mortenhalskolten observation station [77], the temperature varied from  $-18.7^{\circ}$  to  $23.8^{\circ}$  Celcius. For simplicity in the simulations, the constant ambient temperature model was used and it is held constant at  $5^{\circ}$  Celsius throughout the entire simulation period. The HVAC system was employed to ensure this temperature stability within the housing. Even though the thermal simulation will lack the yearly variation of ambient temperature, the choice of constant  $5^{\circ}$  temperature

**Table 3.3:** Technical parameters for the simulations in Case 1-4.

Component	Property	Value
<b>Model</b>	Temporal resolution	3600 sec
	Thermal Simulation	TRUE
	Ambient Temperature	5° C
	HVAC	5° C
<b>BESS</b>	Nominal Energy Capacity	2 MWh
	Nominal Power Capacity	1 MW
	Minimum SOC	0%
	Maximum SOC	100%
	Type	Li-ion SanyoNMC
	End-of-life SOH	70%
<b>Load</b>	Dataset	2021 Husøy Hourly Load

is still within the yearly range.

It's worth emphasizing that temperature is a critical factor affecting battery degradation. Consequently, in the forthcoming discussion section, a comprehensive analysis of how temperature variations impact the overall system dynamics will be carried out.

In Table 3.3 the technical parameters of the simulations in the following simulation cases are shown.

### 3.3.2 Simulation Cases

BESS offers a wide array of operational possibilities, each designed to meet specific objectives. The primary emphasis is on implementing the peak-shaving strategy, studying its potential to alleviate capacity-related issues in Husøy by reducing peak load, and studying the degradation of the BESS related to this operation.

Even within the scope of a single operational strategy, there exist multiple approaches to operating the BESS effectively. To be able to see and compare how a BESS is working under different system parameters and what results this has in the degradation of the battery, it's important to run a sensitivity analysis. In this thesis, a sensitivity analysis has been conducted using various case scenarios. These cases are introduced below:

**a. Case 1 (Base Case)****The BESS remains idle for the whole simulation**

Case 1 serves as the starting point for the following simulations. In this scenario, the battery remains idle, maintaining its SOC throughout the entire year. The purpose behind this case is to observe how the battery degrades when it isn't actively used, which is a phenomenon known as calendric degradation (see Section 2.4). Consequently, this case will be used as a baseline for comparison with three other cases where the BESS is actively utilized.

**b. Case 2****The BESS is used when the load is higher than 1300 kW**

In Case 2, the battery operates to maintain the load consistently below 1300 kW throughout the entire year. This strategy ensures 100% reliability, as it prevents any instances where the load exceeds this limit. The decision to set this threshold was informed by the analysis conducted in Section 3.2. While Figure 3.3 indicated a slightly higher average load of just over 1300 kW, Figure 3.2 revealed occasional peaks reaching up to 1500 kW. Therefore, this strategy aims to keep the load below 1300 kW.

**c. Case 3****The BESS is used when the load is higher than 1250 kW**

In Case 3, a similar approach as in Case 2 is applied, but with a lower peak-shaving limit set at 1250 kW. This case serves a dual purpose: first, it aimed to assess how the additional stress placed on the BESS impacts the system's reliability. This is because the BESS might face challenges meeting the demand consistently, especially during periods of continuous high load. Second, it demonstrates the impact of setting a lower threshold for the peak-shaving strategy on battery degradation.

**d. Case 4**

### **The BESS is used when the load is higher than the average maximum of each month**

In Cases 2 and 3, the peak-shaving limit remained constant throughout the entire year. This meant that the BESS wasn't utilized during periods of lower demand, such as spring and summer when electricity demand decreased. However, even in these months, electricity production might drop, leading to poor voltage quality. Taking this into account, Case 4 was developed. In this scenario, the peak-shaving limit was set at the highest average value for each month, as shown in Figure 3.3 and Table 3.2. For the summer period, between mid-June and the end of July where the demand is very low, the BESS was not utilized.

### **3.3.3 Extra Simulation Cases**

The impact of temperature and depth of discharge on battery degradation was previously discussed in Subsection 2.4. To enable a fair comparison between Cases 1 to 4, these cases were tested under identical stable temperature conditions and depth of discharge (0-100%), and same technology (SanyoNMC). In order to observe how varying temperatures, different charge/discharge ranges, and different technologies affect battery degradation in SimSES, three separate simulations were conducted.

#### **1. Various Resting SOC**

In this section, the initial focus is on conducting a simulation similar to Case 1, where the battery is not utilized. The objective is to observe how different SOC levels, at which the battery is resting, impact its degradation in SimSES. The simulations were carried out with the battery resting at a SOC of 10%, 20%, 30%, 40%, 50%, 60%, 70%, 90%, and 100%.

#### **2. Various Resting Temperature**

The next step involves analyzing the impact of different temperatures on battery degradation. Similar to Case 1, the battery remains idle, but this time, it's exposed to various temperatures. The simulations were conducted with the battery resting at 0°, 5°, 10°, 15°, and 20° Celsius.

### **3. Different technologies**

Battery degradation appears to exhibit variations across different battery cell types. To investigate this further, Case 4 was re-simulated, but this time, three additional battery technologies were included, in addition to the original SanyoNMC technology. Those are, MolicelNMC, PanasonicNCA and SonyLFP.

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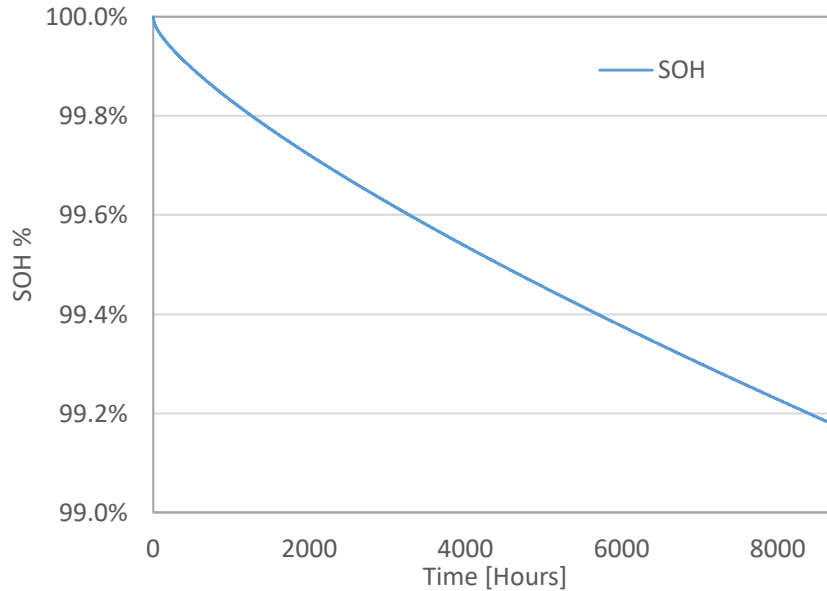
## Results

In this section, the results derived from the simulations discussed in the preceding section will be presented. Firstly, the operational aspects of the BESS will be showcased, highlighting the specific time periods during which it is active and the operational patterns throughout reference periods. As a second part of the analysis, the system's degradation results for each case will be presented.

### 4.1 Simulation Cases

#### 4.1.1 Case 1 (Base Case)

In Subsection 3.3.2, Case 1 serves as a reference point in this study. It offers insights into the system's behavior during periods of complete inactivity, with the SOC maintained at 100%. Since the BESS did not supply any power to the system, the highest load under this case was **1534.84 kW**. The accompanying Figure 4.1 displays the SOH of the battery in this idle state, showcasing the gradual degradation due to calendric factors. Even in a state of rest, the battery exhibits a **0.82%** decline in SOH over time. In this scenario, the BESS remains inactive, eliminating the need for a detailed analytical demonstration of its operations during the simulation period. However, such analysis becomes vital in the next cases, where the system's functionality under different conditions is analyzed.



**Figure 4.1:** Degradation of the BESS in Case 1.

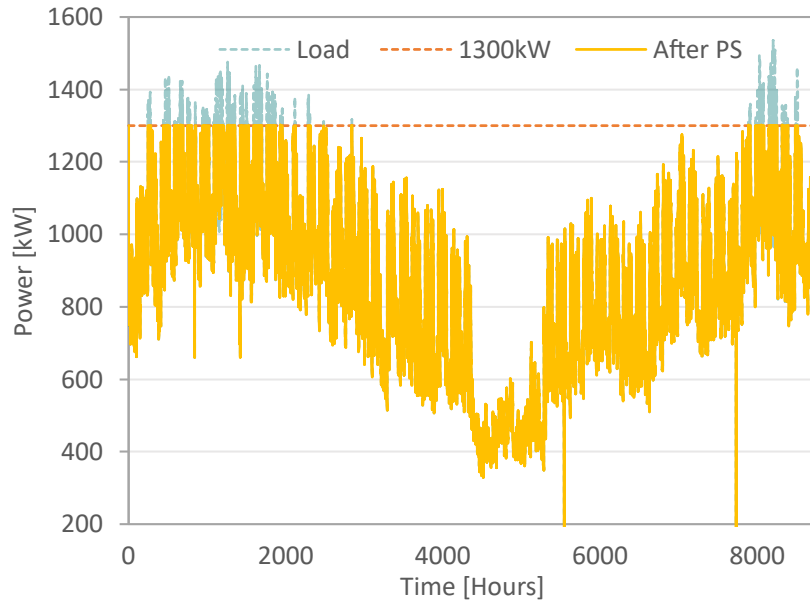
#### 4.1.2 Case 2: 1300 kW Threshold

Case 2 marks the initial active utilization of the BESS. As detailed in Section 3.3.2, the load in Husøy is managed to stay below **1300 kW** in this scenario. The BESS supplies energy whenever the load surpasses this threshold. The outcomes of this simulation, spanning an entire year, are depicted in Figure 4.2. It illustrates the load levels both before and after the implementation of peak-shaving.

