NTNU
Norwegian University of
Science and Technology

Multi-Market Optimization of Energy Storage Taking Into Account Uncertainty

Kasper Emil Thorvaldsen

Master of Energy and Environmental Engineering
Submission date: June 2018
Supervisor: Magnus Korpås, IEL
Co-supervisor: Arild Helseth, SINTEF Energi

Norwegian University of Science and Technology
Department of Electric Power Engineering

Problem Description

Internationally there has been an increasing focus on installation of renewable energy sources like wind and solar. This is happening on both a large and small scale, for producers and for local communities. However, these energy sources are dependent on weather, and thus the production profile might not correlate perfectly with consumption, making energy storage units more important in these areas to help contribute to stable production output.

Energy storage units implemented in small communities can have multiple purposes. Other than participating during peak consumption hours, which can preven congestion problems on the grid, it can also contribute to balancing the grid with flexible production. As unregulated energy sources have low contribution in power flexibility, the need of potent balancing service will become more critical in the future, in both small and large scale applications. As an energy storage unit utilizes the variation in hourly energy prices to create profit, including participation in the balancing market will be another possibility to further increase profit.

These are some of the thoughts and ideas behind this master thesis, where an optimization model for production planning for an energy storage unit will be created and analyzed. The focus has been to implement the use of stochastic dynamic programming to solve this optimization problem for a grid scale storage unit, a method commonly used in hydropower optimization. This report will include the creation process of the model, and also describe the behavior of the storage unit when participating in both the Day-Ahead and the Balancing market.

Preface

This Master Thesis has been written at the Department of Electrical Power Engineering at the Norwegian University of Science and Technology (NTNU). The project has been finalized during the Spring semester in 2018. The work done consists of creating an alternative method of planning storage unit optimization for a short term scheduling model that includes both energy and balancing market accessibility.

Several persons have supported and guided me during this project. I would especially like to thank my supervisor Magnus Korpås for his guidance and help throughout the semester. His knowledge and inspiration in trying to create this model has been a positive driving factor in accomplishing the work in this master thesis.
I would also like to thank Arild Helseth at SINTEF, for learning me how to use and create a stochastic dynamic programming model from scratch.
I would also like to mention Christian Øyn Naversen, for his knowledge on modelling in Python.

Lastly, I would like to thank my other fellow master students, for all the support and help during this project period.

Kasper Emil Thorvaldsen
Trondheim June 2018

Summary

In this master thesis, the main focus has been to create an optimization model for an energy storage unit to consider the potential of storing energy for future use, when also operating in both the energy and balancing markets. The main goal was to successfully implement this model and study the potential of a storage unit maximizing profit within both markets, and how this affects the scheduling of the storage unit for varying storage capacity.

The optimization model that was created, simulates an energy storage unit with the possibility of operating in both the energy and balancing market, which extends the possible markets that storage units usually participate in. This has been done by including primary reserve sales in the balancing market. The model is considered a short-term scheduling model operating at a multi-stage, multi-scenario stochastic level. This model simulates sequential scheduling planning for a user-defined time horizon and time steps, and can therefore be both short-term and long-term depending on the scope and range. The price data used for this simulation is for February 2017, and was obtained from NordPool and Statnett. As this model has been created by the author, some of the work has been to analyze the decision making and the accuracy of its decisions, to find strengths and weaknesses within the model that could be improved.

The model was tested under a deterministic setup to analyze the performance of the stochastic dynamic programming in the strategy phase of the model. The results showed that the model manages to create a detailed storage value curve when the number of discretized points are kept at a reasonable amount. This also kept the accuracy of the simulation phase reasonably good. However, the accuracy and performance of the strategy phase struggled to be consistent when the capacity of the storage unit increased. Especially when the unit capacities exceeded 25 MWh, the deviation in the storage value curves between each iteration got noticeably worse. Increasing the accuracy of the storage value curve did not improve this case. Thankfully, this deviation decreased when changing to a stochastic setup, since all possible scenarios affected each other, and several of these scenarios performed better when the price variation increased.

The potential increase in profit for the storage unit when including one additional market was analyzed for multiple storage unit capacities. The results showed a noticeably increase in profit when utilizing both markets, which at the largest was 83 % for a 2 MWh storage unit, equivalent of an increase of 1160 NOK per week.

Sammendrag

Hovedfokuset i denne masteroppgaven har vært å lage en optimaliseringsmodell for en lagringsenhet som opererer i både energi- og balansemarkedet. Modellen tar også hensyn til fremtidig fortjeneste ved å lagre energi for fremtidig bruk i stedet for å lade ut med en gang. Hovedformålet var å lage en vellykket modell, og studere potensialet for lagringsenheten ved å maksimere profitten innenfor begge markedene, og hvordan dette påvirker produksjonsplanleggingen for enheten ved forskjellig lagringskapasitet.

Optimaliseringsmodellen som er blitt laget, simulerer en lagringsenhet som har mulighet til å operere innenfor både energi- og balansemarkedet, noe som dermed utvider de mulige markedene slike lagringsenheter typisk deltar i. Dette har blitt gjort ved å inkludere salg av primærreserver til balansemarkedet. Modellen vurderes å være en korttidsmodell som opererer på et flerstegs, multi-scenario stokastisk nivå. Denne modellen simulerer sekvensiell planlegging for en brukerbestemt tidshorisont og tidssteg, noe som gjør at den kan være både korttids og langtids avhengig av formålet. Prisdataen brukt er for februar 2017 og er hentet fra NordPool og Statnett. Siden forfatteren av denne rapporten har lagd denne modellen, har noe av arbeidet vært å analysere modellen og se nærmere på hvilke beslutninger den tar og nøyaktigheten av disse, for å finne styrker og svakheter ved modellen som kan forbedres.

Modellen har blitt testet under et deterministisk oppsett for å se nærmere på utførelsen av den stokastisk dynamiske programmeringsdelen i strategifasen av modellen. Resultatene viste at modellen klarer å lage detaljerte lagringsverdikurver når antallet diskrete punkter er relativt høyt, noe som også medførte god nøyaktighet i simuleringsfasen av modellen. Nøyaktigheten og utførelsen av strategifasen slet derimot med å gi konsekvente resultater når størrelsen på lagringsenheten økte. Spesielt størrelser på 25 MWh og høyere ga større forskjeller i lagringsverdikurven mellom iterasjonene. Heldigvis gikk denne differansen ned når det ble brukt stokastiske oppsett, siden alle mulige hendelser påvirket hverandre, og andre analyser viste at høy prisvariasjon forbedret strategifasen.

Potensialet i økningen av profitt ble analysert for forskjellige kapasiteter i lagringsenheten både med og uten reservekapasitetssalg. Resultatene viste at det var en merkbar økning i profitt når en benyttet seg av begge markedene. På det høyeste ble det målt en 83 % økning for en 2 MWh lagringsenhet, noe som tilsvarte en profittøkning på 1160 NOK per uke.

Contents

List of Figures

List of Tables

1 Introduction

With more and more unregulated energy sources installed, the need for storing this energy for use when necessary becomes more important to reduce the need for dispatchable non-renewable energy sources like coal and gas. To reduce these non-renewable energy sources across Europe, more stable and highly flexible production is needed to maintain stability in the grid.

Using energy storage units to solve these problems is one of the possible future solutions. Storage units offer multiple options depending on their purpose. They can store energy for future use, and thereby give the unregulated energy sources more flexibility when combined. Also, they can prevent that the grid experiences a high level of strain by supplying local loads to reduce the power transfer during the few peak hours experienced daily. Energy storage units are mainly used to help with energy load demand, but their capability of storing energy while having quick flexibility in power input/output makes it possible to participate in the balancing market, which is expected to become more important in the future. Therefore, this gives storage units the possibility to participate in multiple markets.

The main goal of this report is to analyze the performance of a storage unit and its increased profitability when participating in both the energy and the balancing market. This is done by creating and testing a short term storage unit scheduling model, implemented in Python and Pyomo by the author. This model is a multi-stage, multi-scenario stochastic model that describes a single storage unit operating in both the energy and balancing market, with the same requirements and possibilities as a power producer.

The model is forecasting the future potential of stored energy by utilizing the same method as is typical for hydropower producers, through the implementation of water values describing the marginal cost for more storage for future use. This marginal cost has been described as the storage value in this report. As this is a method not commonly used for storage unit simulation, testing how the model functions with this implementation is part of the scope of this project. Another factor is that the author included some simplifications to the model, and these impacts will also be compared as part of the scope.

This thesis is divided into three main parts: Literature explanation of key areas, model description and performed runs of the model. Section 2 will focus on the theoretical background needed for understanding this project. Section 3 will explain the optimization model and how the author created the model. Section 4 sets up the case that will be studied using this model, whereas Section 5 and 6 contains the results from the performed analyzes.

As part of this report is similar to the specialization project the author completed during Fall 2017, named "Profitability of a Hydropower Producer Operating in Two Different Markets" [27], there are some sections that have been extracted from that report and used in this report. This consists of some of the theoretical background covered in Section 2 and some of the model explanation in Section 3. The exact parts will be mentioned at the start of each section.

2 Theory, Background and Methodologies

Some of this theoretical explanation is based on an earlier work done by the author, which consisted of studying the performance of a multi-stage, multi-scenario, long-term stochastic model for a hydropower producer operating in both the energy and reserve capacity markets [27]. As the markets are the same, as well as the modelling setup, the theoretical background has certain similarities. Therefore, Sections 2.1, 2.2, 2.4 and 2.6 are the same as in the previous report, with small changes to reflect the use of storage units instead of hydropower.

2.1 European Energy Mix Changing

Due to ambitious goals regarding reduction of greenhouse gases (GHG) in the European Union (EU), the European power grid is expected to go through restructuring in the future. This is mainly due to solar and wind power replacing coal and gas power production. However, these changes will result in less flexibility as more unregulated power production increases [26].
The following sections will take a closer look at the generation mix in the EU, the changing market coupling, and some possible solutions to increase flexibility in the grid.

2.1.1 European Generation Mix

With the new climate and energy policies, the EU is striving towards a more renewable production portfolio. At present, the EU bases their environmental work on two main policies: The 2020 climate and energy package and the 2030 climate and energy framework, in which the main goals are presented in Table 1 [5].

Table 1: Overview of the EUs climate and energy goals for year 2020 and 2030.

Goals	2020	2030
Cut in GHG (from 1990 levels)	20 %	40 %
Share of renewable production	20 %	27 %
Improved energy efficiency	20 %	27 %

In 2015, the generation mix for Europe had a share of 17 % renewable energy (excl. hydro), as shown in Figure 1. As of right now, the goal of 20 % renewable before 2020 seems reachable due to the shared focus.

Figure 1 also shows an increase in annually renewable production from 2011 to 2015, while fossil fuels experience a reduction. To achieve the 2020 and 2030 goals, this trend must continue to

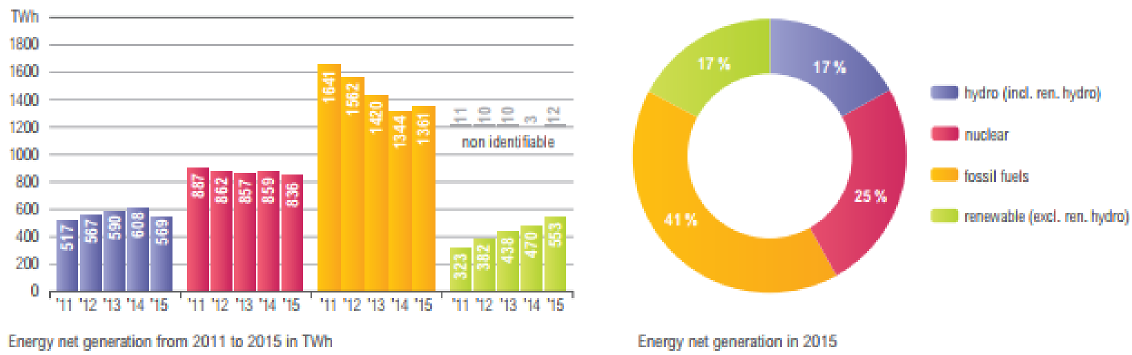

Figure 1: ENTSO-E overall net generation per year between 2011 and 2015, and percentage production for 2015 [9].

increase over time. Contributing to this, the main investments will be in solar and wind [26]. With the increase in unregulated power sources, the power grid will be increasingly in need of power sources to maintain power balance in the future.

2.1.2 Market Coupling

Europe will need to improve the electrical interconnections across borders to accomplish the climate and energy goals, which will lead to more renewable energy in the market, as well as improved security of electrical supply [6].

The Nordic countries have steadily increased their transmission capacity to the rest of Europe over the last years, and proposed further installations in the future. In 2016, the capacity was at roughly 7 000 MW, with a proposed total capacity at around 11 000 MW in 2025 [25]. Table 2 shows the proposed new capacities from the Nordic countries to some European countries.

Table 2: Proposed new cables between the Nordic countries and the rest of Europe.

Name	Country 1	Country 2	Capacity [MW]
NordLink	Norway	Germany	1 400
NSL	Norway	UK	1 400
Cobra	Denmark	Netherlands	700
Viking Link	Denmark	UK	1 000
Krigers Flak	Denmark	Germany	600
HansaPowerBridge	Sweden	Germany	600

This extension of transmission capacity is important to maintain stability in the European power grid, and will become more critical as the unregulated renewable energy sources become more dominant for production.

2.1.3 Better Generation Flexibility

With an increasing installation of unregulated energy sources and a more interconnected power grid, the grid will experience changes in behavior in the future. The power balance in the system will be subject to more fluctuation that needs to be kept under control. Therefore, flexible power production will play an increasingly important part due to the ability to up- and down-regulate at a quick pace, a part that so far has been largely played by coal and gas plants.

Utilizing energy storage units in different parts of the grid can help achieve this type of flexible power production. The storage unit can store energy during certain periods, and discharge when needed. This can be implemented for multiple purposes. The storage unit can help deliver more stable production output from a unregulated power source if connected and optimized together, or it can be placed in different locations in the grid to provide up- and down-regulation of power, to create an improved security of electrical supply. The possibilities are almost limitless, due to the high compatibility with other energy sources.

2.2 The Nordic System

The Nordic countries are countries located in Northern Europe, consisting of Iceland, Finland, Denmark, Norway, and Sweden. With the exception of Iceland, the Nordic countries have connections to the Baltic countries and to continental Europe, interacting with both export and import of electricity. The Nordic countries primarily have hydro and thermal power production, with the addition of nuclear and wind power. However, each country has its own generation mix, as can be seen in Figure 2. The generation mix varies, from almost purely hydro in Norway, to an almost even distribution of different sources in Finland.

With these different energy sources, the countries have the possibilities to trade between them to fully utilize each source. For instance, hydropower in Norway allows for export during wet years, and import during dry years. Denmark can export wind power during high wind conditions, and import when the wind is low.

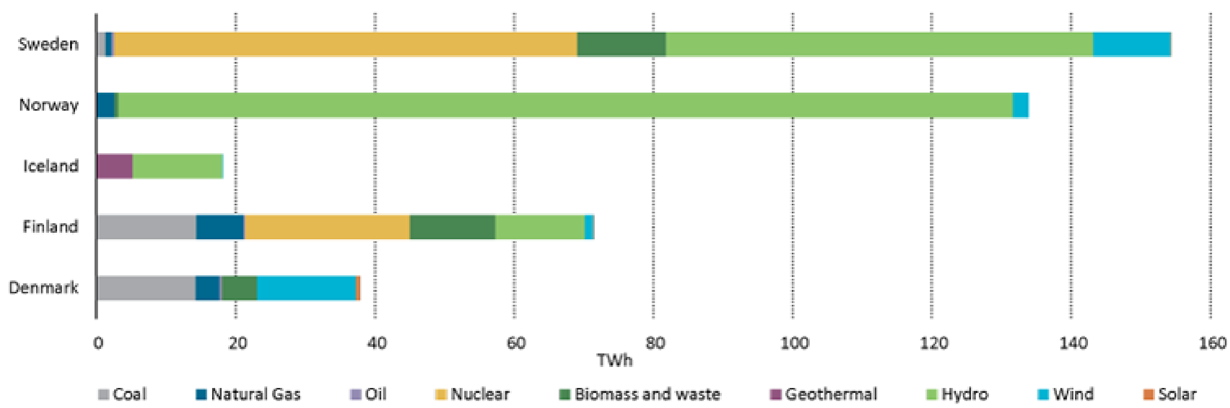

Figure 2: Power production in the Nordic countries for 2013 [15].

In Norway, about 85 TWh of power can be stored in reservoirs, giving a high flexibility of storing water for later usage [24]. Other characteristics such as quick production regulation and cost-efficient flexibility make hydropower a major contributor in the balancing market, as it will be able to improve stability and security of supply. This means that the balancing market on a national level in Norway is well prepared, and that other high flexibility production units are less necessary on a big scale. However, for small-scale and rural areas, often combined with long travelling distances for electrical supply, the transmission grid can be constrained, limiting power flow in that area. In these situations, local, small-scale storage units can contribute to meet load during high load demand periods and provide power production flexibility locally.

2.3 The Norwegian Load Pattern

Over the course of a day, the load consumption from private consumers varies. The typical trend is that the load demand is high in the morning, when people wake up, and in the the evening, when people come home from work. During the rest of the day, the load is considerably smaller and more stable. The high load hours are called peak-hours. This period is short each day, but still requires that the grid meets this short, high demand. This can be reflected in the hourly electricity price, as a higher price is usually the result of higher consumption. Figure 3 shows the price variation over the course of a day in February 2018 for Trondheim, Norway. Here, the prices are considerably higher in the morning and evening than during the rest of the day, due to the higher load demand.