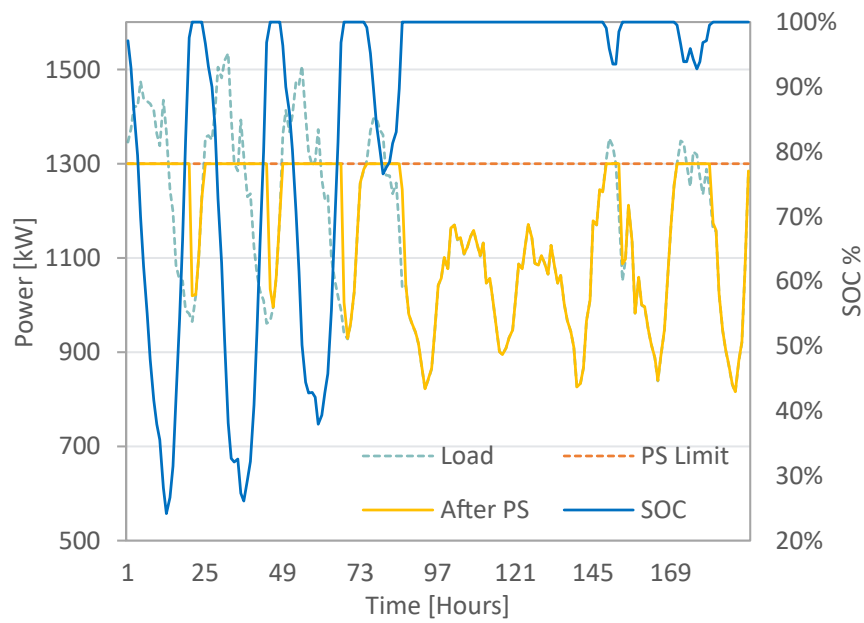
Evidently, the simulation results confirm that the load consistently remains below 1300 kW throughout the entire simulation period. To provide a detailed real-time analysis of the BESS operation, Figures 4.3 and 4.4 were generated, depicting a reference week from 07/12/2021 to 15/12/2021 and the highest load day in the year (08/12/2021), respectively, in Case 2. This visualization not only illustrates the load levels before and after peak-shaving but also includes the SOC of the battery. These additional figures reveal the charging and discharging patterns, showcasing how the battery efficiently manages the electricity demand spikes even during the day with the highest load of the year. In this specific week, the BESS effectively transforms sharp increases in electricity demand into a stable, flat period.

Moving forward in the analysis of this case, the next aspect under investigation is the degradation of the BESS following a year of this specific operational use.

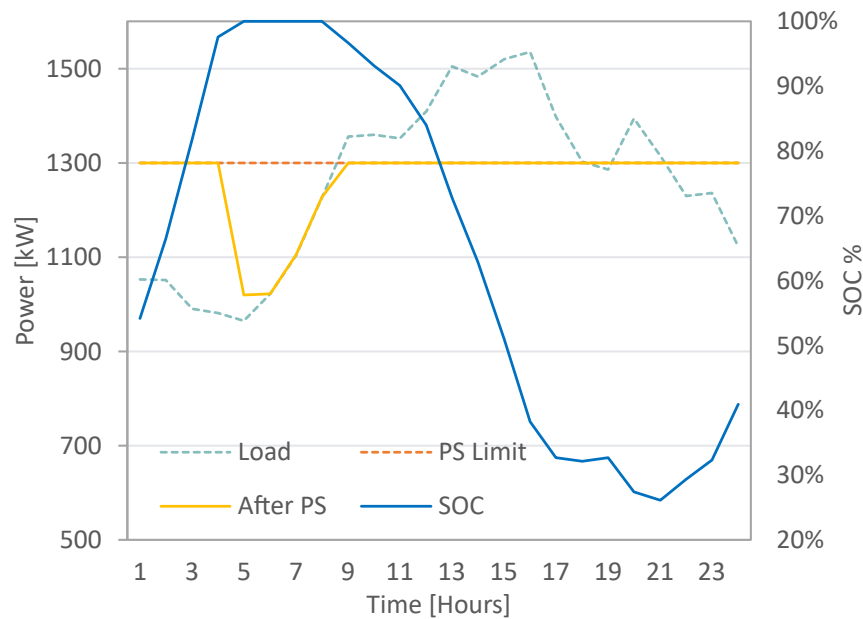




**Figure 4.2:** Yearly load before and after peak-shaving (PS) in Case 2.



**Figure 4.3:** BESS operation in reference week (07/12/2021 - 15/12/2021) in Case 2.



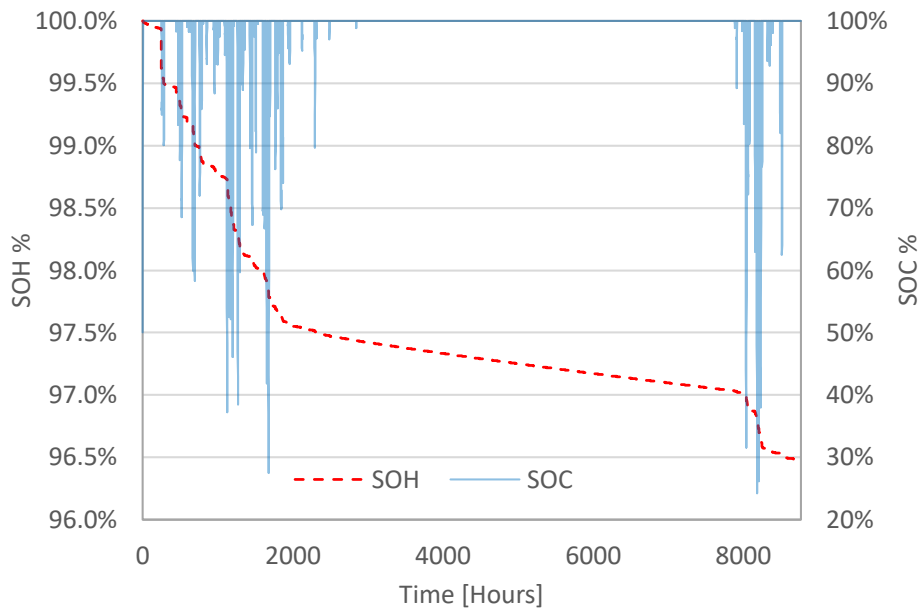
**Figure 4.4:** BESS operation in the day with the highest load in 2021 (08/12/2021) in Case 2.

Figure 4.5 couples the SOH of the battery with its SOC, effectively highlighting periods of utilization. This visualization illustrates that during the periods when the battery is actively charging and discharging, the SOH experiences a more rapid decline. This accelerated degradation can be attributed to cyclic factors. In contrast, during periods of lower demand when the BESS remains idle, the SOH decreases at a significantly slower rate, primarily due to calendric degradation.

One important finding of this simulation is that after one year of use under this specific operation, the SOH percentage loss is **3.53%**. Also, in this whole year, the battery never discharged under **24,22%**. This indicates that there was available energy for an even lower peak-shaving limit.

### 4.1.3 Case 3: 1250 kW Threshold

In Case 3, the peak-shaving limit was lowered to 1250 kW, reducing it by 50 kW compared to Case 2. The primary purpose of this simulation was twofold. Firstly, it aimed to assess how the additional stress placed on the battery impacts the system's reliability, specifically regarding the adequacy of the BESS size to consistently keep the load below this new limit. Secondly, it sought to understand the result that this extra stress caused to the SOH of the battery.

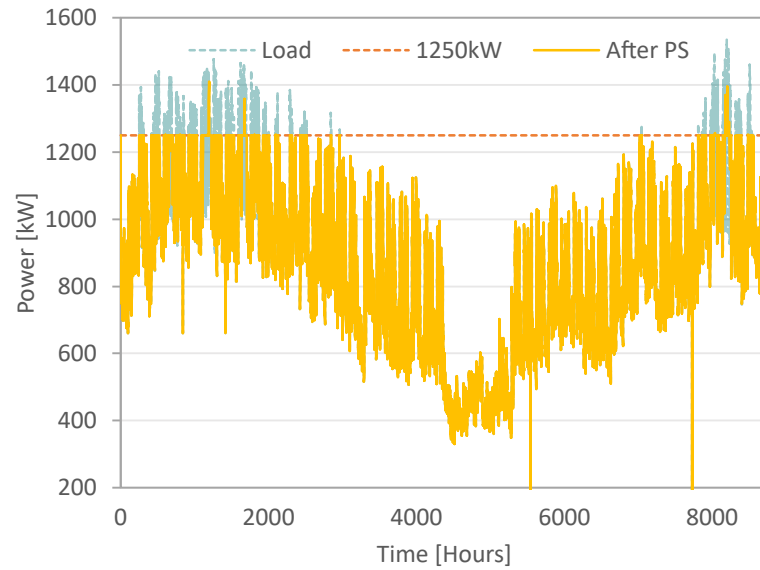


**Figure 4.5:** Degradation of the BESS in Case 2.

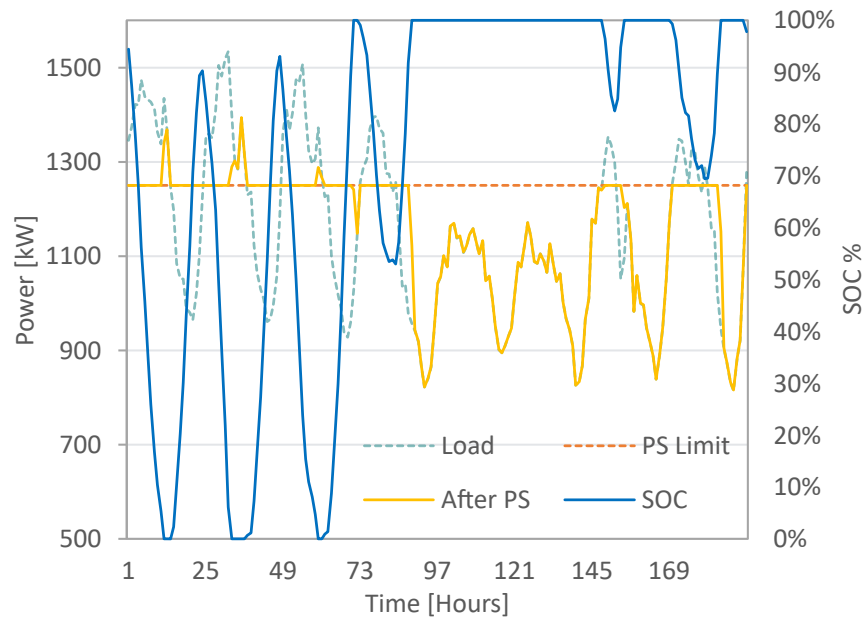
Based on the results, in Figure 4.6 it appears that the operation strategy is generally reliable in terms of keeping the load below 1250 kW. However, there were a few periods where the BESS could not keep the load below the desired level, with the highest load being **1408.29 kW**. In Figures 4.7 and 4.8, the reference week 07/12/2021 - 15/12/2021 and the day with the highest load of the year are depicted. In Figure 4.8, it can be seen how in the 18th hour, the SOC of the BESS is down to 0%, and as a result, a spike of **1394.07 kW** in the load is allowed. However, it is important to mention that the new spike is significantly lower (**140.77 kW** lower) than the original spike during that day if the BESS is not utilized. Looking at the battery's health decline due to this operation, Figure 4.9 illustrates a similar decrease in SOH for Case 3 as in Case 2. However, in Case 3, the loss of SOH of the battery is **4.89%**, 1.45% higher than that in Case 2. This means that by lowering the peak-shaving limit by 50 kW, the battery experienced **1.45%** more degradation.

#### 4.1.4 Case 4: Monthly Adapted Threshold

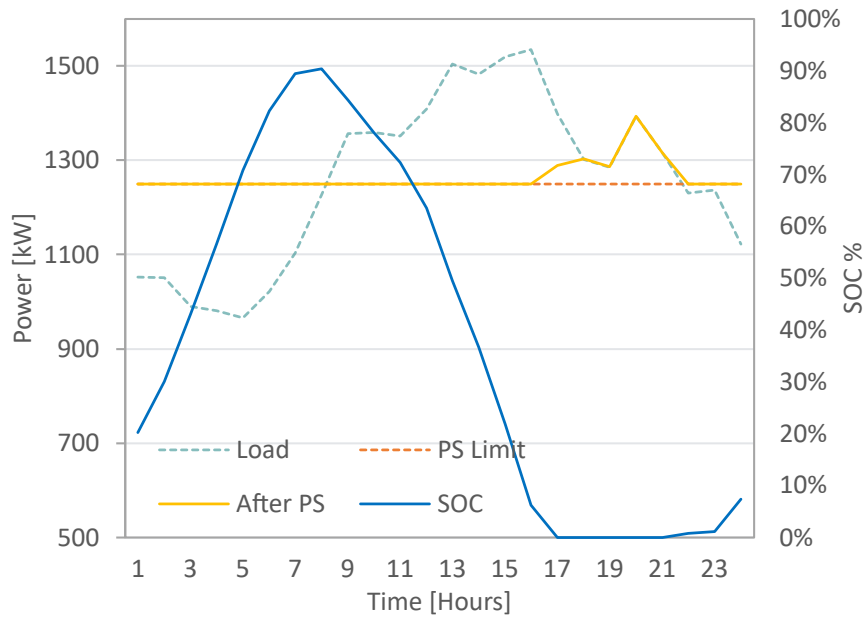
In Case 4, the limit for peak-shaving in each month is determined from Figure 3.3 and Table 3.2. The monthly peak values from this graph serve as the upper threshold. The BESS supplies power to the grid whenever the demand surpasses this limit. From Table 3.2, the highest peak-shaving limit is 1341.72 kW. In this operation, the BESS is active for most part of the year, with the exemption of



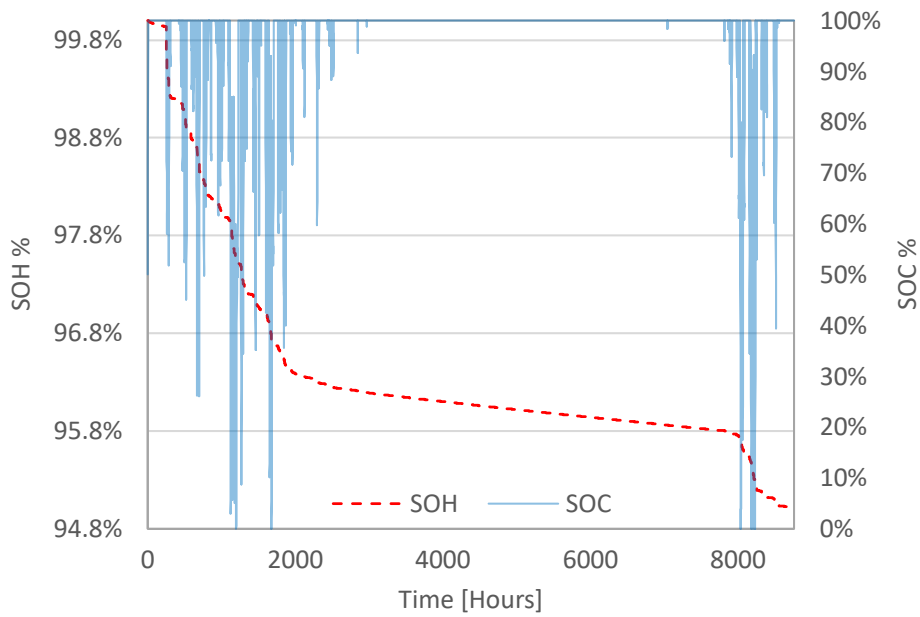
**Figure 4.6:** Yearly load before and after peak-shaving (PS) in Case 3.



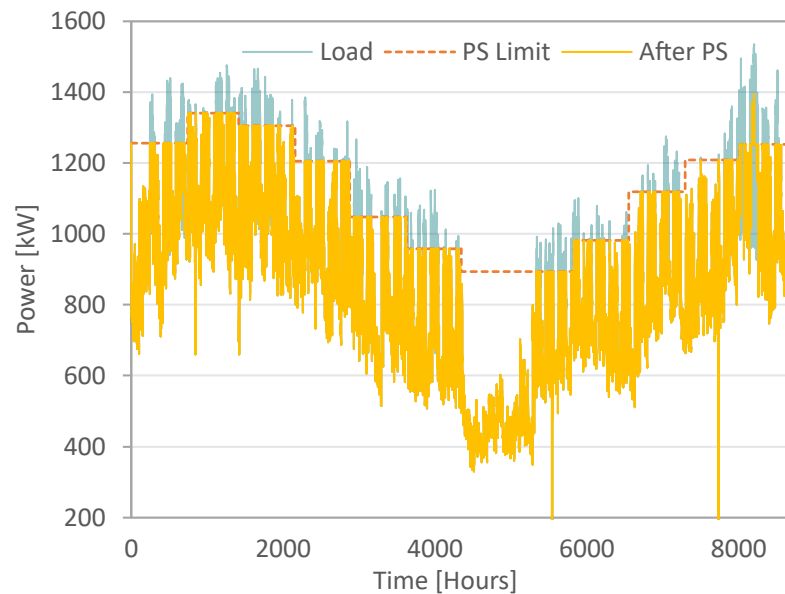
**Figure 4.7:** BESS operation in reference week (07/12/2021 - 15/12/2021) in Case 3.



**Figure 4.8:** BESS operation in the day with the highest load in 2021 (08/12/2021) in Case 3.



**Figure 4.9:** Degradation of the BESS in Case 3.



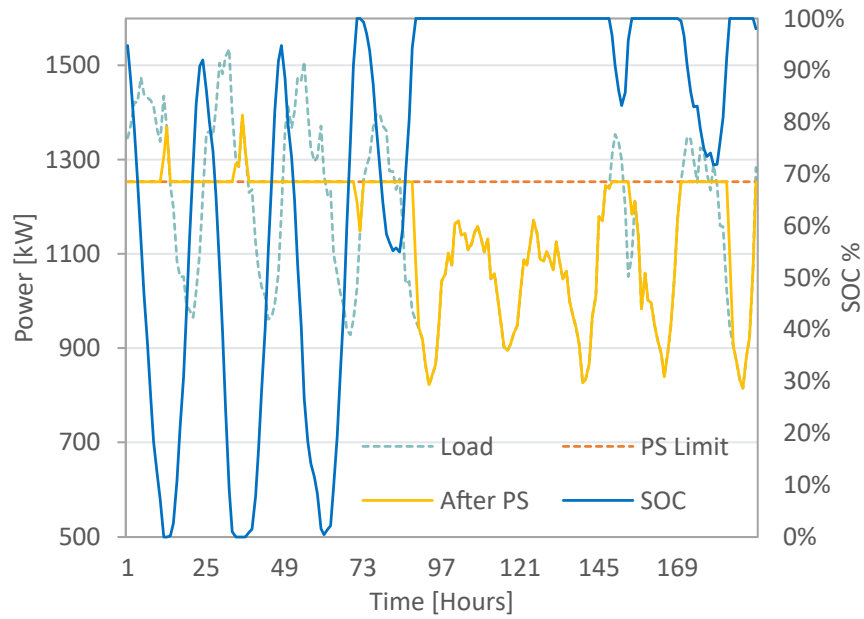
**Figure 4.10:** Yearly load before and after peak-shaving (PS) in Case 4.

the period between mid-June and the end of July. Figure 4.10 provides a visual representation of the yearly load both before and after implementing peak-shaving with the BESS. It shows that the BESS reduces the load every month according to the peak-shaving limits with few exemptions, and except during the summer months when demand is low when the battery is deliberately being kept inactive.