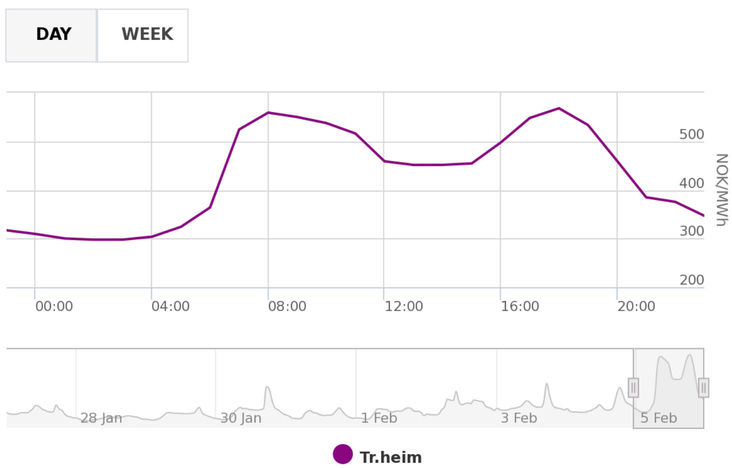

Figure 3: Spot prices during February 5. 2018 for Trondheim. Note the higher prices during the morning and evening. Data retrieved from NordPool [2].

In the future, the grid companies in Norway are expected to invest heavily in the grid due to increased consumer load demand and the need for upgrading weak, old parts of the grid. This is especially the case for rural areas. As mentioned, the grid will need to be dimensioned for the highest peak-hours, which may only occur a couple of hours a year. This added cost will be paid by the consumers through higher grid tariffs. [10]

The grid companies are looking at different ways to solve this challenge. One way is to see whether the consumer load pattern can be adjusted to decrease the high peak-hour demand. With the installation of smart metering (AMS) [17], one hopes to increase consumer awareness of own consumption, so that the peak-hours can be reduced and thus the strain on the existing grid.

Another way to solve this problem, is to install storage units in local communities. Storage units can help reduce the strain on the grid during peak-hours, by charging when the load is low, and discharge when the load is high. Thus, the power transferred in the grid to this community will be decreased during peak-hours. This means that the grid can be upgraded with a smaller dimensioned capacity, or that the current grid can be kept a while longer.

2.4 The Nord Pool Market

For Norwegian power producers, all sales and bids of power are done through the European power market Nord Pool. Nord Pool consists of multiple markets that producers can participate in, based on the wanted role for production. The financial market of Nord Pool will not be included in this project, only the physical market will be described. This is due to the focus of this project.

The physical markets in Nord Pool include the Day-Ahead (DA) and Intra-Day (ID) market, while the Transmission Operators (TSO) of each country run the Balancing (BM) and Capacity (RKOM) market. An illustration of their time window is shown in Figure 4. The following subsections will describe their role and purpose in the power market, and the opportunities each producer has. The information is obtained from Nord Pool [2] and the Norwegian TSO Statnett [1].

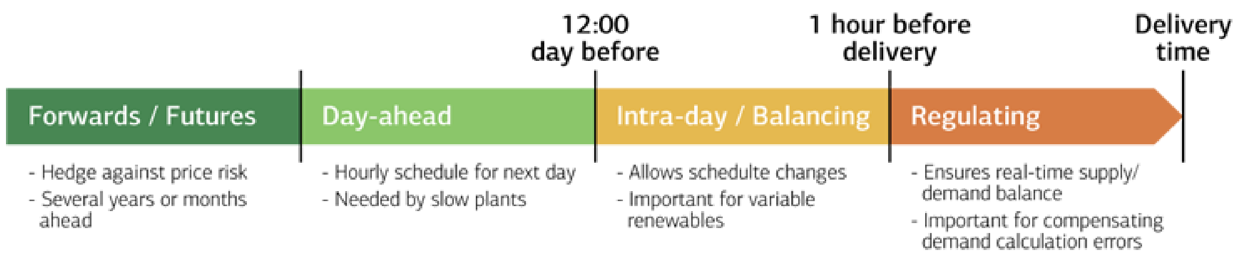

Figure 4: Overview of the different markets in Nord Pool [15].

2.4.1 The Day-Ahead Market

The largest market for power trading is the Day-Ahead market, in which both sellers and buyers make contracts for delivery of power the next day. Nord Pool gathers bids from both sellers and buyers, specifying the quantity of power to sell/buy, and at what price. At noon the day before, the market will close, and the gathered bids will be sorted and separated into supply and demand bid curves. These curves will be determined on an hourly basis, and the final market price and quantity of power will be where the two curves cross, shown in Figure 5. The market price will be the same for all participants.

The ideal setup would be to have the same bidding zone for all participants, but due to transmission constraints, this is hard to achieve. As a result, multiple bidding areas are introduced with their own area price based on their own supply, demand, and transmission capacity to other areas. This is why different regions in Norway can experience different prices at the same time.

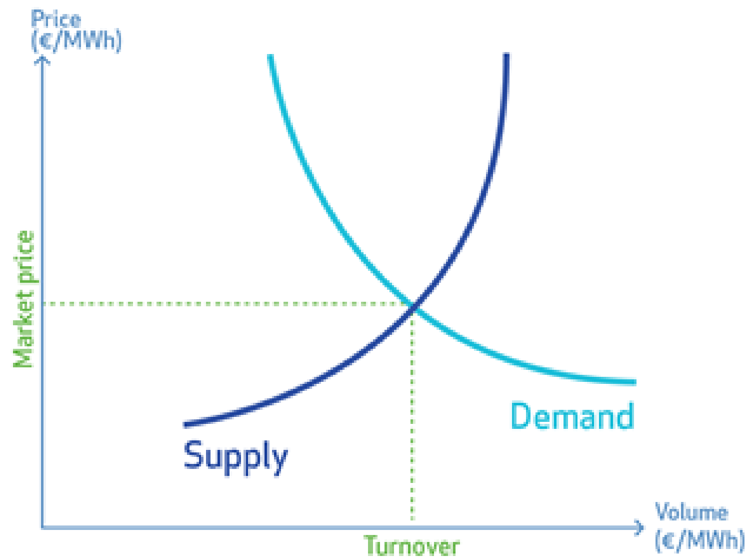

Figure 5: Illustration showing how the market price is determined [2].

2.4.2 The Intra-Day market

The Intra-Day market supplements the Day-Ahead market to prevent imbalances in the market. Since the DA market terminates one day before the chosen hour of operation, there can be events in-between that create problems for balance between demand and supply, such as an unexpected shutdown, or unplanned high production yield. The ID market however, allows buyers and sellers to trade quantities from 14:00 CET till 1 hour before delivery, and thereby contributes to keep the market balanced.

The ID market is expected to have an increased share of trade in the future, due to the higher share of unregulated renewable sources like solar and wind. The uncertainty in these energy sources is reduced as the actual production time approaches, decreasing the imbalance possibility they can create.

2.4.3 The Balancing Market

When there is only one hour left, and the ID closes, the TSOs are responsible for any imbalances that occur from here. They must maintain power balance in the grid at all times, and must thus acquire production sources that can be utilized to help achieve balance. The possible imbalances can be caused by end-user variations, outage of lines or industry, to name a few. The BM is where producers can participate by selling power regulation. There are three regulation reserves; primary, secondary and tertiary reserves.

The primary goal is to keep the system frequency stable in the Nordic system, which is 50 Hz. Figure 6 illustrates how each reserve contributes and at what level. When the frequency deviation occurs, the primary reserves (FCR) will kick in, an automatic regulation that will dampen the deviation till the secondary reserves (FRR) automatically activate after a few minutes.
FRR is activated by a regulation signal from the TSO to the producers control system. This signal will affect the power output from the producer, causing either a down- or up-regulation of power to restore the frequency, releasing FCR. The type of regulation is based on whether there is a power surplus or deficit, respectively. Thus, the producer is obliged to have spinning reserves that can be altered both up and down.
If the frequency cannot be restored, then the TSO will manually activate the tertiary reserves (manual FRR) to secure optimal frequency and release primary/secondary reserves.

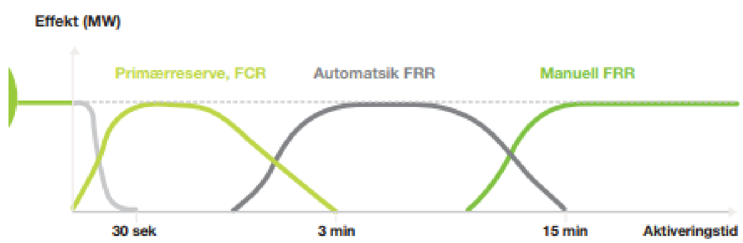

Figure 6: Graphical presentation of when each reserve kicks in [26].

2.4.4 The Norwegian Capacity Market

To ensure stability in the system even during unexpected events, there is a capacity market within the Norwegian Balancing market (other Nordic countries have their own solutions). This market provides up-regulation of power, and is known as the "Regulerkraftopsjonsmarkedet" (RKOM). The principle of this market is that the TSOs pay producers to have excess capacity available, and to contribute with this capacity to the balancing market if prompted. There are two different options in the market, weekly or seasonal trading. The seasonal trading requires producers to have their capacity on standby for the entire season for potential up-regulation. The required demand is considered before every season. The weekly trading is based on current power system and on future forecasts. Each day is split into two periods for weekly trading: RKOM-day [00:00 – 05:00], and RKOM-night [05:00-00:00].

Selling reserve capacity does not imply that the capacity will be utilized. However, the producer is committed to produce when prompted, and must therefore ensure that both the output capacity limit and leftover power can meet the sudden demand at all times. If the producer cannot meet this demand, the producer will be subject to a penalty.

2.5 Energy Storage System

An energy storage unit stores and discharges electricity back and forth depending on the situation and wanted outcome. It can be used for several purposes, for example to lower peak-demand strain on the grid, to serve as a back-up unit for sudden power decreases or increases in the grid or to store excess unregulated power production. Storage units can also be used for small-scale applications, for example in households or small PV systems.

An energy storage unit is basically a physical structure that stores and discharges electricity, and thus has a very general definition. Several different types of energy storage units have been created over time, each having unique qualities and possibilities. This section will describe some of the different energy storage technologies, and some of the limitations.

2.5.1 Technology

As already mentioned, there are several different types of energy storage units, that all serve the same purpose of storing electricity for future use. The "Energy Storage Association" (ESA) has divided the storage systems into 6 main categories [3]. The different categories and their qualities are explained below, mainly based on these categories.

1. Solid State Batteries

A solid state battery (also known as a conventional battery) consists of 1 or more electrochemical cells, that convert chemical energy into electrical energy, and vice versa. A cell consists of two electrodes and an electrolyte separated by a separator. When applying voltage to the cell conductors, the cell will start to conduct a current that can be used to charge or discharge the cell. Figure 7 shows the general setup of a lithium-ion cell, which is one of the possible battery solutions within this definition [4].

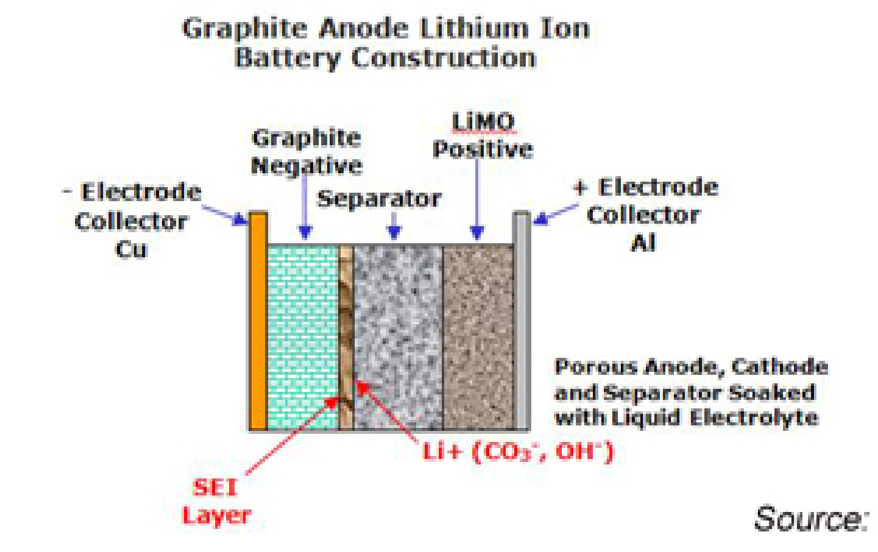

Figure 7: Overview of a lithium-ion solid state battery, that converts chemical energy to electrical energy. Picture taken from [4]

These types of batteries have had a rapid technological and economical development, making them a popular choice for energy storage. There are also other types of these batteries, primarily separated by the kind of materials that are used in the cells. Based on the material, the energy density that the cells can hold differ greatly, as shown in Figure 8. This affects the storage capacity versus size, making it possible to install small batteries with high energy storage.

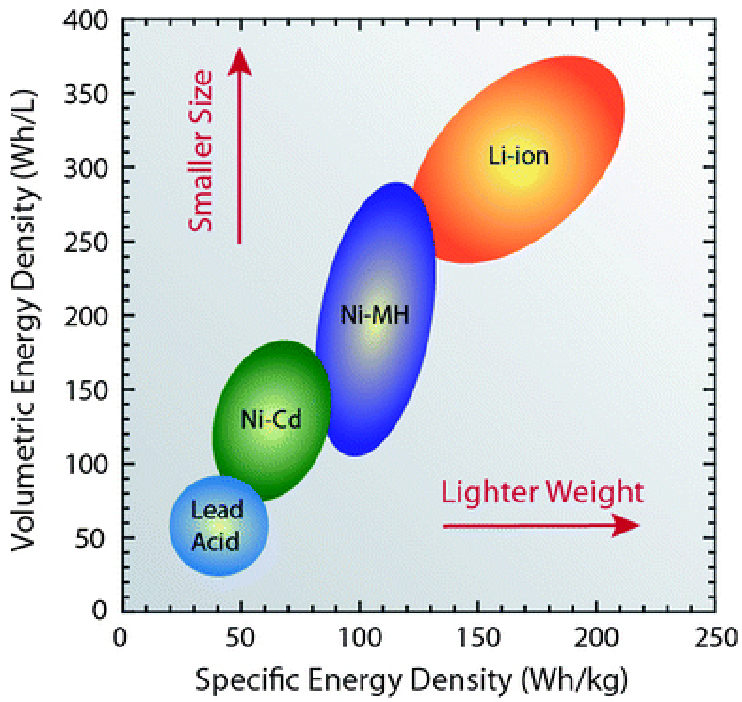

Figure 8: Overview of the energy density for different materials used in battery solutions. Picture taken from [8]

2. Flow Batteries

A flow battery is a combination of a conventional battery and a fuel cell. The difference between flow batteries and conventional batteries is that in flow batteries, the energy is stored as the electrolyte in flow cells, whereas in conventional batteries the energy is stored in the electrode material. The electrolyte is usually stored in tanks operated by pumps. This liquid is pumped between two electrodes and a membrane [28]. During this process, the ion exchange conducts a current that allows for charging and discharging electrical energy. Figure 9 shows an illustration of this procedure.

One of the positive qualities of flow batteries is the possibility to replace the tanks, which enables an almost instant recharge of the battery. The energy density is not usually too high, and the change in power is not that rapid. Thus, these batteries are not considered very flexible, but usable for stable continuous charge or discharge flow.

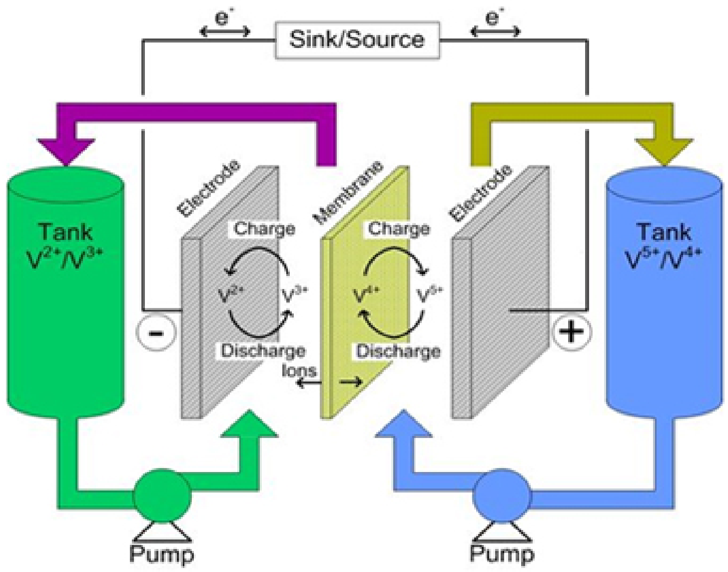

Figure 9: Illustration of a flow battery. Picture taken from [28].

3. Flywheels

A flywheel utilizes rotational power when storing energy, converting electrical energy to kinetic energy. A physical object is storing energy by spinning, and it is charging or discharging by changing the rotational speed. The higher the rotational speed, the more energy is being stored. The higher the rate of change of rotational speed, the faster the flywheel is being charged/discharged.

Flywheels can charge power continuously over time, and have a very fast response time. Thus, it proves very helpful to contribute to frequency stability.

4. Compressed Air Energy Storage

This storage unit utilizes pressure to store energy for future use. Air is compressed and stored under high pressure when charging the unit, and heated and expanded to a turbine during discharging. Usually, the compressed air is stored underground to maintain the temperature. The power output potential and capacity potential is limited by turbine size and size of the pressure tank.

5. Thermal

Thermal energy storage takes advantage of temperature differences to store electric energy. One example is to store the molten salt that is produced from solar thermal power plants, and discharge the capacity it has at a later time. Another example is hydrogen, which is produced by electrolysis and stored for future use. Especially hydrogen storage experiences growing interest due to the high energy density it has, despite having a round-trip efficiency of around 30-40 %.