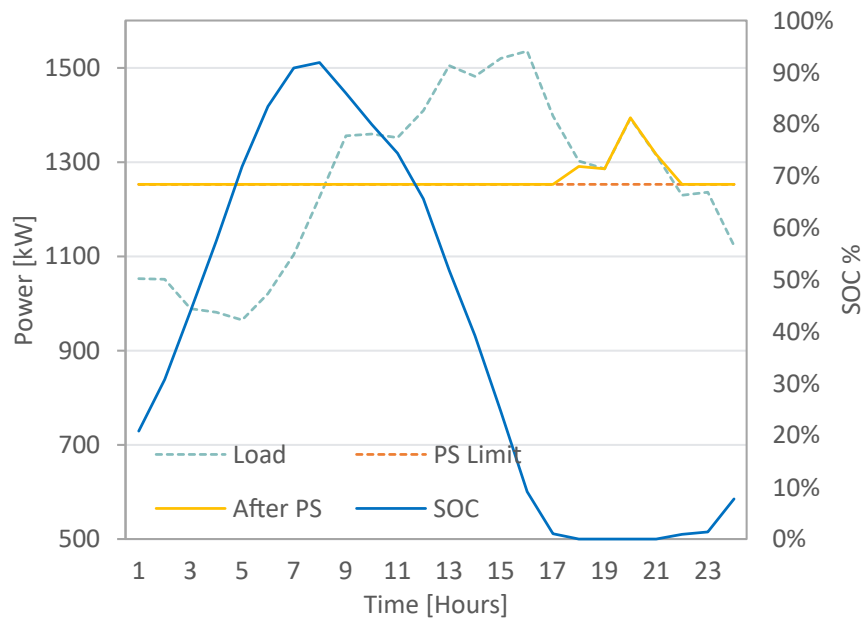
Just like in the previous cases, the same reference week and the day with the highest load of the year are illustrated in Figures 4.11 and 4.12. Specifically, in Figure 4.12, it can be seen how during that day, the BESS is not holding the peak-shaving limit, for which in this month was **1253.5 kW**, after discharging down to **0%** allowing for a spike in the load of **1394.07 kW** (the highest during this case). Figure 4.13 outlines the projected degradation of the BESS in Case 4. By the end of the simulation, the loss in SOH of the battery is **4.89%**.

## 4.2 Summary and Comparison

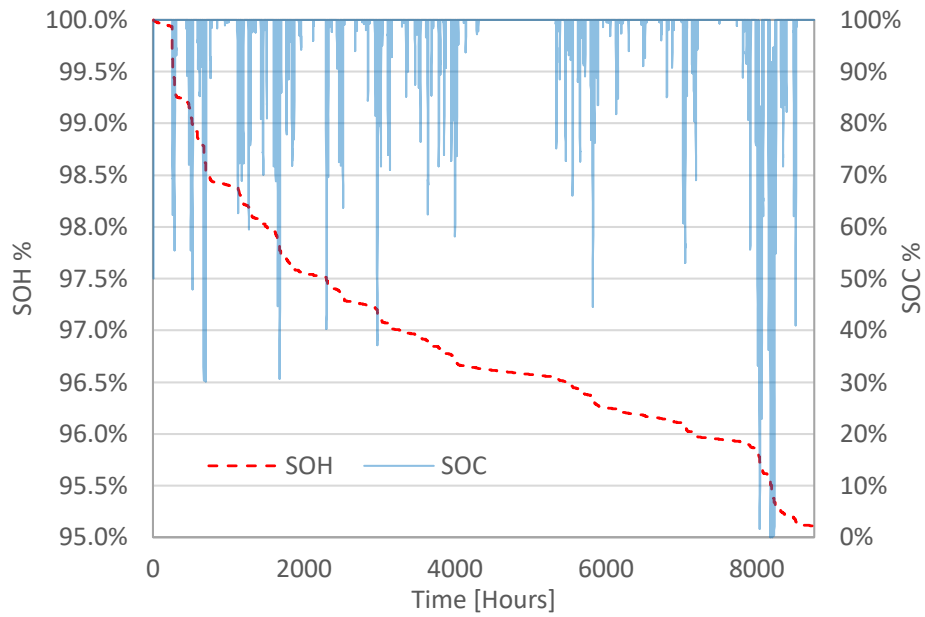
The idea behind every simulation case was explained in Subsection 3.3.2. In this Section, a summary and a comparison of the four cases is presented. Figure 4.14, shows how the BESS's SOH declined over the one year of simulation in each case. In Table 4.1 the exact SOH loss for every case can be seen, as well as



**Figure 4.11:** BESS operation in reference week (07/12/2021 - 15/12/2021) in Case 4.



**Figure 4.12:** BESS operation in the day with the highest load in 2021 (08/12/2021) in Case 4.



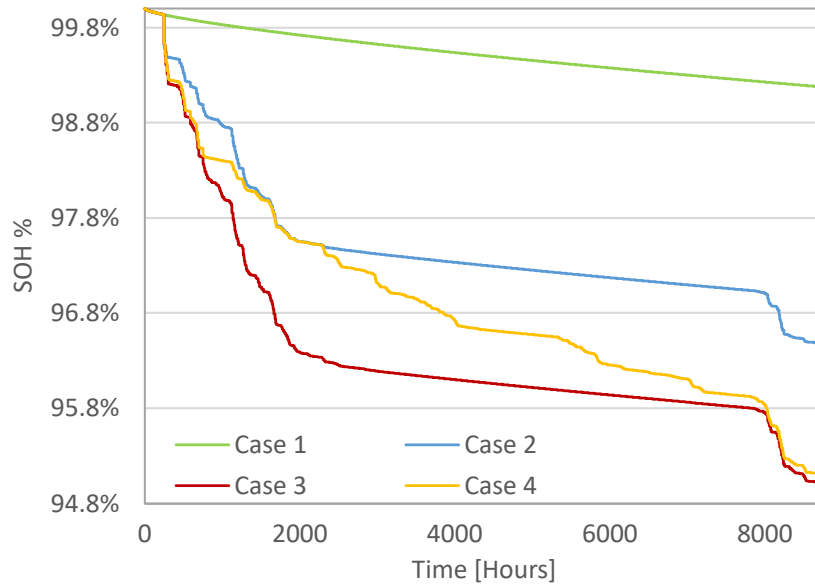
**Figure 4.13:** Degradation of the BESS in Case 4.

**Table 4.1:** SOH % loss, equivalent full cycles, maximum load, number of events above peak limit and SOC range for Cases 1-4.

Case	SOH loss	Equivalent Full Cycles	Max Load (kW)	SOC range (%)
Case 1	0.82%	0.5	1534.84	50-100
Case 2	3.53%	16	1300	24.22-100
Case 3	4.98%	30.26	1408	0-100
Case 4	4.89%	32.88	1394.07	0-100

some other values like the equivalent full cycles that the battery spent across its operation, the maximum load that was allowed during each operation, as well as the SOC range that the battery charged and discharged to during the year in each case. The highest SOH loss was achieved in Case 3 (**4.98%**), the most equivalent full cycles were achieved in Case 4 (**32.88 cycles**), the lowest maximum load was during Case 2 (**1300 kW**) and the highest maximum load during Case 1 (**1534 kW**). The widest range of SOC was during Case 3 and 4 (**0-100%**).





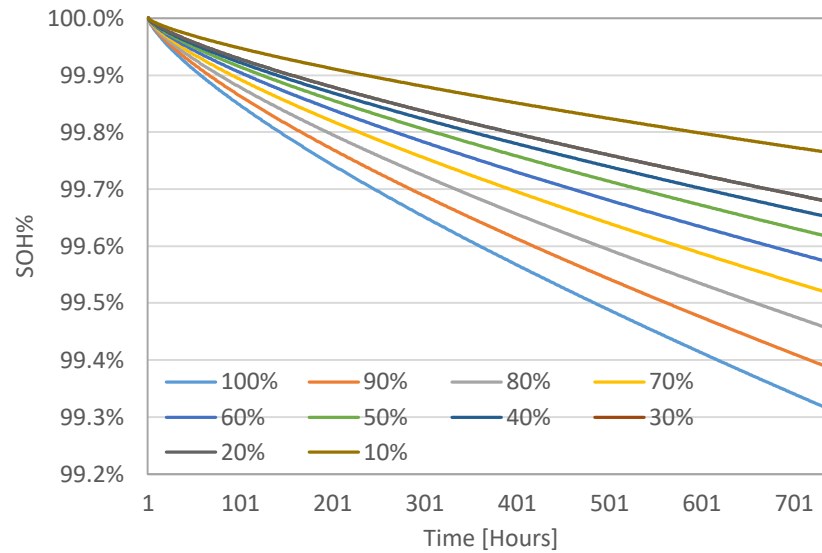
**Figure 4.14:** Degradation of the BESS in all four cases.

**Table 4.2:** Lifetime expectancy for Cases 2,3 and 4.

Case	Case 2	Case 3	Case 4
<b>Lifetime</b>	8.49 years	6.02 years	6.13 years

### 4.3 BESS Lifetime Estimation

The simulations conducted in four distinct scenarios revealed varying SOH losses in the BESS. As discussed in Subsection 3.3.1, a SOH percentage between 70-80% is commonly regarded as the end of life for a BESS. In this analysis, the threshold marking the end of life for the system was set to 70% SOH. Using this criterion, the expected lifespan for each relevant case was calculated. The outcome of this calculation is presented in Table 4.2. Operating the BESS as in Case 2, the system would need to be replaced after **9.43 years**, in Case 3, after **6.81 years**, and in Case 4, after **6.89 years**.



**Figure 4.15:** BESS degradation for resting at different SOC % and constant 5°C over a month.

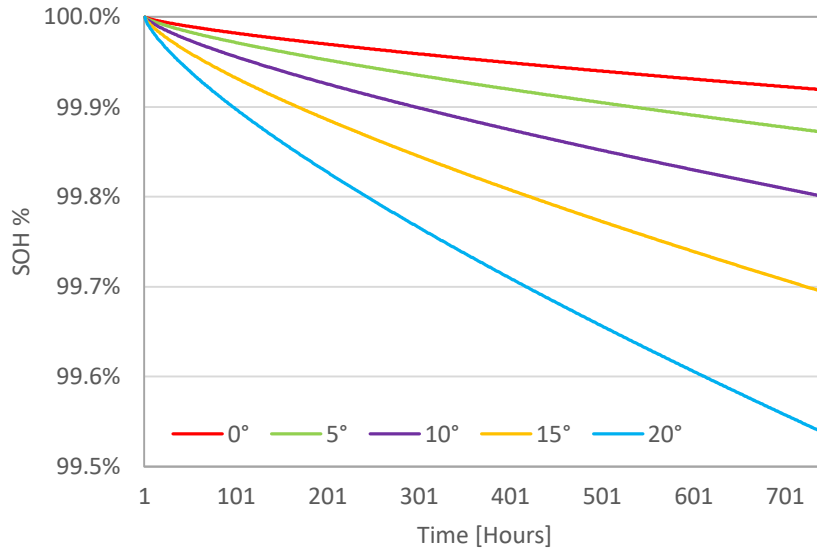
## 4.4 Extra Simulation Cases

### 4.4.1 Various Resting SOC

In this section, the outcomes of simulations conducted at different SOC levels are presented, illustrating how this factor influences battery degradation while the battery is at rest. Figure 4.15 displays the results of ten separate month-long simulations, each performed at a distinct SOC level. Interestingly, the findings indicate that the battery experiences less degradation when it is resting at lower SOC levels.