6. Pumped Hydro-power

A pumped hydro system has the same concept as a normal hydropower station, with water stored in a reservoir and discharged through turbines to produce power. However, the main difference is that there is a pump in this system, which enables water to be pumped back into the reservoir, creating an additional charging direction to the normal filling of the reservoir through inflow. In Norway, this makes it possible to store more water during low electricity prices, which can be utilized when the price is high, typically during winter and high-peak demand periods.

2.5.2 Converter

A storage unit converts electrical energy to the preferred storeable energy type, and vice versa. However, the electrical energy that goes in and out of the storage unit usually needs to be converted to the preferred voltage level and possibly to DC or AC, depending on the storage type and other requirements. This depends on what the system is connected to, whether it be the grid, a private household, or a DC system. This can create a bottleneck for the storage system, as this converter has limitations for power input and output. Converters are usually rated based on their maximum output level. Depending on the size of the converter, the amount of power it can convert will vary, and must therefore be checked against the wished outcome of the system. Also, a converter can experience varying efficiency depending on the output power the converter delivers, creating non-linearity.

2.5.3 Storage unit and converter sizing

When planning a storage system, discussing the capacity of the storage unit, the size of the converter and the ratio between them is essential, as this limits the amount of flexibility the system has, as well as the duration of the output/input power flow. The ratio between these two must fit the purpose of the storage unit. If the role is to provide power during peak-hours to lessen the strain on the grid, the converter must be dimensioned to cover parts of the peak-hour demand, and the storage unit must be big enough to meet the demand during the total duration of the peak-hours. If the storage unit is to be used for frequency stabilization in the grid, then the storage capacity might not need to be so large, but the converter should have high rated power to help with this short-term adjustment.

2.5.4 Maximum depth of discharge

For storage units, there can be external parameters that limit the capacity of the storage system. A typical example of this is the lead-acid battery, a flow battery storage unit that has its storage capacity affected by the ambient temperature. With decreasing temperatures, the maximum depth of discharge, also referred to as MDOD, will decrease, meaning that the capacity of the battery is decreased. This is due to the liquefied sulfuric acid in the battery, which has an increasing freezing temperature when the concentration decreases. If the acid would freeze, there is a risk of destroying the battery. Therefore, the limit of the MDOD is based on how low the ambient temperature is now, and how low it can get. Figure 10 shows how this limitation increases when temperatures decreases. Therefore, it can be beneficial to place the batteries where the external temperature is not too low, or to have some heating appliances present.

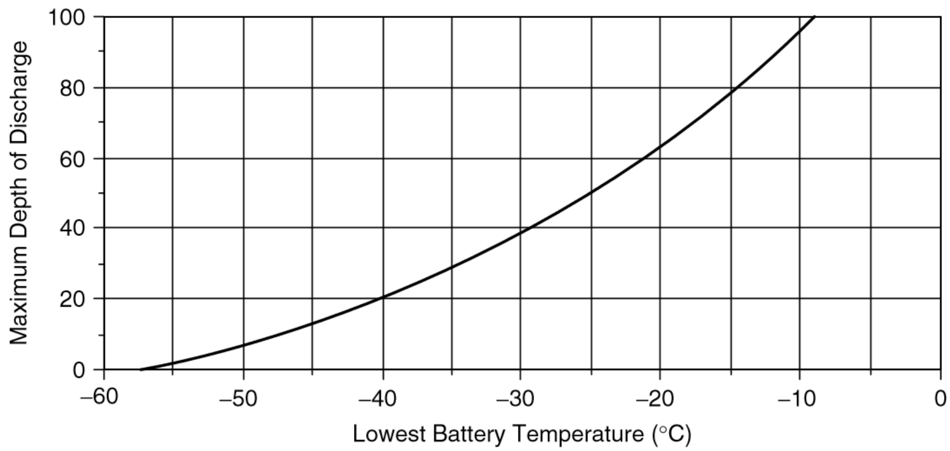

Figure 10: Plot of maximum depth of discharge limits for a lead-acid battery related to decreasing battery temperatures. Picture taken from [23].

2.5.5 Seasonal variation

A storage unit does not have a natural input of energy like a hydropower system. All electricity that goes through the storage unit is obtained by charging it at some points, and discharging it at others. The storage unit will primarily be used to store excess or cheap electricity, which will be used when there is a scarcity of electricity or during high prices. This leads to an interesting discussion on what kind of seasonal dependencies a storage unit can have. For hydropower, the seasons are divided into two; depletion (winter) and filling (summer) seasons .

To determine the seasonal variances the storage unit goes through, it is necessary to look at the reason behind utilizing storage units; the consumption pattern. As has been discussed in

Section 2.3, the consumers usually have peak-hours in the morning and in the evening during weekdays. The scale of this peak is primarily determined by the actual month and period of the year, as winter has high demand due to heating, and summer has low due to low heating needs. Each weekday usually has the same pattern, except when factors like holidays are present. The weekend, however, often shows a different pattern, with decreasing peak-hours amplitude and more flat consumption throughout the day.

Another point is the variation between the different weeks of the year. A load pattern for February is quite different from July, making them not comparable. However, the load pattern difference between week 1 and week 2 of February should be quite low because it is the same season. So the first Monday should be quite similar to the second Monday.

These aspects make it possible to argue that a storage unit experiences variations in consumer pattern over the course of a week, with differences between weekdays and weekends. After a week, one can argue that the storage unit should experience a similar seasonal pattern as the week before. So if one should model the performance of a storage unit for multiple scenarios, one could model it over multiple weeks to find the average performance for that time of the year. To find the yearly expected performance, one would need to run a model with data from the different seasons of a year, such as winter, spring, summer and fall, if not even smaller segments.

2.6 Hydro Power Scheduling

The optimization model created for this report is based on modelling concepts used in hydropower scheduling. The concept used for this model is the Long Term scheduling method used for hydropower. Also, the water value concept has been used, now referred to in the storage unit system as the storage values. The information of hydropower scheduling is based on old lecture and literature given in the course "ELK-15 - Hydro Power Scheduling" held at NTNU by Gerard Doorman during fall 2017 [7].

The main objective of a hydropower producer is to maximize profit from production. The market the producer operates in, is considered a deregulated market, where the price is considered unknown. Scheduling this has proved to be difficult, due to the complicated physical setup and system size, the long time horizon and the uncertainty in inflow, price, and demand. To find ways to meet these challenges, the scheduling process has been divided into different phases, as shown in Figure 11. Only the Long Term Scheduling model will be described here.

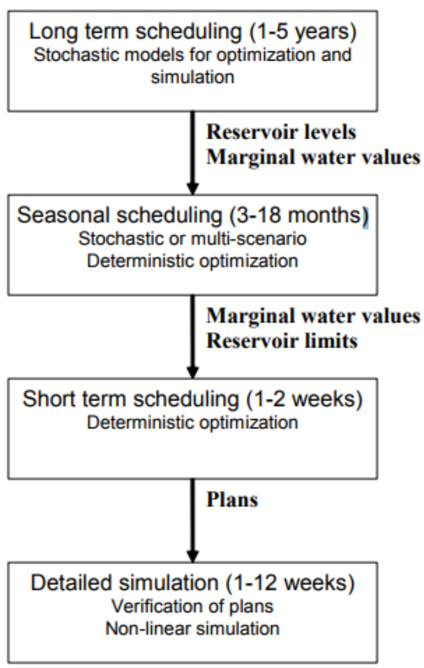

Figure 11: Figure showing the hierarchy of each scheduling type.

2.6.1 Long Term Scheduling

The main goal of LTS is to find the optimal use of the available resources and capacities within a time horizon of normally 1-5 years. A well-known example is the EFI's Multi-Area Power-market

Simulator (EMPS) model, used by many producers. Parameters like inflow, price, demand etc. are represented as discretized stochastic parameters, which include uncertainty into the model. Including stochastic parameters will make the model consider scenarios and events that have a low probability, but where the consequences are considerable. The model allows for global and local analysis, in which parameters like price can be represented as either internal or exogenous variables, respectively.

The LTS is split into two phases; the strategy phase and the simulation phase. In the strategy phase, water values are calculated for the system. For models with multiple areas, these are usually calculated separately. The water values are calculated for every stochastically possible scenario. The simulation phase will simulate the system scheduling with a weekly time resolution for a given number of years. Data from the water balance between reservoirs are used as restrictions in the seasonal scheduling.

The model described in this report consists of a single hydropower station, where the price variables are considered known and unaffected by production volume. Therefore, there exists only one area, and interconnections with other areas/stations can be ignored. The water values calculated in the strategy phase will thus be the optimal values for the hydropower station only. This will be described in detail later.

2.6.2 Water Value Calculation

A variable often mentioned when it comes to hydropower planning is the water value. Shortly, this is described as the expected marginal value of water, and is used as a decision variable for hydro production when compared to cost of operation. Despite water being a resource with no real cost (as water is considered free), the water value is used to set a cost on water to find out if one should produce now or store it for later. Water value is a function based on time and reservoir level. Given Figure 12, J_t is the total operation dependent cost for period t to T. This cost can be represented by Equation 1, where $S(x_t^{res})$ is the value of the reservoir level at the end of week T, and L_t is the operation dependent cost for every week t to T when moving from time step t to $t+1$.

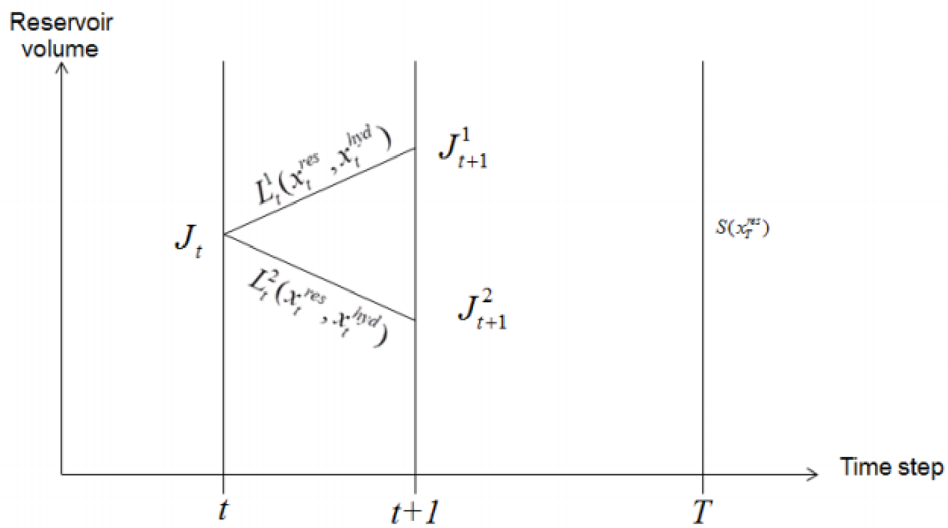

Figure 12: Illustration of planning period for water value calculation [7].

$$J_t(x_t^{res}) = min(\sum_{\tau=t}^{T} L_\tau(x_\tau^{res}, x_\tau^{hyd}) + S(x_T^{res})) \tag{1}$$

The dependent variable in these equations are the x_t^{hyd} variables, determining the released water from the reservoir for hydro production. L_t will vary based on this variable. The main goal here is to find the optimal value x_t^{hyd} that gives lowest cost J_t. Equation 1 can be altered to be dependent on the total operation cost for the next week, see Equation 2.

$$J_t(x_t^{res}) = min(L_t(x_t^{res}, x_t^{hyd}) + J_{t+1}(x_{t+1}^{res})) \tag{2}$$

Derivating from week t to $t+1$ based on released water for production will give Equation 3.

$$\frac{dJ}{dx_t^{hyd}} = \frac{dL}{dx_t^{res}} + \frac{dJ}{dx_{t+1}^{res}} \cdot \frac{dx_{t+1}^{res}}{dx_t^{hyd}} = \frac{dL}{dx_t^{hyd}} - \frac{dJ}{dx_{t+1}^{res}} = 0 \tag{3}$$

This equation gives that the marginal cost of operation connected to price, sales etc. is equal to the future total operation dependent cost depending on reservoir level (which is the marginal water value) for $t+1$. Thus, the water value should be equal to the marginal cost of operation for optimal production, and will be influenced by the production price at the given week.

For instances in which the goal is to maximize profit instead of minimizing cost, J is often referred to as α, known as the expected future profit.

When there are multiple stochastic scenarios for a given week, the water value must be based on all possible scenarios. The water value will thus be weighted on all possible considerations, and will present the optimal value when including uncertainty. The weighted water value is calculated using Equation 4, wherep_i is the probability of scenario i to occur, and $WV(t,i)$ is the water value for week t scenario i. Figure 13 shows how the water value for week t considers multiple scenarios from $t+1$.

$$WV_t^w = \sum_{i=1}^{I} p_i \cdot WV(t,i) \tag{4}$$

Calculating water values is done using backward dynamic programming, by assuming that the water value for week $t+1$ is known. Backward dynamic programming is a method used for calculating the optimal path when the end result is known, to find the optimal initial values. For water value calculation, this is the preferred approach, as the current water value is dependent on the future water values and their probabilities.

Starting at the end of the year, the water values are calculated backwards till week 1, and these values are compared to the initial values. If there is a deviation, the initial water values are adjusted and the process is repeated. This iterative process is done till the values converge.

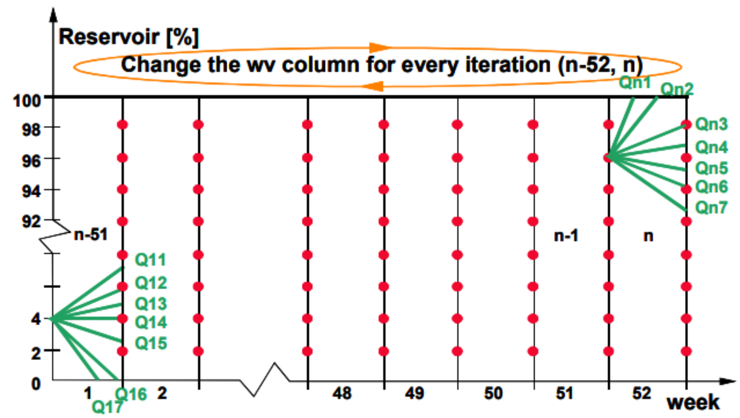

Figure 13: Illustration of the iterative process of calculating water values [7].

2.6.3 Modelling The Reservoir

When modelling using LTS, the water values must be calculated for a given reservoir level. Since the reservoir can take any value between a minimum and maximum size, the number of states that should be calculated is unlimited. To solve this, the reservoir is usually modelled to be a user-defined amount of segments, cutting the reservoir into equally distanced segments holding a unique reservoir level each. This will limit the reservoir to be modelled into $n \in NR$ points, in which NR is the total amount of reservoir segments. The water value will then be calculated for each reservoir segment.

2.7 Short Term Storage Unit Scheduling

This report will focus on modelling a short term storage unit scheduling model operating in both the energy and balancing market, and the performance of the model for several different scenarios. This type of model is inspired by the long term scheduling model described in 2.6, and will therefore use the same concepts as explained there. The whole model is explained in more detail in Section 3. Here, a few notes will be mentioned.

The reason the model is considered short term is because the model considers an energy storage unit to have seasonal variations over the course of a week, as discussed in Section 2.5.5. A hydropower model will simulate for a whole year to cover the seasonal variations, while the storage unit does this for a week. Therefore, the time horizon is short, while the method used stays the same.

Hydropower scheduling uses water values as the marginal cost of storeable energy in the system. As the storage unit has no water present, but should have a marginal cost for storeable energy, this report will use the term "Storage Value", or SV for short, as this marginal cost.

2.7.1 Modelling optimal end value of state of charge

When making a model that considers several sequential days or weeks, the model should include a way to consider the potential in storing energy for future use. For this model, a storage value curve using the method commonly used in hydropower has been implemented to model the marginal value of the stored energy, an unusual choice for a storage unit with short-term time horizon. However, this method of modelling a marginal value curve has seen some usage in other areas for storage unit modelling. The paper "Factoring the Cycle Aging Cost of Batteries Participating in Electricity Markets" [29] explains how a piecewise-linear function setup is used to model the cost of cycle aging based on depth of discharge. The marginal cost of battery cycle aging is found, which then decides the value of utilizing the storage unit versus the cost. This method was called the "rainflow algorithm".

There are also other ways to do this, which will be briefly mentioned here.

For a simple model, setting a required end value for the state of charge at the end of the decision stage is one way to set the optimal end point. The model must then consider power flow while maintaining the set end value for the storage unit. This end value can vary for each day, but the problem with this method is which end values to choose. The criteria for each decision stage could be based on historical behavior, but this can lead to inaccurate planning if the end value is off from the actual optimal value.

Another method that includes several future possibilities is the rolling time horizon. Figure 14 shows how this is laid out. The scheduling horizon is the total sequential time frame for the system, from start till finish. The prediction horizon is the time frame the model knows the certain output of, while the control horizon is the time frame that will be set in stone for each iteration. Rolling time horizon will for each iteration do the following: Simulate the optimal planning for the prediction horizon time frame, and store the results within the control horizon as set behavior. Then, it will move forward equal to the time frame of the control horizon, and re-simulate for the prediction horizon with the results from the end of the control horizon as the initial input data. This will be done iteratively until the end of the scheduling horizon. More information on this method can be found on [22].

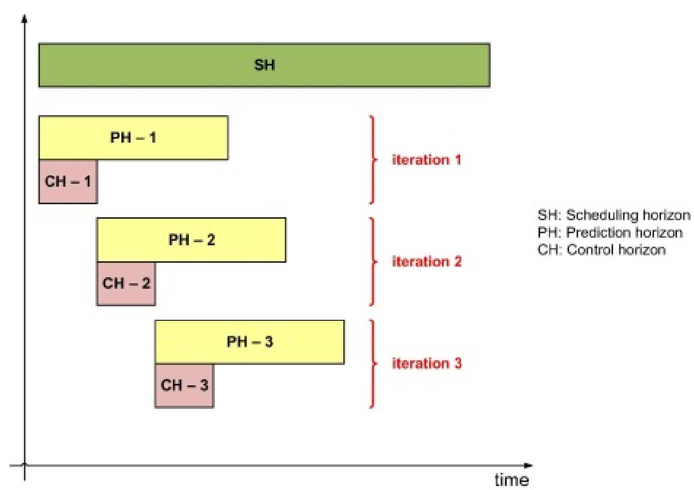

Figure 14: Illustration of the iterative process using the Rolling Time Horizon concept. Figure taken from [22].

2.8 Software Explanation

In this report, the short term storage unit scheduling model has been implemented in Python. Python is considered a high-level programming language, used worldwide for many different purposes [20]. The main pros about this language is that it is open-source, with multiple features and packages. Many features are being worked on continuously, and this helps improve the language. The community offers much help and therefore makes learning the language simpler and more effective. The most important reason that Python has been chosen is the features it offers, and that it is easy to work with.

Within Python, an optimization modelling language called Pyomo has been used to create the optimization problem. Pyomo is a Python-based, open-source software package that is capable of structuring and solving optimization models [18]. It offers the possibility of creating a general abstract model of the optimization problem, and solving it using created instances, which saves time and memory on the computer. Pyomo has a wide range of problem types, including linear and non-linear complex optimization problems. An online book written by the Sandia National Laboratories has helped the author understand how to create and optimize Pyomo, and can be found in the given citation [16].

Pyomo has several software packages available to use as the solver. For this project, Gurobi has been used as the solver for the optimization problems. Gurobi has good experience with non-linear optimization problems, which is essential as this model will include these modelling aspects. Gurobi is also rapidly growing in popularity and usage worldwide. [11]

2.9 Modelling Assumptions and Uncertainties

As mentioned in Section 2.6, hydropower models include assumptions and uncertainties to simulate close to realistic behavior. The same goes for the energy storage unit, as perfect modelling is almost impossible to accomplish. Therefore, this section will cover uncertainties related to electricity prices, as well as some approximations in the modelling aspect.

2.9.1 Input data and Price data

It is important that the input data is precise, reliable and consistent for the scheduling period. Without this detailed data showing what the system is exposed to, the system will not be able to make accurate decisions compared to what one could expect to occur. Therefore, the data given to the scheduling model should be based on historical data, which will generate a historically reliable behavior and realistic pattern. Another important point is that this will include extreme scenarios that have happened earlier, instead of only covering the most likely scenarios. However, to avoid having to analyze too many scenarios, the input data should be cut down to a user-defined number of discretized stochastic variables that represent the possible scenarios that can occur at the given decision stage. This allows some of the variables to be extreme points, where their impact is based on the probability of occurring.

For energy prices, there is a big uncertainty because the price is not known at the time of bidding, which holds true for both the DA and BM. The biggest assumption to make is that the participation of the given system does not impact the market, or in other words that the market is considered inelastic. By using historical data from the markets, the realistic price pattern and behavior can be used to simulate realistic decision making. The model will then use the price data for each decision stage as known variables, and distribute optimal planning in a reactive manner. This still makes the future decision stages unknown, i.e. scheduling for a Monday still keeps the Tuesday prices unknown.

The price data should also be converted into several discretized stochastic variables (named price nodes) based on the historical data, to promote realistic behavior and also include extreme scenarios.

2.9.2 Price Probability

When operating with stochastic models, there are multiple price nodes for each decision stage in this storage unit system that has a probability of occurring. However, future prices are normally dependent on behavior in the past, making modelling and representing this long and complicated. This is especially true for backward dynamic programming, in which the previous stages have not yet been determined for the current stage.

To solve this dilemma, price probability can be modelled using a Markov Chain [14], graphically shown in Figure 15. The main function of a Markov Chain is that future probability decisions are made regardless of past decisions. In other words, the only factor contributing to the decision making is the probability of future states based on the current state. Modelling price probability like this will solve the problem when using backward dynamic programming.

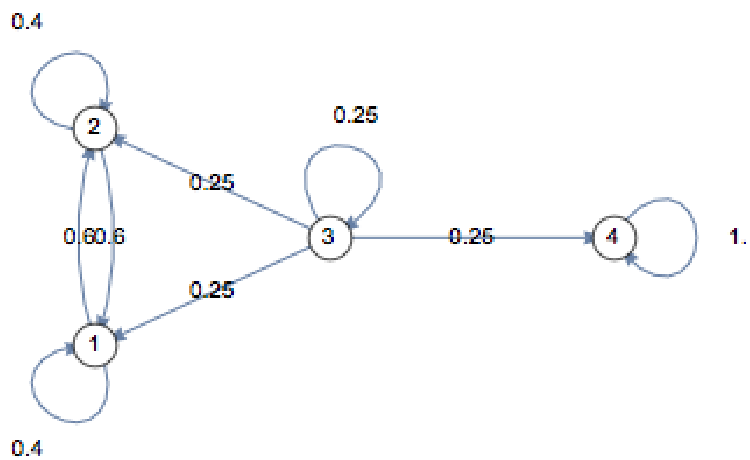

Figure 15: Illustration showing the setup for a Markov Chain [14].

2.9.3 Pyomo Abstract vs Concrete model

In Pyomo, there are multiple ways to generate an optimization model. These can be divided into two separate model setups; abstract or concrete optimization models. Making a concrete model means creating a model where the specific parameter values and such are known when it is constructed. This data is built into the model. E.g. creating a model where you specify that the parameter $Lim = 1$ from the start, is done using a concrete model [16].

Generating an abstract model means making a mathematical model, where the parameters and variables are unspecified. So the core model is laid out, including parameters, sets, objective function and constraints, but there are no specific values known at the time. Using the previous example, the parameter Lim is only set to be a parameter with the given dimensions based on undetermined sets (if given any), but no value is given. To use this model to simulate a given case, one creates a "model instance", where all the relevant data is given, and the model is creating a concrete instance to simulate. In other words, the abstract model is turned into a specified concrete model to solve. Figure 16 shows an abstract and concrete mathematical optimization setup.

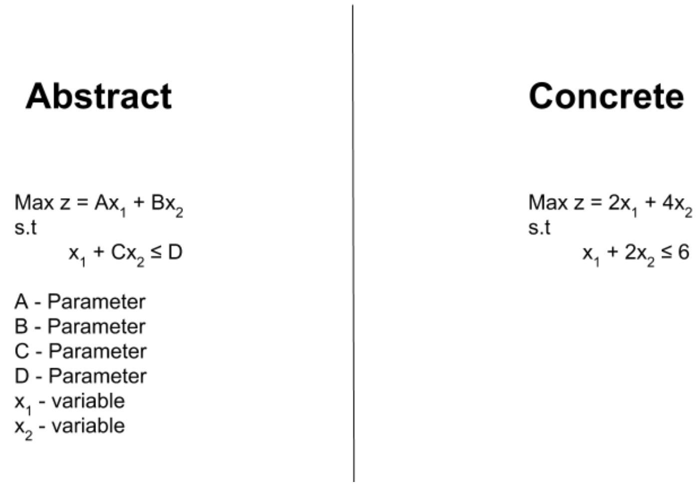

Figure 16: A mathematical optimization problem illustrated concrete and abstract.

The advantage of using an abstract model, is that it enables the user to create a mathematical setup of the model, and then create indefinite amounts of instances based on the model, without having to spend time and memory to rebuild the model for each instance. This saves computational power, which is essential when dealing with numerous instances. Therefore, the principle when creating this optimization model has been to use the abstract model to prevent long simulation time.

2.9.4 Modelling non-linear efficiency curves

For most power producing units, the output power increases as the input power increases. This holds true for hydropower, solar power, wind power etc. Depending on the rated power and how the units are made, they are most likely to have an optimal production point in which they have the highest output/input ratio, where the efficiency is highest. For non-optimal areas, the efficiency varies depending on the type of unit, and typically, the total efficiency curve has a non-linear behavior. This can also be said about storage units and the components within, as they too are rated for peak performance at a given point. The converter in the system is the most likely place to have a non-linear efficiency curve behavior, and is where the efficiency has been modelled.

Modelling a non-linear curve can be quite difficult, especially for non-convex non-linear patterns. This creates a local optimum, which can be difficult for the model to determine and work with. This has been dealt with in the optimization model by enabling two solutions: Having a constant efficiency, or use SOS-2 variables to generate a piecewise-linear approximation. The first solution is straight forward, i.e. that the efficiency is not affected by power flow. The second one will be discussed more in detail below.

Piecewise-linear approximation is a method used to model non-linear behavior. One discretizes the non-linear curve, and finds specific performance on each point. Then, the model will create this curve using these discrete points, in which the lines between the points are linearized. These lines are modelled as SOS-2 variables, which require that a maximum of two neighbouring points have their SOS-2 variable non-zero, and that the sum of them is equal to 1. So, if the optimal point is between two discrete points, the points are linearized and the value is found. This will be visually shown with an example further on.

Pyomo offers a software package where this type of piecewise-linear approximation and the setup of SOS-2 variables can be done in another manner, instead of creating constraints and declaring binary variables to represent the SOS-2 variables. This can be a solution for users that have little experience with setting up SOS-2 variables. The package used is called "pyomo.Piecewise", and information about it can be found in [19]. Equation 5 shows the setup of the package:

$$pyomo.Piecewise\{y, x, pw\_pts = L_x, pw\_constr\_type = z, f\_rule = L_y, pw\_repn = b\} \quad (5)$$

where y is the output variable, x is the input variable, L_x is the list containing the discrete points for the input variable, z is the type of constraint (less, equal, more etc), L_y is the list containing the discrete points for the output variable, b is the type of piecewise representation to use, where the default declaration is SOS-2. By default, SOS-2 is used, but it is also possible to use logarithmic solutions.

Figure 17 shows a graphical representation of this procedure. Note that when using this package, the model cannot be an abstract model at the time of declaring "Piecewise", as it needs to know the dimensions and values of the lists. Therefore, this must be created after a model instance has been declared.

With this method, it is possible to model non-linear efficiency curves and other non-linear curves into the model. This type of modelling gives a higher computation time, depending on the number of discrete points. This also makes the model a mixed-integer programming prob-

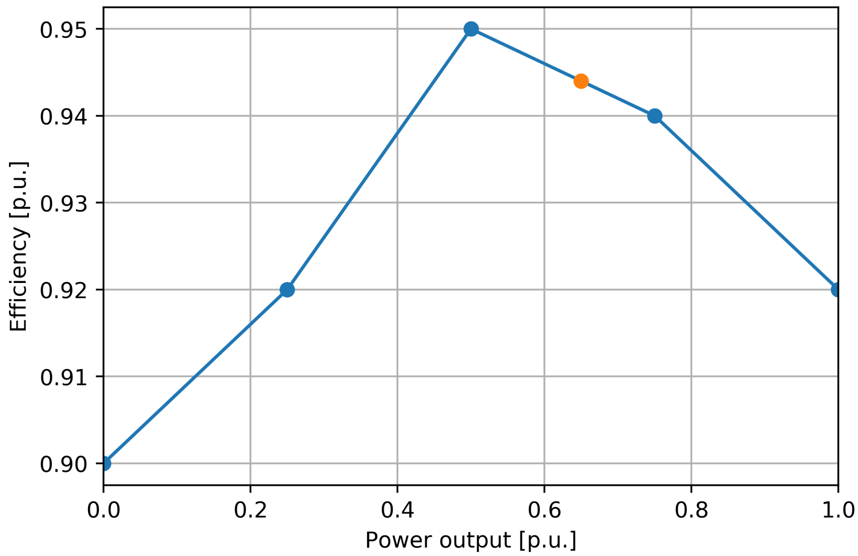

Figure 17: Illustration showing piecewise-linear approximation setup. The orange mark is the wanted point, and it is found by linearizing between the adjacent discrete points.

lem, due to the presence of binary variables.

2.9.5 Model Simplifications

When constructing the abstract model, it is possible to use different parts of the model based on the user preferences from the same model. This is done by creating constraints that are only enabled if the user wants to. This means that some constraints can be chosen over others, giving the model different behavior and considerations that it must maintain. This can be used to simplify parts of the model, and is one of the advantages by using Pyomo.

3 Model Description

To make it possible to analyze the performance of an energy storage unit operating in both the energy and reserve markets, modelling is the preferred approach to give realistic results. Therefore, a multi-stage, multi-scenario, short-term stochastic model has been created for this occasion. The model and problem given has been implemented and solved using Pyomo in Python. The inspiration behind this model comes from a SINTEF project called “Assessing Hydropower Operational Profitability Considering Energy and Reserve Markets”, written by Arild Helseth and Marte Fodstad. The following citations include the original explanation of their model [13] [12], which simulates a hydropower producer operating in both the energy and reserve markets. The authors' own explanation of the model referred here can be found in the following citation [27], as this model was tested to analyze performance in the reserve market.
The following chapter will focus on explaining the whole model created by the author, both the motivation, the execution, and the different options the model provides. This includes the optimization problem that simulates the system and a strategy and simulation phase used to test performance of the model. This model can initialized with the use of the python script "main_initialize.py", and found in "functions_model.py", attached to this report.

The explanation of the strategy phase and simulation phase, found in Sections 3.2 and 3.3, respectively, are based on the explanation the author did in the specialization project [27]. Therefore, there might be similarities in the explanation, since the principle is equal in theory.

The whole model is split into different phases. It consists of a model setup in which the optimization problem is defined, and has a two-step solution procedure to analyze the given input scenarios. It will first execute the strategy phase to calculate storage values for each possible deterministic scenario which are weighted based on the stochastic probability, and then simulate a sequential performance in the simulation phase. Figure 18 shows the general setup of the model, in which each key part is specified.

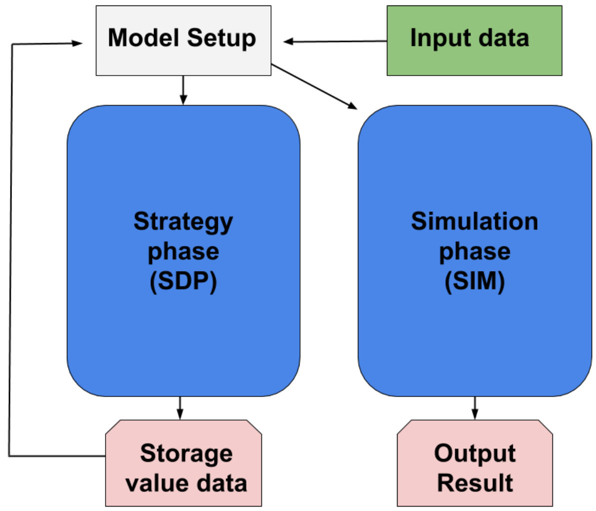

Figure 18: Illustration of the two-step solution procedure and the optimization model as a whole.

3.1 Optimization Problem

"Model setup" from Figure 18 includes generating the abstract version of the optimization problem used in the overall model. The optimization problem represents the scheduling decision for the energy storage system, and will analyze the given input parameters to optimize scheduling for a given deterministic scenario. It is used in both the strategy and simulation phase under different configurations and conditions, and is therefore key for the whole model. Following the next subsections, the optimization problem will be explained more in detail, giving an overall understanding of how it functions and what it considers.

3.1.1 Overview

The model represents a single energy storage unit connected to the grid through a converter, as shown in Figure 19. The figure uses a battery as a visual example of a storage unit, but the way it is modelled, the storage unit can be other solutions as well as long as it stores energy. The grid is considered to have unlimited inflow and outflow capacity, having only constraints in the converters' power capacity. When the battery is charged from the grid, the input power p^b to the converter will be converted from AC to DC and stored in the storage unit as p^{in}, after having been affected by the converter efficiency $\eta_{ch}(p)$ during charging. When the battery is discharging to the grid, the input power to the converter p^{out} will be converted from DC to AC and sold to the grid as p^s, after having been affected by the converter efficiency $\eta_{dch}(p)$ during discharging. The efficiency when converting both ways can be different.

The optimization model will calculate the optimal flow of power and sales to the two markets through $t \in TS$ time steps. The amount of time steps can vary dependent on the user, as well as the duration of each time step. Therefore, the user can analyze short durations like minutes and hours, or longer periods like days or weeks. Of course, the number of time steps will play a huge role in time usage for solving the problem, and a longer time period for each time step will neglect short-time variations.

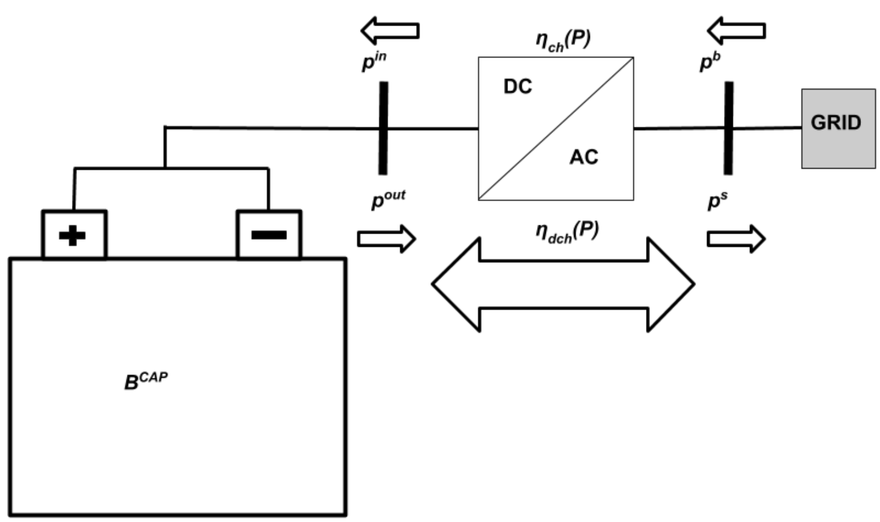

Figure 19: Illustration of the energy storage system in the optimization problem. The use of a battery as the energy storage unit is purely for illustration purposes.