### 4.4.2 Various Resting Temperature

The next focus was on understanding how temperature impacts battery degradation. To investigate this, five separate monthly simulations were conducted, each at a different resting temperature for the battery. Figure 4.16 presents these results, showing a clear trend: the higher the resting temperature, starting from 0°, the more degradation the battery undergoes.



**Figure 4.16:** BESS degradation for resting at different temperatures and 100% SOC over a month.

**Table 4.3:** SOH loss in different battery cells.

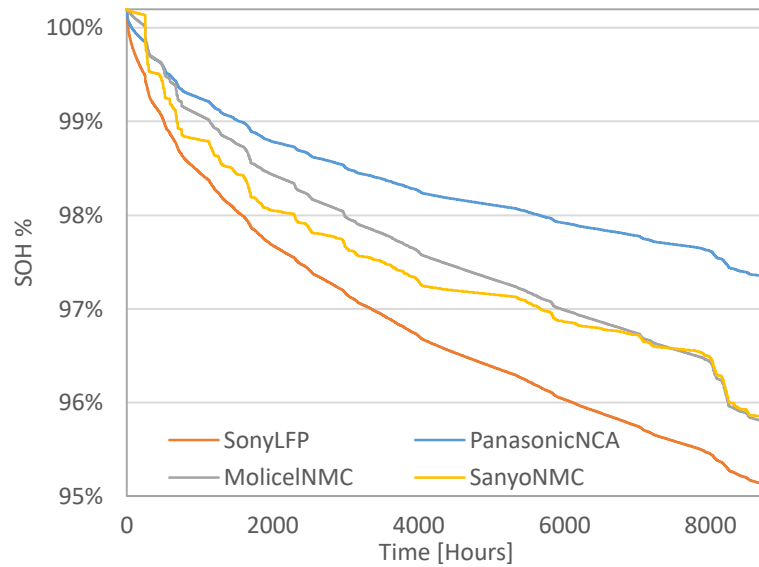
Cell	SanyoNMC	PanasonicNCA	MolicelNMC	SonyLFP
SOH loss	4.89%	2.97%	4.41%	5.08%

### 4.4.3 Different Battery Technologies

In Subsection 2.2.3, it was discussed how Li-ion batteries come in various types based on the structures of their anodes and cathodes, as well as the materials used in them. There, some of the most used chemistries were introduced, which are also listed in SimSES. Those are NMC, NCA, and LFP. To see how those different technologies affect the loss in SOH of the BESS, Case 4 was re-simulated, but every time using a different cell type. The ones that were used are PanasonicNCA, MolicelNMC and SonyLFP.

In Figure 4.17, the results from those simulations are presented, including the original Case 4 simulation with the SanyoNMC cell and in Table 4.3 the exact values of SOH loss of every cell. From the four different cells, the one that had the least SOH loss, is PanasonicNCA, with a **2.97%** loss. SonyLFP had the highest loss of **5.08%**. MolicelNMC was pretty close to SanyoNMC with a **4.41%** loss.

Using the specific losses observed in different technologies, the anticipated



**Figure 4.17:** BESS degradation in Cases 4 for various technologies.

**Table 4.4:** Lifetime expectancy of cells SanyoNMC, PanasonicNCA, MoliceINMC and SonyLFP under Case 4.

Cell	SanyoNMC	PanasonicNCA	MoliceINMC	SonyLFP
<b>Lifetime</b>	6.13 years	10.10 years	6.8 years	5.9 years

lifespan of each technology was calculated. This calculation was based on considering a SOH of 70% as the threshold indicating the end of the system's operational life. Using SanyoNMC, the expected replacement would be needed in **6.89 years**, using PanasonicNCA, in **10.48 years**, using MoliceINMC, in **7.42 years** and using SonyLFP, in **5.96 years**.

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## Discussion

The results of this research provide valuable perspectives on how BESS function and deteriorate within the context of Husøy, in Northern Senja, Norway. The study primarily addressed the significant problem of voltage quality and capacity saturation on the island, which has arisen due to the rapid growth of the fishing industry. This underlines the critical requirement for stable energy solutions. The research had a particular focus on delving into the details of BESS operation strategies, notably peak-shaving. This strategy was analyzed not only for its potential to alleviate high energy demand periods and enhance overall grid reliability but also to gather essential information on system degradation.

In this section, the simulation outcomes will be discussed from two distinct angles: firstly, the operational aspects under what was termed "**Operational Analysis**", where it will be analyzed how the BESS managed the load in Husøy across the simulation scenarios. Secondly, the degradation perspective will be explored in a section labeled "**Degradation Analysis**" focusing on the results related to the BESS's deterioration throughout the simulation cases. Lastly, the study's limitations will be discussed, focusing on how the chosen methodology influenced the simulation results and exploring potential alternative approaches for future research.

## 5.1 Operational Analysis

### 5.1.1 Exploring Stress Factors in Load Management (Case 2 and 3)

In all scenarios, except for Case 1 in which the BESS was not utilized, the focus was on simulating peak-shaving operations. The primary objective was to assess the system's capability to reduce peak loads during high-demand periods in Husøy.

**Case 2** marked the initial attempt to set a peak-shaving limit at **1300 kW**, allowing the BESS to maintain the load below this threshold at all times. The results demonstrated the BESS's effectiveness in consistently keeping the load within the desired limits, with a minimum discharge level of **24.22%**. This indicated the system's potential to manage peak loads even when the limit was set lower than the original target.

Subsequently, in **Case 3**, the peak-shaving limit was further reduced to **1250 kW** to observe its impact on the BESS's ability to control the load below this specified level. The outcomes revealed that, for the most part, the BESS successfully maintained the load within this limit. However, there were a few instances where the system fell short, resulting in a peak load of **1408 kW**. This was 108 kW higher than Case 2 and exceeded the designated peak-shaving limit by 158 kW. These breaches occurred during prolonged periods of high load, highlighting the challenges faced by the BESS in managing continuous high-demand days. Insufficient charging during these periods led to the BESS's inability to handle some peak loads effectively. This underscores the need for precise management of the system and emphasizes the importance of accurate forecasting to anticipate prolonged periods of high load. Adequate SOC preparation is essential to ensure the BESS can effectively handle peak loads and maintain operational efficiency.

Implementing a flexible charging strategy that considers historical load patterns and upcoming weather conditions could significantly enhance the performance of the BESS. For instance, utilizing advanced analytics, such as machine learning algorithms, to analyze past consumption trends could enable precise anticipation of when the BESS should undergo more intensive charging. This adaptable approach ensures that the BESS remains adequately charged during expected high-demand periods, reducing the chances of exceeding the designated peak-shaving limits. Additionally, establishing a reliable communication system between the BESS and the energy management platform enables seamless adjustments in charging patterns based on evolving load scenarios. Through the integration of these measures, the BESS could effectively tackle the challenges associated with continuous high-demand days, thereby optimizing

peak load management and maintaining operational efficiency.

### 5.1.2 Adaptive Monthly Peak-Shaving (Case 4)

In the analysis of Husøy's electricity load presented in Section 3.2, a noticeable seasonal variation in demand was observed throughout the year. This variation was attributed to the active industrial operations during winter months and the prolonged periods of low temperatures, which increased the demand for electricity-powered heating. Considering this fluctuation, it became evident that setting a stable peak-shaving limit for the entire year, as done in Cases 2 and 3, might not be the most efficient approach. Recognizing this, it was proposed to adjust the peak-shaving limit based on the specific electricity demand of each month. This adaptive approach could optimize the BESS utilization, ensuring it operates efficiently during periods of both high and low demand. During months with low electricity demand, employing the BESS for peak-shaving could potentially reduce costs, enhancing the financial viability of the investment. However, the feasibility of this strategy also depended on the system's degradation, a topic explored in Section 5.2.

The simulation referred to as **Case 4**, provided insights into the BESS's year-round operation and degradation, allowing for a comparison with earlier cases where a fixed peak-shaving limit was applied throughout the year. The outcomes of **Case 4** illustrated the BESS's performance for the majority of the year, excluding two summer months with very low demand. The peak-shaving limit peaked at **1341.72 kW** in February, and the BESS effectively maintained the load below this threshold. Another interesting period was during the day with the highest load of the year in which the grid load without BESS, was **1534.85 kW**. The designated peak-shaving limit for the month that included this day was **1253.50 kW**, in which the BESS did not manage to keep the load below this, but still reduced it down to **1394.07 kW**. This showed, that even though the peak-shaving limit might not be kept during a certain period, it still substantially reduces the load of that period.

Case 4 describes a more realistic and adaptable strategy for the operation of the BESS in Husøy, as it suggests a flexible approach by adjusting the peak-shaving limit based on the specific electricity demand of each month. This strategy recognizes and responds to the observed seasonal variations in demand, taking into consideration the influence of factors such as active industrial operations and temperature fluctuations. By adjusting the peak-shaving limit to the unique characteristics of each month, Case 4 demonstrates an ability to optimize BESS operation in a way that is reflective of real-world, month-to-month fluctuations in electricity demand. This adaptability ensures that the BESS is responsive to varying demands and able to deliver peak load management more effectively

throughout the year.

## 5.2 Degradation Analysis

### 5.2.1 Significance of Minimal Degradation (Case 1)

In the simulations, it was observed that the battery system's SOH declined most significantly when the BESS actively supplied power to the grid, a phenomenon referred to as cyclic degradation. This degradation occurs due to multiple charging and discharging cycles. However, this isn't the sole factor contributing to the battery's declining SOH, as evidenced in Case 1. In this scenario, where the BESS remained idle throughout the simulation and was not utilized to support the grid, thus avoiding cyclic degradation, it still experienced a **0.82%** decline in SOH, primarily due to calendric degradation.

Although this decline might appear minor, it underscores the importance of monitoring even subtle degradation. These seemingly small changes might have implications for the battery's long-term performance and life expectancy.