3.1.2 Objective Function

The main objective of the optimization problem is to maximize total profit for the producer. The optimization problem can be found as a whole in Section A. The objective function is as described in Equations A1-A4:

$$OBJ = \sum_{t\in TS} E_{price,t} \cdot p_t^f \cdot T_t \tag{A1}$$

$$+ \sum_{t\in TS} T_t \cdot C_{price,t} \cdot cap_t \tag{A2}$$

$$- \sum_{t\in TS} A_{price,t} \cdot p_t^{art} \cdot T_t \tag{A3}$$

$$+ SV + DVal \tag{A4}$$

where the profit originates from the sales of energy (Equation A1) and reserve capacity (Equation A2), the value of the remaining stored energy in the storage unit and the future profit (Equation A4). The only cost present comes from a penalty of storing artificial power in the storage unit (Equation A3).

Due to the energy storage unit having no natural input of power, the profit from sales of energy must come from regularly buying and selling energy from the grid, preferably at low and high energy prices, respectively. This results in the possibility of having negative profit from sales of energy.

3.1.3 Model Variables

This model has a lot of different variables that will be mentioned several times during this explanation. Therefore, there will be given a short explanation of their definition here. This can also be found in Appendix A.

soc_t - state of charge at the end of the time step t.
p_t^{in} - power flowing into the storage unit at time step t.

p_t^{out} - power flowing out of the storage unit at time step t.
p_t^b - power bought from the grid at time step t.
p_t^s - power sold to the grid at time step t.
p_t^f - total power flow on the grid side at time step t.
cap_t - reserve capacity sold at time step t.
p_t^{art} - artificial power bought and stored in the storage unit at time step t.
SV - total storage value of the stored capacity in the storage unit at the end of the decision stage.

3.1.4 Model Constraints

The optimization problem has implemented several constraints to make the model behave like a realistic storage unit system. These are crucial for correct scheduling decisions, and it is important that they are performed correctly when implementing new strategies.

Energy Storage Unit
The energy storage unit in this model is characterized to only store, hold, and discharge power based on the wanted outcome. The unit is considered ideal in terms of possible losses for storing energy between time steps. The storage unit has for each time step a state of charge (SOC) that represents the stored amount at the end of each time step. The only factors that change this is incoming power, outgoing power and artificial power. This is shown in Equation A5.1 and Equation A5.2, for both an initial condition and continuous condition:

$$soc_0 \cdot B^{MAX} - p_0^{in} \cdot T_0 + p_0^{out} \cdot T_0 - p_t^{art} \cdot T_0 = SOC^{Start} \cdot B^{MAX} \tag{A5.1}$$

$$soc_{t-1} \cdot B^{MAX} + p_t^{in} \cdot T_t - p_t^{out} \cdot T_t + p_t^{art} \cdot T_t = soc_t \cdot B^{MAX}, \quad t \in TS \backslash [ord(t) > 0] \tag{A5.2}$$

where SOC^{Start} is the per unit energy stored in the storage unit at the start of the decision stage, and B^{MAX} is the total capacity of the storage unit. With this setup, the model will simulate changes in storage level based on power flow, but also have the possibility of using an artificial power source if needed. This artificial power source is a costly implementation, and should only be used when absolutely necessary because it will worsen the objective function.

The amount of capacity the energy storage unit can use, can be affected by external surroundings, as has been mentioned in Section 2.5.4. To include this in the model, the lower state-of-charge boundary is limited by the maximum depth of discharge, referred to as the MDOD. The value consists of the per unit amount of total capacity the storage unit can use, where the value 1 equals full utilization. This limitation on capacity utilization has been modelled to only limit the lower boundary. Despite this limitation having the possibility of affecting both the lower and upper boundary, utilizing this to give a lower boundary is equivalent, as this only limits the capacity range. This limitation is modelled as shown in Equation A15:

$$(1 - MDOD) \le soc_t \le 1, \quad t \in TS \tag{A15}$$

where $MDOD$ is the maximum depth of discharge in per unit.

The Converter

The converter in the model has been created to convert the bought AC from the grid to the wished output for the energy storage unit, and vice versa. In this model, it is used to represent the limit of transferable power in and out of the storage unit, and to represent the efficiency losses in the model during this power transfer.

For the input and output power of the converter, during both charging and discharging, the power transferred will be limited by the output capacity. With this, the following boundaries can be set, as shown in Equations A16.2 and A17.2:

$$0 \le p_t^s \le P_{dch}^{max} \tag{A16.2}$$

$$0 \le p_t^{in} \le P_{ch}^{max} \tag{A17.2}$$

where P_{ch}^{max} is the maximum output power the converter can reach during charging, and P_{dch}^{max} is the highest output power the converter can reach during discharging.

In the model, the possibility of providing varying output limitations on the converter has been implemented. This is to make it possible to analyze the performance of a power inflow/outflow limit that can change for each time step. This is implemented as shown in Equations A16.2 and A17.2, however, it differs from the previous equations in that P_{dch}^{max} and P_{ch}^{max} will be varying for each time step and thus have a unique dependency for each time step $t \in TS$.

Converters and common efficiency-affected units usually have a varying efficiency curve for the output, depending on power transferred, as discussed in Section 2.5.2. This has been in focus for this model, which creates a non-linear behavior that does not necessarily have the global optimum on the end points. In other words, the efficiency of the converter is not constant.

With a varying efficiency curve, the correlation of input/output power on the converter in both directions are equivalent to Equations 6 and 7:

$$p_t^{in} = \eta_{ch}(p_t^b) \cdot p_t^b \tag{6}$$

$$p_t^{out} = \frac{p_t^s}{\eta_{dch}(p_t^{out})} \tag{7}$$

where the efficiencies η_{ch} and η_{ch} are the efficiencies for the converter during charging and discharging for a specific input power.

Modelling this into the optimization problem requires the use of SOS-2 variables, also known as special ordered sets of type 2. Pyomo has a built-in function called "Piecewise", that enables the user to create a SOS-2 setup for this kind of problem. This is explained more in detail in Section 2.9.4. This setup has be done for both charging and discharging.

Modelling this for charging is shown in Equations A11.2 and A11.3:

$$\sum_{k=1}^{K} \delta_{k,t}^1 = 1, \quad \delta_{k,t} \quad \epsilon\{0,1\}, \quad t \in TS, SOS-2 \tag{A11.2}$$

$$p_t^{in} = (\sum_{k=1}^{K} \delta_{k,t}^1 \cdot P_k^{cha}(p_t^b)), \quad t \in TS \tag{A11.3}$$

where $\delta_{k,t}^1$ is the SOS-2 binary variable for every discrete point $k \in K$, and P^{cha} is a list of K discrete points specifying the output power of the converter based on the input power. This list combined with the SOS-2 binary variables, allows for a piecewise-linear approximation of the efficiency curves. Figure 20 shows an example of how this is graphically represented.

The same modelling is done with the converter for discharging, as shown in Equations A12.2 and A12.3:

$$\sum_{k=1}^{K} \delta_{k,t}^2 = 1, \quad \delta_{k,t} \quad \epsilon\{0,1\}, \quad t \in TS, SOS-2 \tag{A12.2}$$

$$p_t^{out} = (\sum_{k=1}^{K} \delta_{k,t}^2 \cdot P_k^{dis}(p_t^s)), \quad t \in TS \tag{A12.3}$$

where $\delta_{k,t}^2$ is the SOS-2 binary variable for every discrete point $k \in K$ for discharging, and P^{dis} is a list of K discrete points specifying the input power of the converter based on the output power. This follows the exact same procedure as previously mentioned.

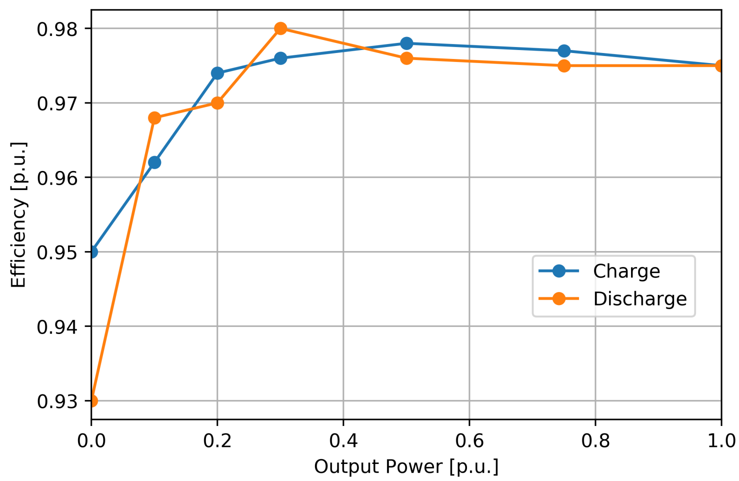

Figure 20: Plot of piecewise-linear approximation for possible efficiency curve for varying charge/discharge behavior. Note that between each discrete point, the behavior is assumed linear.

Included in this model, is the option to negate the efficiency curves and instead have constant efficiencies for the converter. This is something the user can specify, and the model will be generated according to that specification. If the efficiency curves are negated, the model will utilize Equations A12.1 and A13.1 shown below, where the efficiencies η_{ch} and η_{dch} are assumed constant.

$$p_t^{in} \cdot T_t = \eta_{ch} \cdot p_t^b \cdot T_t \quad t \in TS \tag{A11.1}$$

$$p_t^s \cdot T_t = \eta_{dch} \cdot p_t^{out} \cdot T_t \quad t \in TS \tag{A12.1}$$

The grid

The grid in this model is where energy is bought and sold. There are no limits to how much power can be sold or bought at the given time step, as the grid is considered unsaturated and inelastic. The only constraint here will be the limit on the converter output for both charging and discharging.

To simplify the grid side, the variables for both buying and selling power have been put into one single variable, as shown in Equation A10:

$$p_t^f \cdot T_t = p_t^s \cdot T_t - p_t^b \cdot T_t \tag{A10}$$

where p_t^f is the total amount of power transfer from the grid, where a positive value results in sale of energy and a negative value is equivalent to purchasing energy.

Reserve capacity

Reserve capacity is an insurance of production regulation based on the current production and available flexibility. This is true for both directions, both up- and down-regulation of power, e.g. 5 MW sold reserve capacity means the producer must be able to provide 5 MW increase or decrease in power output. Based on this, reserve capacity will be limited by the converter power flexibility and the storage capacity flexibility in both directions. The lowest limitation will be the deciding factor. For storage, it has been modelled so that the storage unit must have enough capacity to provide the regulation for the whole time step. Reserve capacity has been modelled to not change the power flow.

For the converter flexibility, the reserve capacity flexibility will be limited by the available tuning of the grid power variables and the total remaining tuning of the converter. As a storage unit can go from charging to discharging and vice versa, the range of this is wider than for a hydropower station, unless something like a pump is installed. Equation A6.2 shows the up-regulation limit and Equation A7.2 shows the down-regulation limit modelled for the reserve capacity:

$$-p_t^f \geq cap_t - P_{dch}^{max} \tag{A6.2}$$

$$-p_t^f \leq -cap_t + \frac{P_{ch}^{max}}{\eta_{ch}^{max}} \tag{A7.2}$$

where cap_t is the amount of reserve capacity sold, P_{dch}^{max} is the highest output capacity of the converter during discharging, P_{ch}^{max} is the highest output capacity of the converter during charging, and η_{ch}^{max} is the highest efficiency of the converter during charging.

These two equations limit the reserve capacity based on the limitations on the converter and the current power flow. If there is a low power flow, the reserve capacity potential increases, and if the power flow is high, the reserve capacity is limited further. The model includes the possibility of going from charging to discharging. For example, a converter output limit at 1 MW in both directions, with no power losses, and a power flow of $p_t^f = -0.2MW$ (meaning charging 0.2 MW), results in a reserve capacity potential of 1.2 MW up-regulation, and 0.8 MW down-regulation, in which the latter will be the deciding constraint. Figure 21 shows a graphical illustration of this.

Equation A7.2, however, also includes the efficiency of the converter and thus increases the limit of down-regulation. As the converter output is the limiting factor, the input side during charging

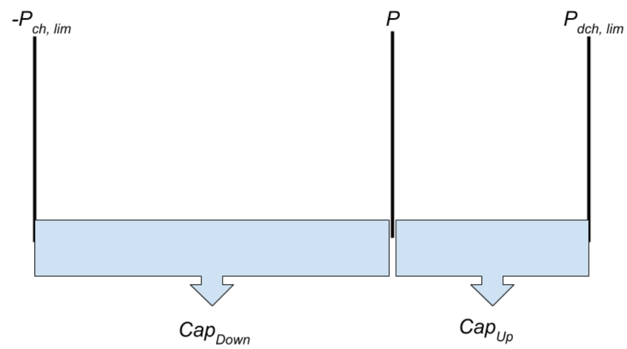

Figure 21: Graphical illustration of reserve capacity limits based on power flow. Here, the up-regulation is limited the most and thus the deciding constraint.

can be greater based on the efficiency, as some power will be lost in the converter. The highest charging efficiency is used to simplify this process, to prevent selling more reserve capacity than the power input can provide. This process could be dealt with by using piecewise-linear approximation, but the deviation is considered small and unnecessary compared to the increase in computation time due to the added complexity.

As this is not the same during discharging, this creates an interesting balancing point for optimal reserve capacity sales. Using the example previously mentioned, and now assuming a charging efficiency of 0.5, the down-regulation would be equal to 1.8 MW instead of 0.8 MW. The optimal point if maximizing reserve capacity would be to charge the storage unit with $p_t^f = -0.5MW$, giving a reserve capacity limit at 1.5 MW in both directions. This creates a possibility of charging the storage unit during the time steps, while optimizing reserve capacity sales, depending on the optimal profit between the two markets.

For the storage capacity flexibility, the reserve capacity will be limited by the remaining storage capacity and the actual stored energy. This is to ensure that the storage unit can withhold the power change due to the up- and down-regulation during the whole time step. Also, as described for the converter flexibility, the efficiency of the converter contributes to limiting the reserve capacity sales based on storage, as shown in Equations A8 and A9:

$$cap_t \cdot T_t \leqslant (1 - soc_t) \cdot \frac{B^{MAX}}{\eta_{ch}^{max}} \quad t \in TS \tag{A8}$$

$$cap_t \cdot T_t \leqslant (soc_t - (1 - MDOD)) \cdot B^{MAX} \cdot \eta_{dch}^{min} \quad t \in TS \tag{A9}$$

where η_{ch}^{max} and η_{dch}^{min} are the highest charging efficiency and lowest discharging efficiency for the converter, respectively.

The efficiency values are included to ensure that the power that is either up- or down-regulated, must pass through the converter and be the end product on the grid side, and thus will experience power losses. On the charging side, this will result in a higher potential, while on the discharging side, this will result in a lower potential. For the charging efficiency, the highest value has been used to ensure that there will never be a situation where more reserve capacity is sold than the storage unit at best will be able to store. Likewise during discharging, the lowest efficiency value has been used to ensure that there will not be a shortage of actual up-regulation based on converter efficiency. The $MDOD$ is included to ensure that the lowest storage capacity level is regulated based on this parameter, and also reflected in the reserve capacity limit.

Figure 22 shows how the reserve capacity is limited based on remaining storage capacity and stored energy. This setup will ensure that the storage unit has the available resources to fully sell reserve capacity.

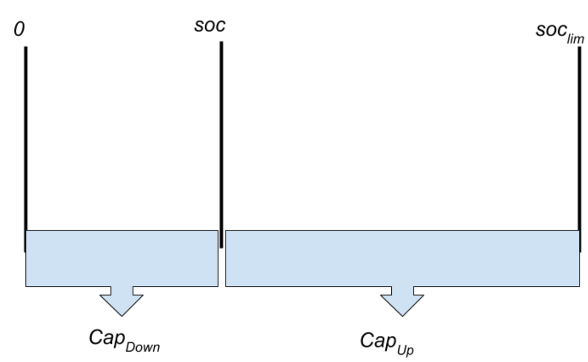

Figure 22: Graphical illustration of reserve capacity limits based on remaining energy and available energy storage in the storage unit. The available energy in the storage unit is what is limiting reserve capacity sales here.

The Energy Market

For the energy market, the price is given for each time step, and can vary. The model will seek to buy energy during low prices, and sell energy during high prices. Due to the efficiency, the model will optimize this market by ensuring that the profit from selling energy when the price is high, is more beneficial than the lost value from the total lost energy.
The energy market is modelled like what is shown in Equation 8:

$$E_{profit,t} = E_{price,t} \cdot p_t^f \tag{8}$$

where E_{price} is the energy price for time step t, and $E_{profit,t}$ is the energy sales profit for this time step t. Since the storage unit is charging and discharging, there could be situations of both negative and positive energy profit.

The Reserve market

The reserve capacity market has the same setup as the energy market, except that reserve capacity is always sold, never bought. The profit from reserve capacity is given by Equation 9:

$$C_{profit,t} = C_{price,t} \cdot cap_t \tag{9}$$

where $C_{profit,t}$ is the total profit of selling reserve capacity for time step t, and $C_{price,t}$ is the price of reserve capacity for time step t. When comparing this market with the energy market, where the storage unit will try to maximize selling and buying energy, selling reserve capacity will restrict the participation in that market. Thus, they will limit each others profits when looked at separately, while trying to obtain a greater total profit for the system.

One limitation to the reserve capacity sales was included based on the possible market mechanisms. Some reserve capacity markets might have requirements for the duration of selling reserve capacity, and the quantity sold. This can be for an hour, or for several consecutive hours, depending on the reserve capacity market as mentioned in Section 2.4.4. The time steps in the model can be varying in length. To include this in the model, a constraint connecting reserve capacity sold to the grid for various time steps has been created, as shown in Equation A14:

$$cap_t = cap_{t-1}, \quad t \in TS \backslash [ord(t) > 1, t \neq R_c^{list} for c \in C] \tag{A14}$$

where cap_t and cap_{t-1} are the reserve capacities sold at time step t and t-1, respectively, R_c^{list} is a list with C inputs containing the start of the next equalized reserve capacity period. With this, the reserve capacity will be connected between the time steps, depending on the user inputs for the list.

To provide an example, assume t is for 10 time steps 1-10. R_c^{list} has the value 6, which will result in equal reserve capacity sales between time steps 1-5 and 6-10.

Storage Value

As the model will optimize power transfer and reserve capacity sales, the flow of power will vary and the storage unit will experience variation in stored energy. However, this will only occur during the time steps for the decision stage, and without including some future value of the stored energy, the value of storing energy over to the next decision stage is none. To promote this planning, the future value of the stored energy at the end of the decision stage has been implemented and included in the model. This is based on how water values are calculated for hydropower, explained in 2.6.2.

This has been done using piecewise-linear approximation, the same way the non-linear efficiency curve for the converter has been implemented. The model implementation is described in Equations A13.1 and A13.2:

$$\sum_{n=1}^{NR} \delta_n = 1, \quad \delta_n \epsilon \{0,1\} \tag{A13.1}$$

$$SV = (\sum_{n=1}^{NR} \delta_n \cdot SV_{pts}[n, soc_{TS}]) \tag{A13.2}$$

where δ_n is the SOS-2 variable for every discrete point $n \in N$, SV is the total value of the stored energy at the end of the decision stage based on the remaining energy stored in the storage unit, soc_{TS} is the storage level at the end of the decision stage, and SV_{pts} is a list of storage values based on storage levels, with NR discrete values. The storage value is the marginal cost of storing 1 more kWh of energy in the storage unit, serving as a marginal opportunity value. Between each discrete point, linearization is done to find the value for a given storage level.

This promotes the strategy of storing energy in the storage unit for future use, for a future decision stage that is not known at this point. However, to do this, the storage value list SV_{pts} must be created based on the possible future scenarios, and the number of discrete values NR must be determined. To find these values, one would need to simulate for the future possible scenarios, and find the increased profitability with increasing initial storage level. For this model, a stochastic dynamic programming method has been implemented, which will be explained further in Section 3.2.

3.2 Strategy Phase

For the short-term scheduling model, a strategy phase is needed to pre-emptivly find the optimal planning for each possible scenario before simulating it later on. In other words, the marginal value of power flow, also known as the storage values, are calculated for each possible outcome to have the proper planning strategy when testing the performance of the storage unit. To find these storage values, the strategy phase is executed using stochastic backward dynamic programming. As mentioned in Section 2.6.2, this is the preferred approach for hydropower, as the future stage affects the current stage decision making. As this is also what this created model will test, it is assumed the same in this case.
The next subsections will further describe how the strategy phase is laid out, and how these optimal storage values are found.

3.2.1 Overview

Figure 23 shows a schematic of how the strategy phase is laid out. The following points will explain the role and function of each part.

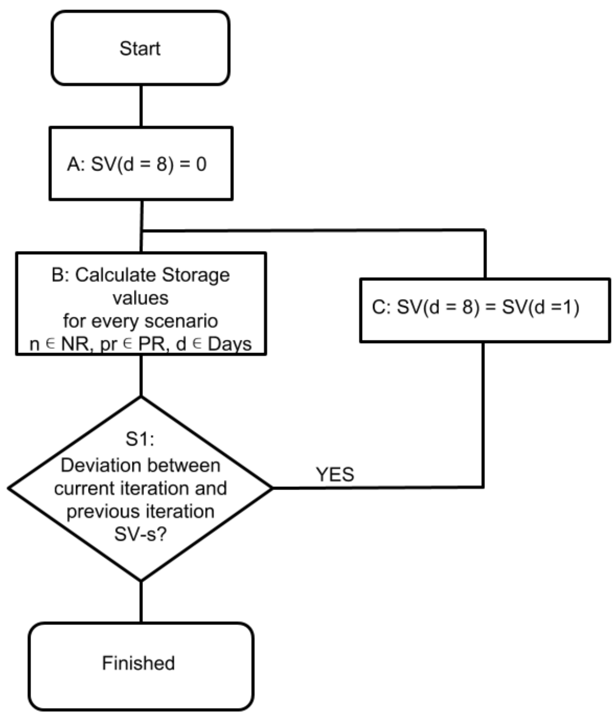

Figure 23: Flow schematic of the strategy phase.

Box A: Setting Starting Values
Since the model is using backward dynamic programming to compute the storage values, the

initial values must be set before calculating. Thus, the initial storage values and expected future profit values for day 8 are set to 0 here, or any given number. The model operates with 7 days per week, however, as the storage values are based on the values for the end of the day, which is equivalent to the start of the next day, an 8th day is needed to symbolize the start of next week/end of current week. Therefore, the 8th values are set to 0 at the start.

Box B: Calculating Storage Values

Here, the storage values for all scenarios are found. The number of scenarios calculated are based on the given size of price nodes ($pr \in PR$), storage level segments ($n \in NR$) and days ($d \in Days$). The storage values are needed for each possible combination, resulting in a total of $Days \cdot NR \cdot PR$ calculations.

For the storage level segment NR, this is a user-defined number of discrete values. As explained in Section 3.1.2, the optimization problem uses a piecewise-linear approximation to find the optimal total storage value in the storage unit between the discrete points. If these discrete points are too far away from each other, the linearization can result in a deviation between the actual and simplified curve pattern that affects the accuracy. Figure 24 shows how the linearization becomes more accurate as the number of discrete points increases.

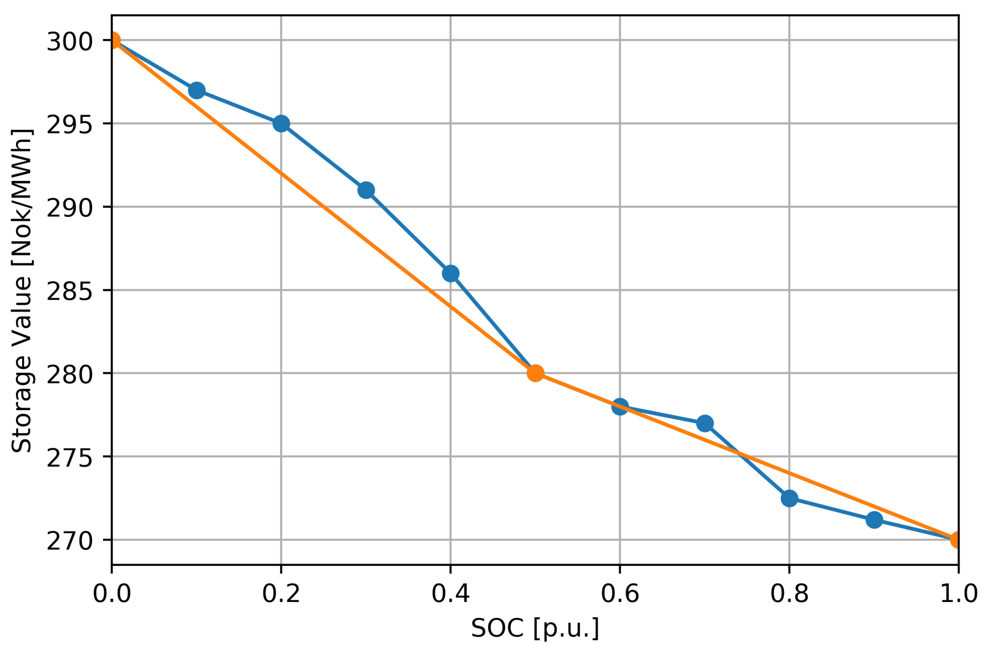

Figure 24: Plot of Storage value linearization based on two separate number of discrete points. Note that the accuracy increases with increasing discrete points.

Calculating the storage values are done as follows:

For a given day d and storage level segment n, the optimal production profile is calculated using the optimization problem for every $pr \in PR$, storing the objective function α for each calculation.

Since the price data has a stochastic setup, the weighted objective function for the given day and storage level segment must be calculated based on all possible future scenarios. This is done in Equation 10, where $prob_{pr}$ is the probability of moving from price node pr to price node $pr^{'}$, and α is the objective function for the given price node. This is done to include the uncertainty connected to multiple possible outcomes, which will affect the profit.

$$\alpha(pr,d) = \sum_{pr^{'} \in PR} prob_{pr}(pr,pr^{'},d) \cdot \alpha(pr^{'},d) \tag{10}$$

If the current storage level segment is the first, when the storage unit is initially empty, then the weighted objective function is stored as the offset in value function $DVAL$, also referred to as the expected future profit. Figure 25 shows how the expected future profit varies with the storage unit level, including a positive value for an initially empty storage unit. This value is included in the optimization problem for optimal calculation as it stores the potential future profit for the storage unit for the future $Days$ [12]. Note that this figure is based on the concept of performing this on a hydropower station, but the concept still holds true for an energy storage unit.
For storage levels not equal to zero, the storage values are calculated based on the found weighted objective functions. This is shown in Equation 11:

$$SV(n-1,pr,d) = \frac{\alpha(pr,n) - \alpha(pr,n-1)}{SOC(n) - SOC(n-1)} \tag{11}$$

where α is the weighted objective function for the given price and day, and SOC is the storage level for the chosen storage level segment. This procedure is the concept described in Figure 25.

When calculating the storage values in this manner, the storage segment $n+1$ is used with n to calculate the storage value at the storage segment n. This leaves no additional segment to find the storage value for the last segment where the storage unit is initially full. By definition, the storage value is the marginal cost of storing 1 more kWh in the storage unit, which will be 0 when it is already full. However, as the model uses linear approximation between all segments,

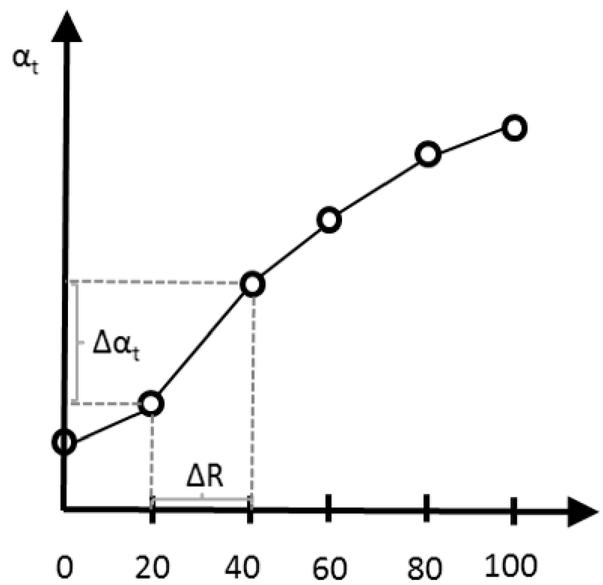

Figure 25: Plot of expected future profit for different reservoir levels for a hydropower station. Illustration from [12].

the storage value linearization between the second to last and the last point will have a steep slope towards 0, giving an unnatural storage value decrease between these discrete points. This is dealt with by adding a storage level segment point that is close to a SOC level of 1 (soc = 0.999), which is included in the total computation. Figure 26 shows how this makes the steep slope cover a tiny specter of the SOC boundary. The use of extrapolation could have been another way of solving this problem.

This storage value calculation is repeated for all $n \in NR$, $d \in Days$.

Box S1: Deviation between iterations

Consistent storage values are calculated through an iterative process, making sure the values at the end are close or equal to the starting values. Therefore, all the storage values will be checked for consistency in this box. When having completed an iteration, the storage values will be checked against the storage values from the previous iteration. If this is the first iteration, then there is no other file to compare to, and the deviation will be large, causing the statement to be "YES". If, after some iterations, the deviation is under a user-defined tolerance, then the statement will be "NO", causing the storage values generated to be accepted.

Box C: Adjusting the initial values

If the deviations from box S1 were too large, the process must be repeated in a new iteration.

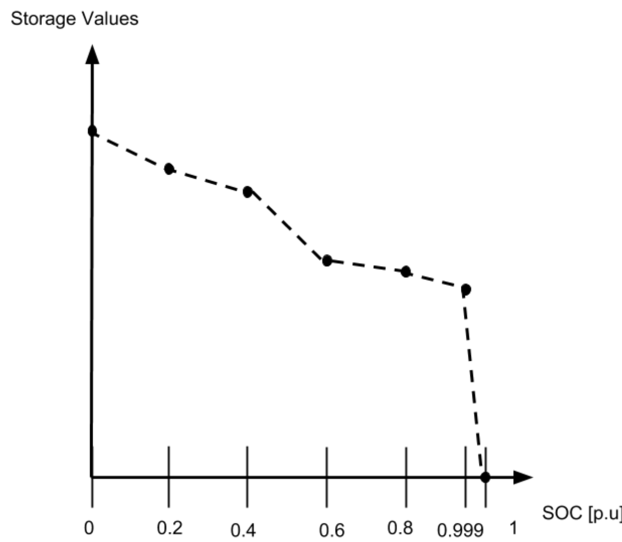

Figure 26: Illustration of possible SV-values behavior based on storage level.

The storage values and expected future profit from day 1 of the previous iteration will be the new initial condition for day 8 of the next iteration. By adjusting the initial values like this, the process could slowly reach optimum in which the starting values are close or equal to the ending values, causing convergence in the system.

3.2.2 End result of strategy phase

The final output will be a storage value table listing the storage values for every scenario. These values will in detail help the optimization problem find the optimal production profile for the given values by giving an accurate value of the stored power in the storage unit. However, the storage values are calculated with a stochastic approach, weighting each alternative, and will thus not give the perfect solution for each scenario. Further on, these values can be used to simulate behavior in the model for several periods like in the simulation phase, which will be further described in the next subsection.

3.3 Simulation Phase

After having calculated storage values for every scenario possible for the given model, the next step is to find out how the system will function under the different price alternatives. As mentioned, the storage values will not give the perfect solution for each scenario, but if used as a decision criterion, they will give the best solution when uncertainty is included. Therefore, one will want to simulate for multiple periods, finding the average behavior and trends. Therefore, the simulation phase is executed to calculate proper behavior, which will include scheduling profile, storage levels and overall knowledge of properties for the given system.
The next sections will describe how the simulation phase is carried out, and what it can be used for.

3.3.1 Overview

Figure 27 shows a schematic of how the simulation phase is laid out. The following points will explain the role and function of each part.

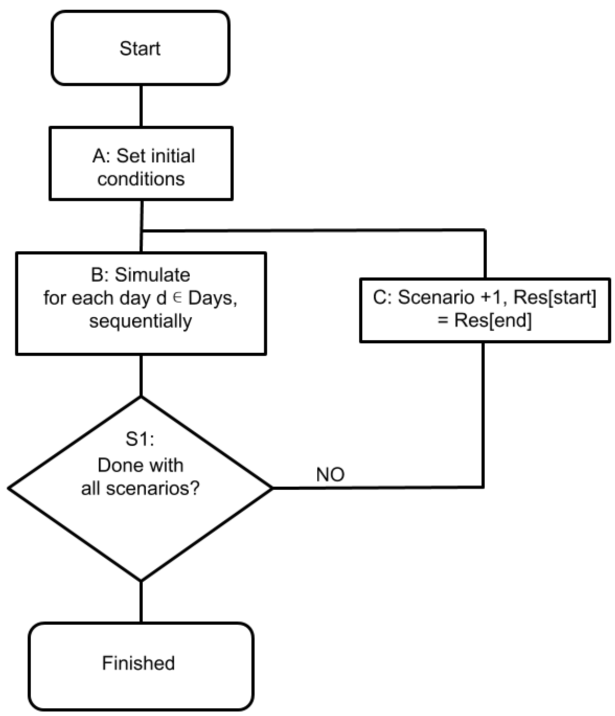

Figure 27: Flow schematic of the simulation phase.

Box A: Set initial conditions
Here, the initial conditions for the model are defined. These initial values consist of starting storage level, initial price node and number of periods to be calculated. Each period will be for one week.

Box B: Simulate the given period
For every day $d \in Days$, a given price node will be randomly chosen, and the optimization problem will run on the given conditions to find optimal scheduling profile. The days will be run sequentially, meaning that the storage level at the end of day d will be transferred to be the beginning level at day $d+1$. The simulations start at day 1 till day 7. The price nodes for each day are set randomly, only affected by the probabilities between each transition.

The method of determining the next random price node is by retrieving a random fraction. The price node probabilities are summed up until the sum is larger than the random factor. The price node that managed this is then the price node that will occur.

The model utilizes a user-defined random seed, which enables the possibility of re-creating the performed sequence again for another storage unit profile and giving the option to compare the results.

Box S1: Done with all periods?
If the wished number of periods are met, then the simulation phase is done, and the generated data will be stored for further analysis. If the condition is not met, then it will move to box C.

Box C: Update initial values
As with Box C in Figure 23, the initial values for the period must be set when iterating again. This time, the storage level at the end of the period is set to be the starting level. This will keep the simulation sequential.

3.3.2 The End Result

After the simulation phase has finished, data regarding performance of the system for all periods will be generated and stored for analysis. With these data, one can check the storage level, charge and discharge power flow, energy/reserve profits etc. for each time step.