### 5.2.2 Additional Stress Assessment (Case 2 and 3)

Cases 2 and 3 were designed with the specific intention of comparing the outcomes resulting from a 50 kW reduction in the peak-shaving limit, both operationally and in terms of degradation. While the operational impacts of this alteration were previously discussed, this discussion will focus on its effects on degradation.

In Case 2, with a 1300 kW peak-shaving limit, there was a **3.53%** decline in SOH over one year. Case 3, with a 1250 kW limit, experienced a **4.98%** SOH reduction in the same timeframe. This indicates an additional **1.45%** SOH loss for just a 50 kW reduction in the limit. This increased degradation in Case 3 could be attributed to the battery discharging to lower SOC levels in pursuit of keeping the load within the desired level, indicating higher DOD, a known factor leading to higher degradation.

The observed difference in SOH degradation between Cases 2 and 3 underscores the important role of peak-shaving limit selection in influencing battery performance. The 1.45% additional SOH loss in Case 3, resulting from a 50 kW reduction in the peak-shaving limit, emphasizes the intricate balance required in setting operational parameters for the BESS. The increased degradation in Case 3, attributed to the battery discharging to lower SOC levels to meet the



more strict limit, shows the impact of higher DOD on degradation. This insight serves as a valuable consideration for BESS users, urging a cautious and well-informed approach when making adjustments to peak-shaving limits. These findings highlight the need for a careful assessment of the trade-offs between load management objectives and the long-term health of the battery.

### 5.2.3 Longer vs Deeper Use (Case 3 and 4)

The key distinction between Cases 2,3 and 4 lies in their approach to the peak-shaving limit. Case 2 and 3 maintained a fixed limit throughout the simulation, while Case 4 adjusted the limit monthly based on maximum average peaks. Case 4's strategy allowed the BESS to be utilized over a more extended period, including months with lower demand, whereas Case 2 and 3 restricted BESS usage to high-demand months only.

Despite the differences in utilization periods, both strategies generally achieved their respective peak-shaving goals with few periods as exemptions. Surprisingly, Case 3, which operated only during high-demand months, experienced a **4.98%** SOH loss, slightly higher than Case 4's **4.89%** loss. This outcome was influenced by the higher DOD during Case 3, as discussed in 5.2.2.

This finding highlights a crucial dilemma: whether to use the BESS for shorter duration, achieving higher load reduction during high-demand months, or for longer periods, resulting in reduced load reduction throughout the year. It underscores the trade-off between short bursts of intensive usage and prolonged, moderate utilization of the BESS. This trade-off could be further investigated with the use of decision support system tools based on mathematical optimization, in order to achieve an optimal trade-off balance between those two strategies.

### 5.2.4 Exploring Environmental Factors and Idle State Parameters

In addition to the primary simulation scenarios, two additional simulations were conducted to explore the impact of SOC levels and temperature on the SOH of the battery during idle states. Throughout the main simulations, varying rates of SOH decline were observed during charging, discharging, and resting, known as cyclic and calendric degradation, respectively. In Subsection 2.4.2, it was highlighted how different SOC levels and temperatures influence the battery's SOH. To further investigate these factors, two sets of simulations were designed: one where the battery remained idle at different SOC levels and another where it remained idle at different temperatures. This allowed

to assess the specific effects of SOC levels and temperature on the battery's SOH.

### **Significance of Resting SOC**

In the first set of simulations involving different SOC levels, the role of resting SOC levels in battery degradation was highlighted. It became evident that maintaining lower SOC levels during idle periods substantially decreased degradation. This finding implies that deliberately keeping the battery at lower SOC levels during inactive phases could extend its lifespan and improve overall system efficiency. This insight holds significant value for industries utilizing BESS, suggesting a strategy of controlling SOC levels to remain lower during periods when the BESS is intentionally inactive.

In Cases 2 and 3, a substantial duration exists during which the electricity load does not surpass 1300 kW and 1250 kW, the peak-shaving limits for the two cases respectively. During these extended periods, the BESS could potentially be in a resting state with a lower SOC level, thereby minimizing the resultant degradation. It's noteworthy that in the simulations, the BESS was maintained at 100% SOC, as this was the level at which it was last charged. However, considering the infrequency of load surpassing the peak-shaving thresholds during these periods, a more strategic approach involving a lower resting SOC could be explored to extend the BESS's operational lifespan.

### **Significance of Resting Temperature**

During the second set of simulations exploring various resting temperatures for the BESS, a clear trend emerged: higher resting temperatures were directly associated with accelerated degradation rates. This highlights the crucial necessity for efficient thermal management strategies, such as active cooling or insulation, especially in areas prone to temperature fluctuations. Implementing these measures to counteract heat-induced degradation is essential to ensure the durability and reliability of BESS, particularly in environments characterized by elevated temperatures.

Notably, Husøy experiences cold temperatures for the majority of the year, which favors the BESS's performance and longevity. However, during summer, temperatures can significantly rise, making it vital to carefully regulate the BESS's exposure temperature.

### 5.2.5 Impact of Different Battery Technologies

Various chemistries of lithium-ion battery storage were explored, as detailed in Subsection 2.2.3. Using the SimSES simulation tool, the impact of those technologies on the battery's SOH was assessed in Case 4. Specifically, the technologies that were utilized were SanyoNMC, MolicelNMC, SonyLFP, and PanasonicNCA cells. Among these, PanasonicNCA exhibited the least SOH loss, standing at **2.97%**.

This observation raises important questions about the choice of technology for Husøy's current usage of NMC. It prompts consideration of whether NMC is the optimal choice for the BESS in Husøy, or if alternative technologies like NCA should be explored further.

## 5.3 Study Limitations

While this study provides valuable insights into the behavior of BESS under various conditions, several limitations need to be acknowledged, which may have affected the accuracy of the findings.

### Temporal Resolution

One significant limitation of the simulations is the use of hourly data. The hourly resolution might not capture the small variations in energy storage and discharge patterns and most likely has impacted the overall aging of the system. Future research could benefit from employing higher temporal resolutions, such as minutes, to obtain more precise and detailed results, thus enhancing the accuracy of the simulations.

### Full capacity utilization

During the simulations, the peak-shaving strategy made full use of the entire BESS capacity to ensure maximum energy availability for load reduction. However, in practice, it is uncommon to utilize the entire battery capacity for a single operation. Thus, in a more realistic scenario, the battery would be used for coupling different operational strategies at the same time.

### **Simplified Thermal Modeling**

The thermal modeling assumed a constant ambient temperature of 5° Celsius and a stable internal temperature maintained by the HVAC system. In reality, temperature fluctuations occur throughout the year, impacting the BESS performance. Utilizing a temperature profile specific to the location could offer a more realistic simulation of thermal conditions, leading to a more accurate representation of the system's degradation patterns.

### **Depth of Discharge (DOD) Range**

In the simulations, a 100% DOD range was considered, allowing the battery to charge up to 100% and discharge down to 0%. This scenario, while advantageous for peak-shaving, may not reflect real-world constraints. Tighter DOD ranges, such as 10% to 90%, are often implemented to prolong battery life. Implementing a more realistic DOD range would yield different load reduction outcomes, potentially lowering the efficacy of the system in certain cases.

### **Degradation Model Variability**

The degradation model utilized in this study was based on the SanyoNMC cell type, which may not precisely match the NMC cells used in the Husøy system. Differences between these cell types could lead to variations in SOH degradation rates. Therefore, the results obtained in the simulations might not perfectly align with the actual degradation patterns of the BESS in Husøy.

### **Lack of Real-World Constraints**

The simulations did not consider real-world constraints and limitations, such as maintenance activities, system failures, or unexpected events. These factors can significantly impact the performance and longevity of BESS in practical applications. Including these constraints in future studies would provide a more comprehensive understanding of the system's behavior under diverse conditions.

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## Conclusion and Further Work

In conclusion, this work provides important insights into the operational strategies and degradation patterns of BESS in the context of Husøy, Northern Senja, Norway. Considering the critical issue of voltage fluctuations resulting from the rapid growth of the fishing industry, this study analyzed peak-shaving as a possible solution to the existing challenges. Through detailed simulations and analyses, various operational scenarios, peak-shaving limits, adaptive strategies, and degradation factors were explored, gaining knowledge regarding the complex dynamics of BESS.

The operational analyses revealed the effectiveness of BESS in managing peak loads, even during days with the highest load. Notably, different peak-shaving thresholds impacted the system's reliability in terms of keeping the load below those limits. Even small adjustments, such as 50 kW, to this threshold, led to significant increases in the load that was allowed. Precise management, accurate forecasting, and adequate SOC preparation emerged as important factors in ensuring BESS's ability to handle high-demand periods, underlining the importance of these considerations in real-world applications. By dynamically adjusting the peak-shaving limit according to the specific electricity demand of each month, the suggested approach extended the usability of the BESS. This allowed the BESS to respond to seasonal variations in electricity demand, accounting for factors such as active industrial operations and temperature

fluctuations.

The degradation analyses demonstrated the complex nature of BESS degradation, considering cyclic and calendric degradation, and the influence of various stress and environmental factors. Even minor adjustments to the peak-shaving limit significantly impacted the BESS degradation. Two almost identical cases with a 50 kW difference in the peak-shaving limit had a substantial difference in SOH decline. By comparing stable and adaptive peak-shaving thresholds, an important trade-off between short bursts of intensive usage and prolonged, moderate utilization of the BESS, was identified. Additionally, the choice of technology and careful management of SOC levels and resting temperatures were identified as important determinants of the BESS's longevity.

This study has offered valuable insights into BESS degradation and operation. However, there are several areas that require further research to bridge the gap between theoretical understanding and practical application. Also, the focus of this study was more on operational management strategies assuming a given system, rather than on investment decision-making. With this in mind, future work could involve:

- A detailed economic analysis to assess the cost-effectiveness of implementing different BESS strategies, considering factors such as initial investment, operational costs, and potential revenue from peak-shaving.
- Optimal sizing of the BESS for peak-shaving operation.
- Analysing more operational strategies with SimSES, like Frequency Containment Reserve, Intraday Continuous Market, etc.
- Analysing a more comprehensive model that would use a combination of different battery services as well as analyzing their effect on voltage quality.
- Implement the most promising BESS strategies identified in this research in real-world scenarios on Husøy, monitoring their performance, degradation patterns, and economic viability over an extended period to validate the simulation outcomes.