4 Case Study

The main motivation behind this report is to test a concept of planning optimal strategy with uncertainty for an energy storage unit connected to the grid operating in multiple markets. Thus, the case study will be to test the functionality of the created model and analyze the behavior and decision making. Especially the backward stochastic dynamic programming part found in the strategy phase will be analyzed for varying accuracy. Also, the model will be tested with and without the participation in the balancing market, to check the potential profit when operating with a stochastic price setup, and for varying storage capacity.

4.1 Energy Storage Unit Near Trondheim, Norway

For this case study, the model will be tested in the area around Trondheim, Norway. In the Nord Pool overview, this area is within the NO3 price node region, and the price data will be based on that area. The capacity of the energy storage unit will be tested in the range of 0.5 and 35 MWh, and all will be connected to the grid through a 1 MW bi-directional converter, which will be the limiting factor for power input/output to the grid when the capacity increases. The performance of the storage unit will be checked for the duration of a week to analyze the change in profit and the performance of the model.

4.2 Input Data

This energy storage unit model needs varying input data to be able to function properly. The various input data must consist of price data, energy storage system specifications, and other various data. This section will specify in more detail the input data given and describe their origin, and also the reason behind their setup.

4.2.1 Time Step and Resolution

The planning period of the model is one week, with decision stages set to every day, based on the discussion from Section 2.5.5. This will result in 7 stages per week. To include realistic price changes on an hourly basis, each stage consists of 24 time steps, and every time step simulates 1 hour. This is favorable as price data from NordPool is stored on an hourly time resolution.

4.2.2 Stochastic Price Data

When generating price data for a stochastic dynamic programming model, the data should originate from historical data so that the scenario tested is realistic. Usually, the use of time series modelling is preferred, as this will use historical data for multiple years to create a wished amount of price nodes that have both the extreme scenarios and most likely scenarios included, with a proper probability factor between each scenario jump. With the use of Markov Chain, the problem of using backward dynamic programming is eliminated.

For this case, the availability and knowledge of creating price nodes like this was limited, and also not the main objective of this report. As the focus is more to see the performance of the model created, creating the price data will be simplified and includes some non-logical assumptions.

The author has created price nodes from the python files "create_price_data.py" and "create_price_data_scripts.py" attached to this report. These scripts use price data from 2017 obtained from NordPool and Statnett [2] [1]. Following is an explanation of the assumptions made when creating them.

As has already been established, the energy storage unit is assumed to experience seasonal variation over the course of a week, as explained in Section 2.5.5. Also, during a month like February, one can assume for simplicity that each Monday, Tuesday, etc. can be modelled as independent of each other, and therefore have no correlation. It can be defended by the fact that each week experiences similar variations as the season in February is close to equal for each week on the load demand side. This makes it possible to create a model that can go from Monday 06.02.2017 to Tuesday 14.02.2017 sequentially, and create multiple price nodes based on a couple of weeks.

If one also assumes that there is no correlation between energy and reserve capacity prices, the number of different price nodes will increase further. With this assumption, having 4 weeks with 4 energy prices and 4 reserve capacity prices for each day will enable the model to create $4 \cdot 4 = 16$ different price scenarios for each day. Each day consists of price data given on an hourly basis.

The next assumption is that the probability of transition between each price node from day d to day $d+1$ is completely random, set by a random value generator. Each possible jump is given a random value between 1 and 75, except for the scenarios that should realistically be connected, which are given a value of 100 to give higher probability for the historically connected nodes. Then, the values are summed up for each day, and based on the value, their weighted probability is found. The sum of the probabilities will always be 1.0 (100 %).

For the script mentioned above, the random variable generator uses the following seed: 15041994.

The scripts will store all this data in the file "pricemod.dat". Figure 28 shows a screenshot of how the data is stored in the file, and its setup.
The author specifies that this method is not 100 % correct and thus cannot be used to support any actual decision making based on the results from this report.

```
#Created on 2018-05-07 18:49:44
Param Eprice :=
7,16
#[Day 1, week 1]
243.57         244.81         244.19         249.63         256.14         264.87
#[Day 1, week 1]
243.57         244.81         244.19         249.63         256.14         264.87
#[Day 1, week 1]
243.57         244.81         244.19         249.63         256.14         264.87
#[Day 1, week 1]
243.57         244.81         244.19         249.63         256.14         264.87
#[Day 1, week 2]
270.71         265.66         263.89         266.37         273.63         278.23
```

Figure 28: Screenshot of energy prices from pricemod.dat. Note that the first four energy price scenarios are equal due to four different reserve capacity scenarios.

4.2.3 Deterministic Price Data

When testing this model, it can be beneficial to use a deterministic setup, which will allow to quickly analyze the behavior and decision making of the model under certain circumstances. For this model, the only stochastic input data is the price data, which as previously discussed, consists of 16 different stochastic options for each day in this case study.

For this case study, two deterministic price data lists have been created and will be used for testing deterministic behavior. The price data for each list varies considerably, where the first is labelled "low-variance" and does not consist of high peaks of energy prices, while the other is labelled "high-variance" and often have high peaks of energy prices during the week. These two price data lists are shown in Figure 29, and will both be used later on. Both of these price lists are real data taken from the stochastic price list.

The reason for wanting to test both these options, is due to the participation in both markets. For the "low-variance" case, the reserve capacity market should see a much higher participation rate than for the "high-variance" case. Analyzing how the model performs in both situations separately will help find key observations on how the stochastic setup will function.

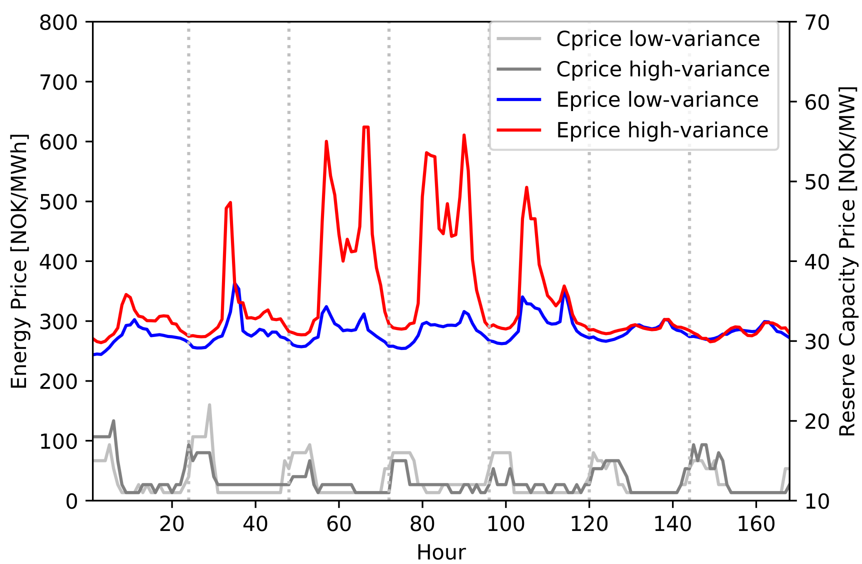

Figure 29: Plot of the two different deterministic lists of energy and reserve capacity sales for a week.

4.2.4 Reserve capacity sale blocks

As has been mentioned in 2.4.4, some reserve capacity markets sell reserve capacity in blocks of several hours. To simulate a possible setup of how reserve capacity can be sold, reserve capacity sale blocks have been implemented for this analysis. The blocks require equal reserve capacity sales during the time steps k1-k8, k9-k20 and k21-24. This means splitting the day into selling equal reserve capacity during morning, day and night.

4.2.5 Energy Storage Unit

This model allows any type of energy storage unit to be utilized, with the requirement that the power flows through a non-ideal converter. This type of energy storage unit will only need to store energy and have capacity potential for the planning of energy and reserve capacity sales. Thus, it can be a battery, a simplified fuel cell etc. This case study has visualized using a battery.

For this case, the author has focused on using an ideal storage unit, with no losses present. The only losses that will be experienced are through the converter during charging and discharging. This is because some of the purpose is to see how a non-linear efficiency curve affects the scheduling of energy and reserve capacity sales, and how the model functions with this type of setup. If the storage unit was non-ideal, it would be included in the efficiency curve with lower efficiencies.

4.2.6 Storage unit capacity

Part of the analysis is to check the performance and possible profit when using different storage unit capacities with a constant input/output limit. The storage unit should be checked for capacities that make the unit struggle to fully charge/discharge over the course of a day, and thus should have a wide specter of capacities analyzed. This has been the case for each run performed, with variations between 0.5 and 35 MWh. Each separate run will specify the capacities that have been analyzed in their respective section.

4.2.7 Converter

Between the storage unit and the grid, a converter is implemented to convert the power from AC to DC or from DC to AC, depending on whether the storage unit is charging or discharging. These converters usually have a non-linear efficiency curve, depending on their percentage output.

For this analysis, the inverter "Satcon PowerGate Plus PV" from Satcon has been chosen [21], a 1 MW inverter. Usually used as an inverter for PV power, the datasheet provides a non-linear efficiency curve of the output power it can provide. For simplicity, the author has used this efficiency curve for the analysis, and assumed that the same efficiency curve would apply for a rectifier. Figure 30 shows the power efficiency of the inverter. It has been modelled so that the rated power is the output power of the converter. This is set for both charging and discharging.

Power Efficiency

Power Level	Efficiency*
10%	96.2%
20%	97.4%
30%	97.6%
50%	97.8%
75%	97.7%
100%	97.5%

* Measured at 420V

Figure 30: Screenshot of the efficiency points based on the output power. Data obtained from [21]

When using this curve to implement a non-linear efficiency curve, the starting efficiency value must be stated. However, the power efficiency table found provided no efficiency at 0 %. This can be because the efficiency varies greatly with low output power, or that the inverter does not operate at such a low output. So, for simplicity, the initial efficiency point has been created by extrapolating between the 10 % and 20 % discrete points. This results in the efficiency curve shown in Figure 31 for both charging and discharging, which is the basis for this case study.

For the situation where the efficiency of the converter is assumed constant, the lowest output value of $\eta_{ch} = \eta_{dch} = 0.95$ has been used.

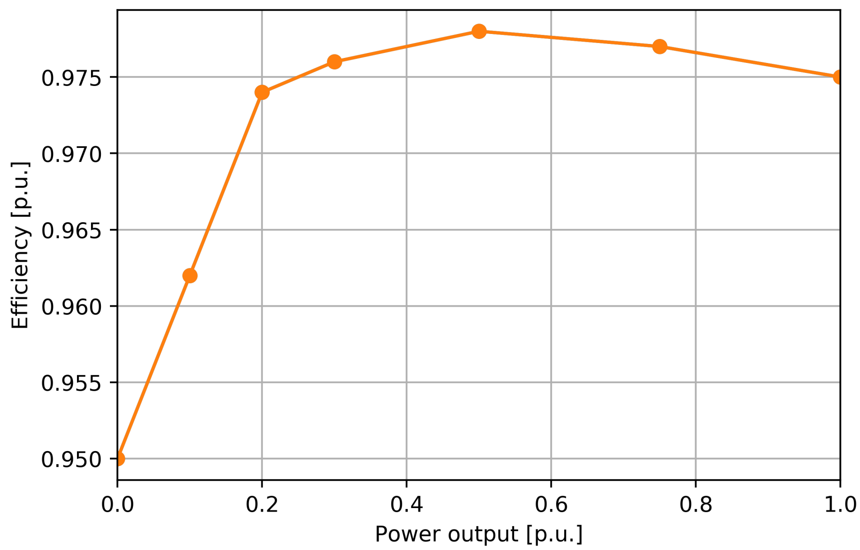

Figure 31: Plot of efficiency curve for the converter for both discharging and charging.

4.2.8 Storage level segments (SLS)

The storage unit needs to be cut into segments for the computation, to be converted into state variables used for the strategy and simulation phase. The number of segments plays a huge role in the model, as a higher amount might result in more accurate values at the cost of an increased computation time. At least this should be the case in theory. To find the impact of the number of storage level segments (or shortened to SLS), this was analyzed in a deterministic run described further on, to check the consequence of changing the SLS between 7 and 42 points. For the strategy phase, the number of SLS must have low deviation between each iteration to obtain convergence. Based on experience from a hydropower model, the convergence criterion was set to 0.001, and is considered a strict criterion.

For the simulation phase, the initial storage capacity at the start of the simulation has been set to $SOC^{Start} = 0.5\,[p.u]$ for all cases unless stated otherwise. The number of weeks simulated has been set to 100, which means that this initial value will have little to no impact when using the average values for the analysis.

4.2.9 Computer Power and Time limit

When simulating this model, the complexity and size of the model requires strong computational power to both decrease time usage and ensure accurate results. For this report, all simulations have been done using an **Intel i5-3570k processor with 3.40 GHz and 16 GB ram** installed.
To prevent situations where a simulation uses an abnormal high amount of time, due to the

complexity and difficulty of the given problem, the model has been given a time limit for each simulation step. Initially, this time limit was set to 60 seconds, but was changed to 20 seconds, as will be discussed later.

4.3 Performed Model Runs

In the following sections, each separate run will be declared, describing their purpose and motivation. The results will be shown in Section 5, and analyzed and discussed in Section 6. Some of these runs are tests used to decide the final scope and layout that should be used for the final case. For further reference, the term "storage level segments" has been abbreviated to SLS, describing the number of discretized points the storage value curve consists of.

4.3.1 Test 1: Testing the strategy phase for deterministic setup with different SLS

Knowing the preferred accuracy of the discretized SLS is something that is best observed through testing and analyzing the results. These curves are important for the optimal planning of each day, and should therefore be precise and detailed. The main goal for this test will be to test the performance of the strategy phase for different storage level segments under a deterministic setup. Here, the convergence criteria, time usage, and also storage value behavior is analyzed to find support for the optimal decision of the number of SLS.

The model will be tested for the SLS values and the storage unit capacities specified in Table 3. The deterministic prices for both markets are labelled "low-variance" in Figure 29. The deterministic setup is used due to the low computation time, as the model only will consider 1 set of price data. To analyze the impact reserve capacity sales has on the strategy phase, this analysis is done for both with and without the reserve capacity market included. This is referred to as Case A and Case B, respectively.

Table 3: List consisting of the varying SLS and storage unit capacities that will be tested during Test 1.

Test 1

Parameters	Value
SLS	7, 12, 22, 32, 42
Storage unit Capacity	1, 5, 15, 25, 35 MWh

4.3.2 Test 2: Testing the strategy phase for deterministic setup with different restrictions

As the model has been made with several options possible, like constant efficiency, reserve capacity sales done in blocks and so on, it proves useful to analyze the impact that these options have on the strategy phase. Also, testing the performance with a different set of prices can also give interesting results, as the one used in Test 1 had low variation in the energy price section.

Test 2 has been performed to supplement Test 1 and analyze the reasons behind the lack of convergence for higher storage unit capacities. Therefore, this test will analyze the strategy phase for each of the following cases:

1. Constant η: No non-linear curve of the converter efficiency, now constant at $\eta = 0.95$.
2. No Res Blocks: Reserve capacity sales are no longer done in blocks, and can vary for every time step.
3. High Pricemod: The "High-variance" price curve shown in Figure 29 has been used.

Each case will be tested for SLS = 22 and 32, and for storage unit capacities of 15, 25 and 35 MWh.

4.3.3 Test 3: Testing the simulation phase for deterministic setup with different SLS

Just as testing the strategy phase for a deterministic setup is important to understand the performance of the model, the same goes for the simulation phase. Therefore, the simulation phase will be tested using the results acquired from Test 1. The purpose is to analyze the weekly change in state of charge and the weekly value of the storage unit, and use these to find an optimal number of SLS that can be used for further testing. Each simulation phase will have 100 scenarios (weeks) simulated.

4.3.4 Test 4: Testing the strategy and simulation phase for stochastic setup with different SLS

With the deterministic analyzes performed in Tests 1-3, there is a need to analyze the performance with a stochastic setup with different number of SLS, to confirm that the stochastic setup should result in less deviation in the strategy phase. Another point that is important to find, is the optimal SLS combination to prevent long and tedious computations.

Test 4 will analyze the strategy and simulation phase for a 20 MWh storage unit, with the same SLS combinations as in Test 1. It has been done for both with and without reserve capacity sales included, which have been given the names Case C and Case D, respectively.

4.3.5 Case E/EC: Optimal scheduling with and without reserve capacity sales for varying storage capacity

An energy storage unit connected to the grid will primarily take advantage of the hourly differences in the energy price, to maximize profit. With the inclusion of reserve capacity sales, the storage unit will try to utilize both markets, finding the preferred strategy in both at the same time. Investigating this impact further is important to check the increased potential of the storage unit. Also, the storage unit should have an increased potential of profit with increasing storage capacity, due to the ability of storing more energy for future use. However, how much more is what would be interesting to find out.

The model has been run for two cases. Case EC consists of running the model with the option of utilizing both the energy and reserve capacity markets, whereas for Case E, only energy sales have been enabled.

For this run, multiple previously tested parameters have been finalized beforehand. This includes the number of SLS and the upper time limit for each decision stage. Some of these final parameters were based on the results from Tests 1-4, and have been listed in Table 4. For the varying storage unit capacities, the capacities that have been analyzed are found in Table 5.

Table 4: List of finalized parameters/decisions

Strategy Phase		Simulation Phase	
Parameter	Value	Parameter	Value
Convergence criteria ΔSV	0.001	Num. Periods	100
Max iterations	15	Timelimit	20 s
Number of storage level segments	22	SOC_{Start}	0.5 p.u
Number of discretized states	2464		
Timelimit	20 s		

Table 5: Overview of the different storage unit capacities that will be tested.