## Acronyms

**BESS** Battery Energy Storage System

**SOC** State of Charge

**SOH** State of Health

**DOD** Depth of Discharge

**HVAC** Heating, Ventilation, Air Conditioning

**PS** Peak Shaving

**Li-ion** Lithium Ion

**LFP** Lithium Iron Phosphate

**NMC** Lithium Nickel Manganese Cobalt Oxide

**NCA** Lithium Nickel Cobalt Aluminum Oxide

**DSO** Distribution System Operator





# Bibliography

- [1] Daniele Groppi et al. “A review on energy storage and demand side management solutions in smart energy islands.” In: *Renewable and Sustainable Energy Reviews* 135 (2021), p. 110183. ISSN: 1364-0321. DOI: <https://doi.org/10.1016/j.rser.2020.110183>. URL: <https://www.sciencedirect.com/science/article/pii/S1364032120304731>.
- [2] Odin Foldvik Eikeland et al. “Uncovering Contributing Factors to Interruptions in the Power Grid: An Arctic Case.” In: *Energies* 15.1 (2022). ISSN: 1996-1073. DOI: 10.3390/en15010305. URL: <https://www.mdpi.com/1996-1073/15/1/305>.
- [3] Omid Palizban and Kimmo Kauhaniemi. “Energy storage systems in modern grids—Matrix of technologies and applications.” In: *Journal of Energy Storage* 6 (2016), pp. 248–259. ISSN: 2352-152X. DOI: <https://doi.org/10.1016/j.est.2016.02.001>. URL: <https://www.sciencedirect.com/science/article/pii/S2352152X1630010X>.
- [4] Abraham Alem Kebede et al. “A comprehensive review of stationary energy storage devices for large scale renewable energy sources grid integration.” In: *Renewable and Sustainable Energy Reviews* 159 (2022), p. 112213. ISSN: 1364-0321. DOI: <https://doi.org/10.1016/j.rser.2022.112213>. URL: <https://www.sciencedirect.com/science/article/pii/S1364032122001368>.
- [5] M. Mahesh et al. “Lifetime estimation of grid connected LiFePO<sub>4</sub> battery energy storage systems.” In: *Electrical Engineering* 104 (2021), pp. 67–81. URL: <https://api.semanticscholar.org/CorpusID:253719338>.
- [6] Arpit Maheshwari. “Modelling, Aging and Optimal Operation of Lithium-ion Batteries.” In: 2018. URL: <https://api.semanticscholar.org/CorpusID:105027102>.
- [7] “Smart Senja.” In: (2023). URL: <https://smartsenja.no/en/>.
- [8] Arva. “REGIONAL POWER SYSTEM INVESTIGATION FOR AREA 21.” In: <https://arva.no/hjem> (2022).
- [9] Troms Kraft. “Sluttrapportering på konseptutredning, Smartinfrastruktur Nord Senja.” In: (2019).
- [10] Moslem Uddin et al. “A review on peak load shaving strategies.” In: *Renewable and Sustainable Energy Reviews* 82 (2018), pp. 3323–3332. ISSN: 1364-0321. DOI: <https://doi.org/10.1016/j.rser.2017.10>.

056. URL: <https://www.sciencedirect.com/science/article/pii/S1364032117314272>.
- [11] Marc Möller et al. “SimSES: A holistic simulation framework for modeling and analyzing stationary energy storage systems.” In: *Journal of Energy Storage* 49 (2022), p. 103743. ISSN: 2352-152X. DOI: <https://doi.org/10.1016/j.est.2021.103743>. URL: <https://www.sciencedirect.com/science/article/pii/S2352152X21014171>.
- [12] Nasif Mahmud and A. Zahedi. “Review of control strategies for voltage regulation of the smart distribution network with high penetration of renewable distributed generation.” In: *Renewable and Sustainable Energy Reviews* 64 (2016), pp. 582–595. ISSN: 1364-0321. DOI: <https://doi.org/10.1016/j.rser.2016.06.030>. URL: <https://www.sciencedirect.com/science/article/pii/S136403211630243X>.
- [13] Daiva Stanelyte and Virginijus Radziukynas. “Review of Voltage and Reactive Power Control Algorithms in Electrical Distribution Networks.” In: *Energies* 13.1 (2020). ISSN: 1996-1073. DOI: 10.3390/en13010058. URL: <https://www.mdpi.com/1996-1073/13/1/58>.
- [14] Choton K. Das et al. “Overview of energy storage systems in distribution networks: Placement, sizing, operation, and power quality.” In: *Renewable and Sustainable Energy Reviews* 91 (2018), pp. 1205–1230. ISSN: 1364-0321. DOI: <https://doi.org/10.1016/j.rser.2018.03.068>. URL: <https://www.sciencedirect.com/science/article/pii/S1364032118301606>.
- [15] Tobias Thørnquist Jacobsen. *Distributed Renewable Generation and Power Flow Control to Improve Power Quality at Northern Senja, Norway*. 2019.
- [16] Karl Henrik Rochmann. *Network Analysis and Boosting the Distribution to Local Consumers at Northern Senja, Norway with Potential Renewable Generation Using Power Flow Control*. 2022.
- [17] Ina Løvvold. *Pumped Hydropower Conversion and Renewable Hybrid Power Plants at Senja*. 2022.
- [18] Odin Foldvik Eikeland et al. “Predicting Energy Demand in Semi-Remote Arctic Locations.” In: *Energies* 14.4 (2021). ISSN: 1996-1073. DOI: 10.3390/en14040798. URL: <https://www.mdpi.com/1996-1073/14/4/798>.
- [19] Odin Foldvik Eikeland et al. “Detecting and interpreting faults in vulnerable power grids with machine learning.” In: *IEEE Access* 9 (2021), pp. 150686–150699.
- [20] Oskar Marthinussen. *Smart Senja electrical network expansion modeling*. 2023.
- [21] Chao Lu et al. “Optimal Sizing and Control of Battery Energy Storage System for Peak Load Shaving.” In: *Energies* 7.12 (2014), pp. 8396–8410. ISSN: 1996-1073. DOI: 10.3390/en7128396. URL: <https://www.mdpi.com/1996-1073/7/12/8396>.
- [22] Armin Ebrahimi and Amirhossein Hamzeiyan. “An ultimate peak load shaving control algorithm for optimal use of energy storage systems.”

- In: *Journal of Energy Storage* 73 (2023), p. 109055. ISSN: 2352-152X. DOI: <https://doi.org/10.1016/j.est.2023.109055>. URL: <https://www.sciencedirect.com/science/article/pii/S2352152X23024532>.
- [23] Fatemeh Bagheri, Hanane Dagdougui, and Michel Gendreau. “Stochastic optimization and scenario generation for peak load shaving in Smart District microgrid: sizing and operation.” In: *Energy and Buildings* 275 (2022), p. 112426. ISSN: 0378-7788. DOI: <https://doi.org/10.1016/j.enbuild.2022.112426>. URL: <https://www.sciencedirect.com/science/article/pii/S0378778822005977>.
- [24] Kjersti Berg et al. “Economic evaluation of operation strategies for battery systems in football stadiums: A Norwegian case study.” In: *Journal of Energy Storage* 34 (2021), p. 102190. ISSN: 2352-152X. DOI: <https://doi.org/10.1016/j.est.2020.102190>. URL: <https://www.sciencedirect.com/science/article/pii/S2352152X20320119>.
- [25] Benedikt Tepe et al. “Lithium-ion battery utilization in various modes of e-transportation.” In: *eTransportation* 18 (2023), p. 100274. ISSN: 2590-1168. DOI: <https://doi.org/10.1016/j.etrans.2023.100274>. URL: <https://www.sciencedirect.com/science/article/pii/S2590116823000498>.
- [26] Daniel Kucevic et al. “Standard battery energy storage system profiles: Analysis of various applications for stationary energy storage systems using a holistic simulation framework.” In: *Journal of Energy Storage* 28 (2020), p. 101077. ISSN: 2352-152X. DOI: <https://doi.org/10.1016/j.est.2019.101077>. URL: <https://www.sciencedirect.com/science/article/pii/S2352152X19309016>.
- [27] “Ministry of Petroleum and Energy.” In: (). URL: <https://www.regjeringen.no/en/dep/oed/id750/>.
- [28] Pieter Schavemaker and Lou Van der Sluis. *Electrical power system essentials*. John Wiley & Sons, 2017.
- [29] Micah S Ziegler and Jessika E Trancik. “Re-examining rates of lithium-ion battery technology improvement and cost decline.” In: *Energy & Environmental Science* 14.4 (2021), pp. 1635–1651.
- [30] J. Mitali, S. Dhinakaran, and A.A. Mohamad. “Energy storage systems: a review.” In: *Energy Storage and Saving* 1.3 (2022), pp. 166–216. ISSN: 2772-6835. DOI: <https://doi.org/10.1016/j.enss.2022.07.002>. URL: <https://www.sciencedirect.com/science/article/pii/S277268352200022X>.
- [31] Kyle Bradbury. “Energy Storage Technology Review.” In: (2010).
- [32] D. Linden. “Handbook of Batteries.” In: *McGraw-Hill, New York, 2 ed* (2020).
- [33] MIT. “A guide to understanding battery specifications.” In: (2008).
- [34] Manh-Kien Tran et al. “Comparative Study of Equivalent Circuit Models Performance in Four Common Lithium-Ion Batteries: LFP, NMC, LMO, NCA.” In: *Batteries* 7.3 (2021). ISSN: 2313-0105. DOI: [10.3390/batteries7030051](https://doi.org/10.3390/batteries7030051). URL: <https://www.mdpi.com/2313-0105/7/3/51>.

- [35] Carlo Cunanan et al. “A Review of Heavy-Duty Vehicle Powertrain Technologies: Diesel Engine Vehicles, Battery Electric Vehicles, and Hydrogen Fuel Cell Electric Vehicles.” In: *Clean Technologies* 3.2 (2021), pp. 474–489. ISSN: 2571-8797. DOI: 10.3390/cleantechno13020028. URL: <https://www.mdpi.com/2571-8797/3/2/28>.
- [36] Manh-Kien Tran et al. “Design of a Hybrid Electric Vehicle Powertrain for Performance Optimization Considering Various Powertrain Components and Configurations.” In: *Vehicles* 3.1 (2021), pp. 20–32. ISSN: 2624-8921. DOI: 10.3390/vehicles3010002. URL: <https://www.mdpi.com/2624-8921/3/1/2>.
- [37] Satyam Panchal et al. “High Reynold’s Number Turbulent Model for Micro-Channel Cold Plate Using Reverse Engineering Approach for Water-Cooled Battery in Electric Vehicles.” In: *Energies* 13.7 (2020). ISSN: 1996-1073. DOI: 10.3390/en13071638. URL: <https://www.mdpi.com/1996-1073/13/7/1638>.
- [38] Xianxia Yuan, Hansan Liu, and Jiujun Zhang. *Lithium-ion batteries: advanced materials and technologies*. CRC press, 2011.
- [39] Odile Capron et al. “On the Ageing of High Energy Lithium-Ion Batteries—Comprehensive Electrochemical Diffusivity Studies of Harvested Nickel Manganese Cobalt Electrodes.” In: *Materials* 11.2 (2018). ISSN: 1996-1944. DOI: 10.3390/ma11020176. URL: <https://www.mdpi.com/1996-1944/11/2/176>.
- [40] Hannah E Murdock et al. “Renewables 2021-global status report.” In: (2021).
- [41] Chem Nayar. “Innovative remote micro-grid systems.” In: *International Journal of Environment and Sustainability* 1.3 (2012).
- [42] Holger C. Hesse et al. “Lithium-Ion Battery Storage for the Grid—A Review of Stationary Battery Storage System Design Tailored for Applications in Modern Power Grids.” In: *Energies* 10.12 (2017). ISSN: 1996-1073. DOI: 10.3390/en10122107. URL: <https://www.mdpi.com/1996-1073/10/12/2107>.
- [43] Yann G Rebours et al. “A survey of frequency and voltage control ancillary services—Part I: Technical features.” In: *IEEE Transactions on power systems* 22.1 (2007), pp. 350–357.
- [44] Daniel-Ioan Stroe et al. “Operation of a grid-connected lithium-ion battery energy storage system for primary frequency regulation: A battery lifetime perspective.” In: *IEEE transactions on industry applications* 53.1 (2016), pp. 430–438.
- [45] Joern Hoppmann et al. “The economic viability of battery storage for residential solar photovoltaic systems—A review and a simulation model.” In: *Renewable and Sustainable Energy Reviews* 39 (2014), pp. 1101–1118.
- [46] Marcus Müller et al. “Evaluation of grid-level adaptability for stationary battery energy storage system applications in Europe.” In: *Journal of Energy Storage* 9 (2017), pp. 1–11.

- [47] Andrej Gajduk, Mirko Todorovski, and Ljupco Kocarev. “Stability of power grids: An overview.” In: *The European Physical Journal Special Topics* 223.12 (2014), pp. 2387–2409.
- [48] Kalpesh A Joshi and Naran M Pindoriya. “Day-ahead dispatch of battery energy storage system for peak load shaving and load leveling in low voltage unbalance distribution networks.” In: *2015 IEEE power & energy society general meeting*. IEEE. 2015, pp. 1–5.
- [49] Christopher C Thompson et al. “Optimization of data center battery storage investments for microgrid cost savings, emissions reduction, and reliability enhancement.” In: *IEEE Transactions on Industry Applications* 52.3 (2016), pp. 2053–2060.
- [50] VK Mehta and Rohit Mehta. *Principles of Power System: Including Generation, Transmission, Distribution, Switchgear and Protection: for BE/B. Tech., AMIE and Other Engineering Examinations*. S. Chand Publishing, 2005.
- [51] Vaiju Kalkhambkar, Rajesh Kumar, and Rohit Bhakar. “Energy loss minimization through peak shaving using energy storage.” In: *Perspectives in Science* 8 (2016), pp. 162–165.
- [52] John Malinowski and Keith Kaderly. “Peak shaving-a method to reduce utility costs.” In: *Region 5 Conference: Annual Technical and Leadership Workshop, 2004*. IEEE. 2004, pp. 41–44.
- [53] David Cartes et al. “Novel Integrated Energy Systems and control methods with economic analysis for integrated community based energy systems.” In: *2007 IEEE power engineering society general meeting*. IEEE. 2007, pp. 1–6.
- [54] Jason Leadbetter and Lukas Swan. “Battery storage system for residential electricity peak demand shaving.” In: *Energy and buildings* 55 (2012), pp. 685–692.
- [55] Menglian Zheng, Christoph J Meinrenken, and Klaus S Lackner. “Smart households: Dispatch strategies and economic analysis of distributed energy storage for residential peak shaving.” In: *Applied Energy* 147 (2015), pp. 246–257.
- [56] Xuebing Han et al. “A review on the key issues of the lithium ion battery degradation among the whole life cycle.” In: *eTransportation* 1 (2019), p. 100005. ISSN: 2590-1168. DOI: <https://doi.org/10.1016/j.etrans.2019.100005>. URL: <https://www.sciencedirect.com/science/article/pii/S2590116819300050>.
- [57] Jacqueline S. Edge et al. “Lithium ion battery degradation: what you need to know.” In: *Phys. Chem. Chem. Phys.* 23 (14 2021), pp. 8200–8221. DOI: 10.1039/D1CP00359C. URL: <http://dx.doi.org/10.1039/D1CP00359C>.
- [58] K. Amine, J. Liu, and I. Belharouak. “High-temperature storage and cycling of C-LiFePO<sub>4</sub>/graphite Li-ion cells.” In: *Electrochemistry Communications* 7.7 (2005), pp. 669–673. ISSN: 1388-2481. DOI: <https://doi.org/10.1016/j.elecom.2005.07.011>.

- //doi.org/10.1016/j.elecom.2005.04.018. URL: <https://www.sciencedirect.com/science/article/pii/S1388248105001177>.
- [59] K. Takei et al. "Cycle life estimation of lithium secondary battery by extrapolation method and accelerated aging test." In: *Journal of Power Sources* 97-98 (2001). Proceedings of the 10th International Meeting on Lithium Batteries, pp. 697–701. ISSN: 0378-7753. DOI: [https://doi.org/10.1016/S0378-7753\(01\)00646-2](https://doi.org/10.1016/S0378-7753(01)00646-2). URL: <https://www.sciencedirect.com/science/article/pii/S0378775301006462>.
- [60] Minggao Ouyang et al. "Low temperature aging mechanism identification and lithium deposition in a large format lithium iron phosphate battery for different charge profiles." In: *Journal of Power Sources* 286 (2015), pp. 309–320. ISSN: 0378-7753. DOI: <https://doi.org/10.1016/j.jpowsour.2015.03.178>. URL: <https://www.sciencedirect.com/science/article/pii/S0378775315006126>.
- [61] Minggao Ouyang et al. "Overcharge-induced capacity fading analysis for large format lithium-ion batteries with LiyNi1/3Co1/3Mn1/3O2+LiyMn2O4 composite cathode." In: *Journal of Power Sources* 279 (2015). 9th International Conference on Lead-Acid Batteries – LABAT 2014, pp. 626–635. ISSN: 0378-7753. DOI: <https://doi.org/10.1016/j.jpowsour.2015.01.051>. URL: <https://www.sciencedirect.com/science/article/pii/S037877531500052X>.
- [62] Rui Guo et al. "Mechanism of the entire overdischarge process and overdischarge-induced internal short circuit in lithium-ion batteries." In: *Scientific reports* 6.1 (2016), p. 30248.
- [63] Guodong Fan et al. "Modeling of Li-Ion cells for fast simulation of high C-rate and low temperature operations." In: *Journal of The Electrochemical Society* 163.5 (2016), A666.
- [64] Thomas Waldmann et al. "Temperature dependent ageing mechanisms in Lithium-ion batteries—A Post-Mortem study." In: *Journal of power sources* 262 (2014), pp. 129–135.
- [65] Aiping Wang et al. "Review on modeling of the anode solid electrolyte interphase (SEI) for lithium-ion batteries." In: *npj Computational Materials* 4.1 (2018), p. 15.
- [66] Yuqing Yang et al. "Modelling and optimal energy management for battery energy storage systems in renewable energy systems: A review." In: *Renewable and Sustainable Energy Reviews* 167 (2022), p. 112671.
- [67] Bolun Xu et al. "Modeling of lithium-ion battery degradation for cell life assessment." In: *IEEE Transactions on Smart Grid* 9.2 (2016), pp. 1131–1140.
- [68] Electric Power Research Institute. "Storage value estimation tool (StorageVET)." In: <http://www.storagevet.com/> (2020).
- [69] Maik Naumann et al. "SimSES: Software for techno-economic Simulation of Stationary Energy Storage Systems." In: *International ETG Congress 2017*. 2017, pp. 1–6.

- [70] National Renewable Energy Laboratory. “Blast: Battery lifetime analysis and simulation tool suite.” In: <https://www.nrel.gov/transportation/blast.html> (2020).
- [71] HOMER Energy. “HOMER energy.” In: <https://www.nrel.gov/transportation/blast.html> (2020).
- [72] Maik Naumann et al. “Simses: Software for techno-economic simulation of stationary energy storage systems.” In: *International ETG congress 2017*. VDE. 2017, pp. 1–6.
- [73] Odin Foldvik Eikeland et al. “Detecting and Interpreting Faults in Vulnerable Power Grids With Machine Learning.” In: *IEEE Access* 9 (2021), pp. 150686–150699. DOI: 10.1109/ACCESS.2021.3127042.
- [74] C.G. Heaps. “LEAP: The Low Emissions Analysis Platform.” [Software version: 2020.1.105] Stockholm Environment Institute. Somerville, MA, USA. URL: <https://leap.sei.org>.
- [75] Maik Naumann. “Techno-economic evaluation of stationary battery energy storage systems with special consideration of aging.” PhD thesis. Technische Universität München, 2018.
- [76] Kandler Smith et al. “Life prediction model for grid-connected Li-ion battery energy storage system.” In: *2017 American Control Conference (ACC)*. IEEE. 2017, pp. 4062–4068.
- [77] “Meteorological Institute.” In: (). URL: <https://www.yr.no/nb>.