	Capacity [MWh]		Capacity [MWh]
B^{MAX}	0.5	B^{MAX}	7
B^{MAX}	1	B^{MAX}	10
B^{MAX}	2	B^{MAX}	15
B^{MAX}	3	B^{MAX}	20
B^{MAX}	4	B^{MAX}	25
B^{MAX}	5	B^{MAX}	30
		B^{MAX}	35

5 Results

This section covers the results obtained through simulations of the model. The work has been divided into two segments: The first results have been labelled "Tests", as it was important to test the model and check the behavior. This is also part of the results. Test 1 analyzes a deterministic setup of the strategy phase for both with and without reserve capacity sales enabled with different number of storage level segments. Test 2 analyzes the deterministic performance of the strategy phase with different parts of the model simplified, while Test 3 analyzes the simulation phase for the same deterministic setup and with the results from Test 1. Finally, Test 4 tries a stochastic setup with different number of storage level segments, to confirm the observations from Tests 1-3.

In Case EC and Case E, the stochastic setup is performed for both the strategy and simulation phase for varying storage capacity. The results show the expected profit for each week with varying storage capacity, which help find the potential profit per MWh installed capacity.

5.1 Test 1: Testing the Strategy Phase for Deterministic Setup with Different SLS

Table 6 includes an overview of the strategy phase results from the different tests in Case A, with information of total deviation between the last iterations if the test did not obtain convergence. Table 7 shows the same for Case B, where reserve capacity is disabled. Figure 32 plots the average time usage for the strategy phase in Case A, and also includes an overview of the total amount of iterations performed, where 20 was the maximum.

Figure 33 shows the storage value plot for a given day with varying SLS and changing state of charge, for both Case A and Case B with a storage capacity of 1 MWh. Figure 34 and Figure 35 show the same plots, but for a 15 and 35 MWh of storage capacity, respectively.

Table 6: Table showing convergence performance for the different storage capacities and number of storage level segments for Case A.

Size \SLS	7	12	22	32	42
1 MWh	True	True	True	True	True
5 MWh	True	True	True	True	True
15 MWh	True	False, $\Delta SV = 218$	False, $\Delta SV = 285$	False, $\Delta SV = 534$	False, $\Delta SV = 1617.8$
25 MWh	True	True	False, $\Delta SV = 619$	False, $\Delta SV = 700$	False, $\Delta SV = 1308.3$
35 MWh	True	True	False, $\Delta SV = 1037$	False, $\Delta SV = 1060$	False, $\Delta SV = 2065$

Table 7: Table showing which combinations acquired convergence, and the deviation if not, for Case B. All of the converging ones did so in 3 or less iterations, the rest used all 20 iterations.

Size \SLS	7	12	22	32	42
1 MWh	True	True	True	True	True
5 MWh	True	True	True	True	True
15 MWh	True	True	True	True	True
25 MWh	True	True	True	False, $\Delta SV = 507.3$	True
35 MWh	True	False, $\Delta SV = 177.3$	False, $\Delta SV = 874.2$	False, $\Delta SV = 567.7$	False, $\Delta SV = 1171$

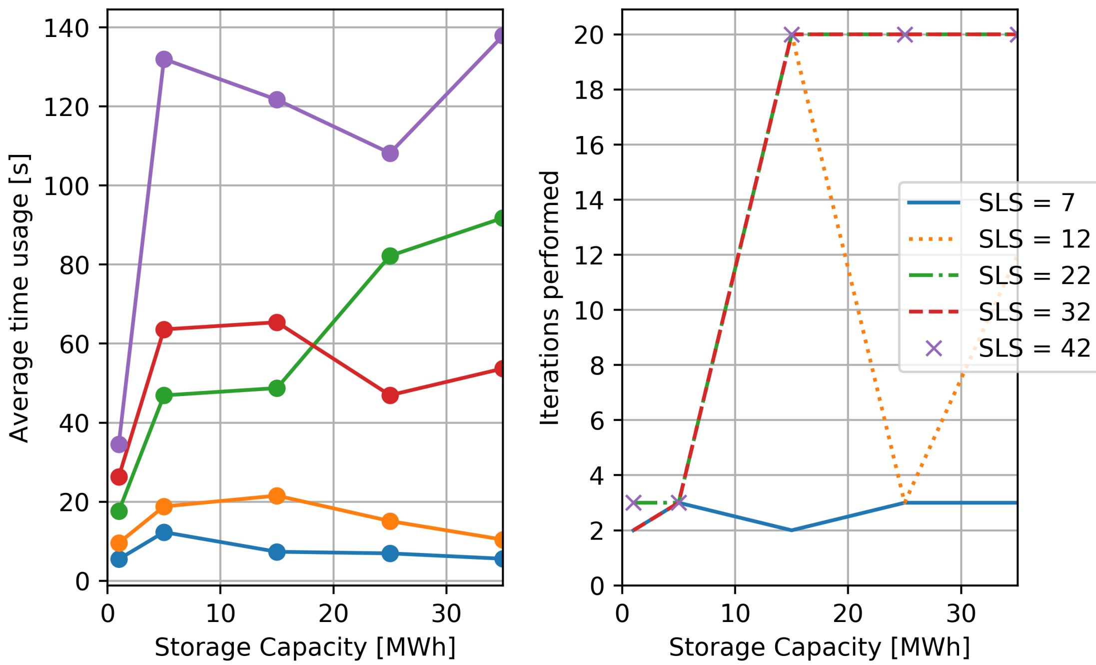

Figure 32: Plot of average time spent per iteration and the total amount of iterations done for Case A.

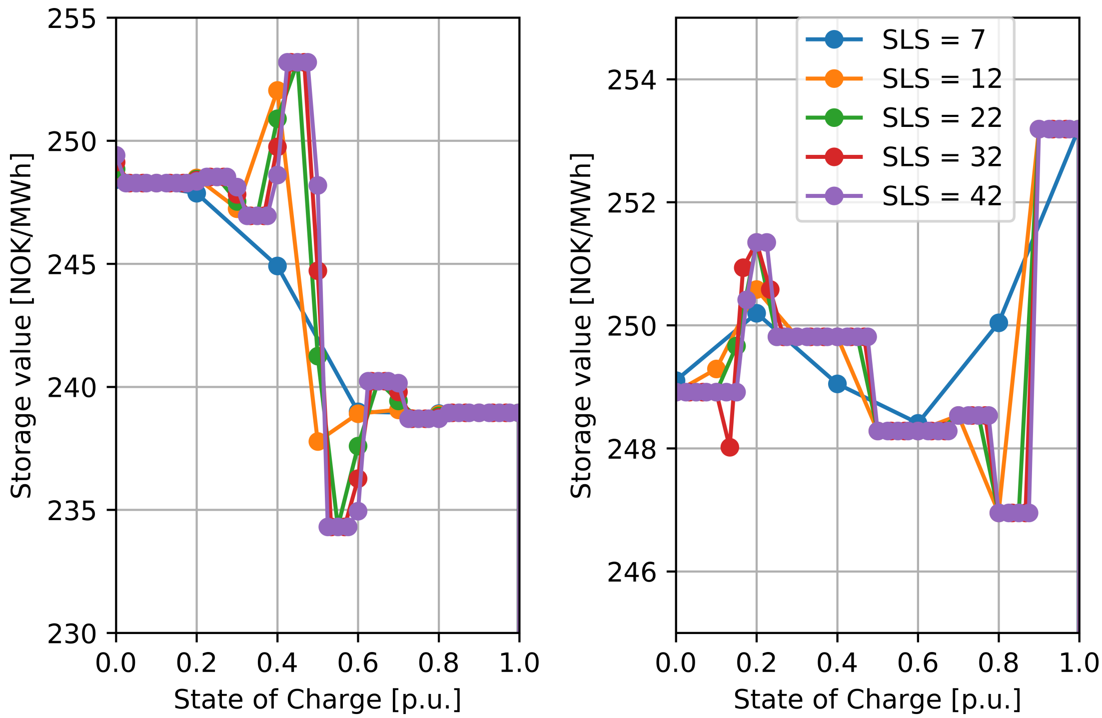

Figure 33: Plot of Storage values over 1 day for both Case A (left) and Case B (right) for a 1 MWh storage unit with different storage level segments.

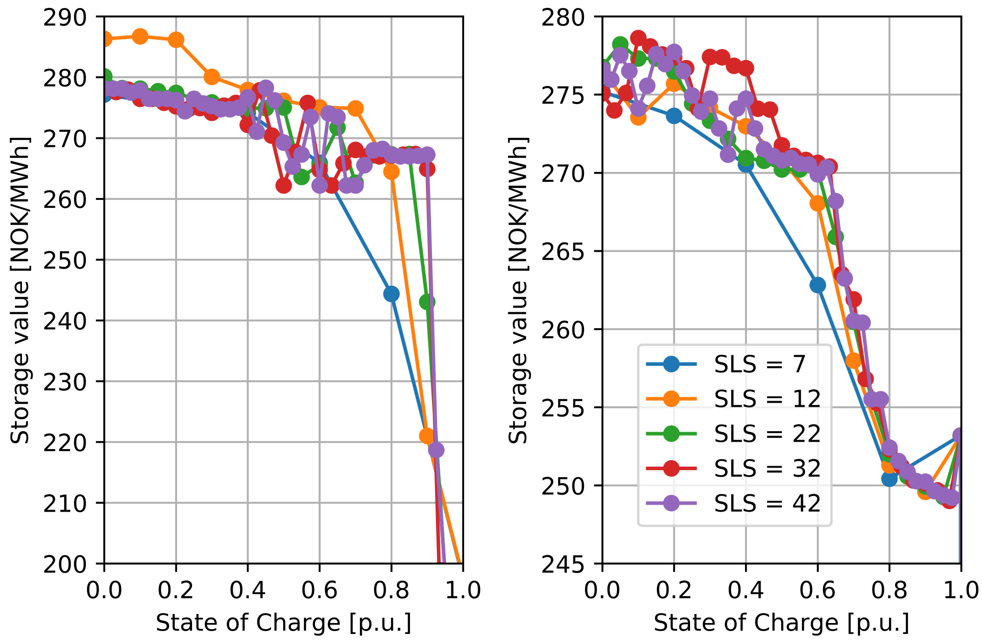

Figure 34: Plot of Storage values over 1 day for both Case A (left) and Case B (right) for a 15 MWh storage unit with different storage level segments.

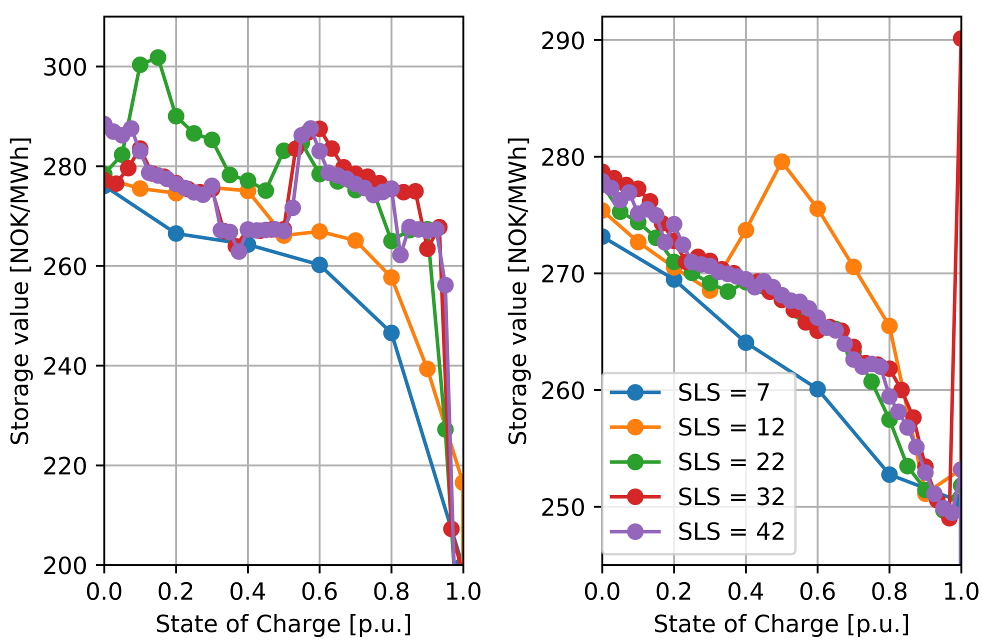

Figure 35: Plot of Storage values over 1 day for both Case A (left) and Case B (right) for a 35 MWh storage unit with different storage level segments.

5.2 Test 2: Testing the Strategy Phase for Deterministic Setup with Different Restrictions

Table 8 shows the strategy phase results from the three different cases tested, with varying storage unit capacities. The performance, as well as the deviation in case convergence was not obtained, is included in this table. Figure 36, Figure 37 and Figure 38 show the plots of the storage value curve for the 15 MWh storage unit for a given day, for both SLS combinations tested.

Table 8: Overview of the strategy phase results for Test 2, showing when convergence was obtained, and the deviation if not.

Type \SLS	22	32
High pricemod 15 MWh	True	True
High pricemod 25 MWh	True	True
High pricemod 35 MWh	True	False, $\Delta SV = 2.9$
No Res Blocks 15 MWh	False, $\Delta SV = 143$	True
No Res Blocks 25 MWh	False, $\Delta SV = 488$	False, $\Delta SV = 862$
No Res Blocks 35 MWh	False, $\Delta SV = 1065$	False, $\Delta SV = 1582$
Constant η 15 MWh	True	True
Constant η 25 MWh	False, $\Delta SV = 1084$	False, $\Delta SV = 1249$
Constant η 35 MWh	False, $\Delta SV = 1663$	False, $\Delta SV = 2865$

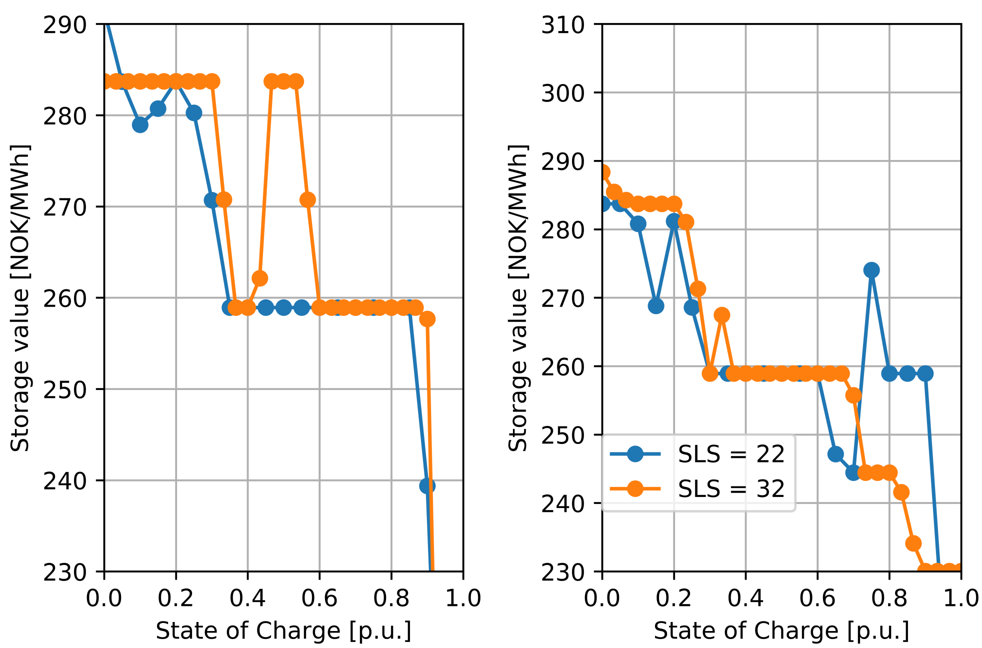

Figure 36: Plot of the storage value curves with different number of SLS for the 15 and 35 MWh storage unit (left and right), when the efficiency is constant.

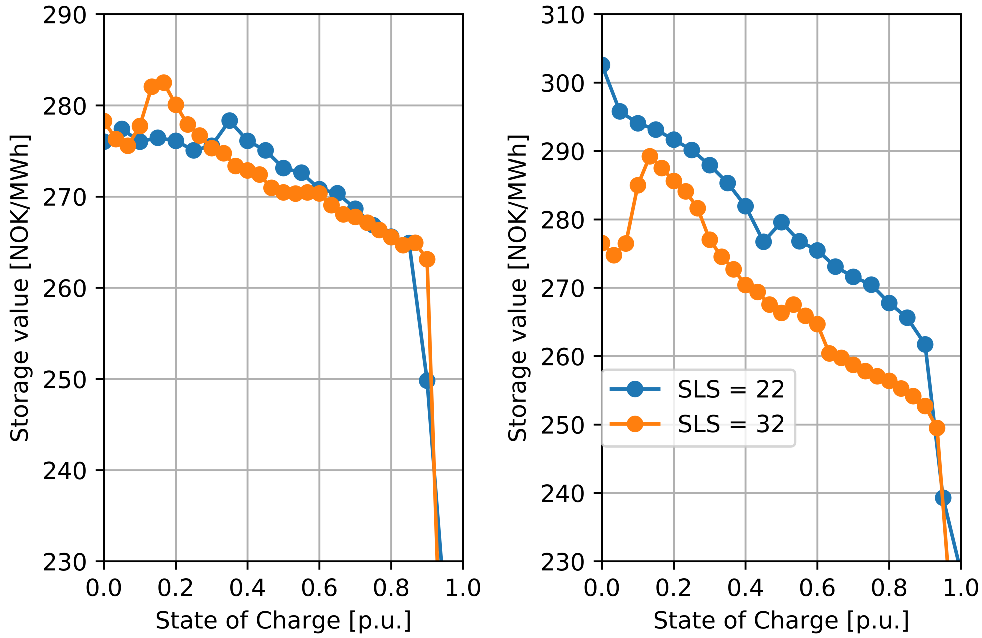

Figure 37: Plot of the storage value curves with different number of SLS for the 15 and 35 MWh storage unit (left and right), when reserve capacity sales are not restricted by block sales.

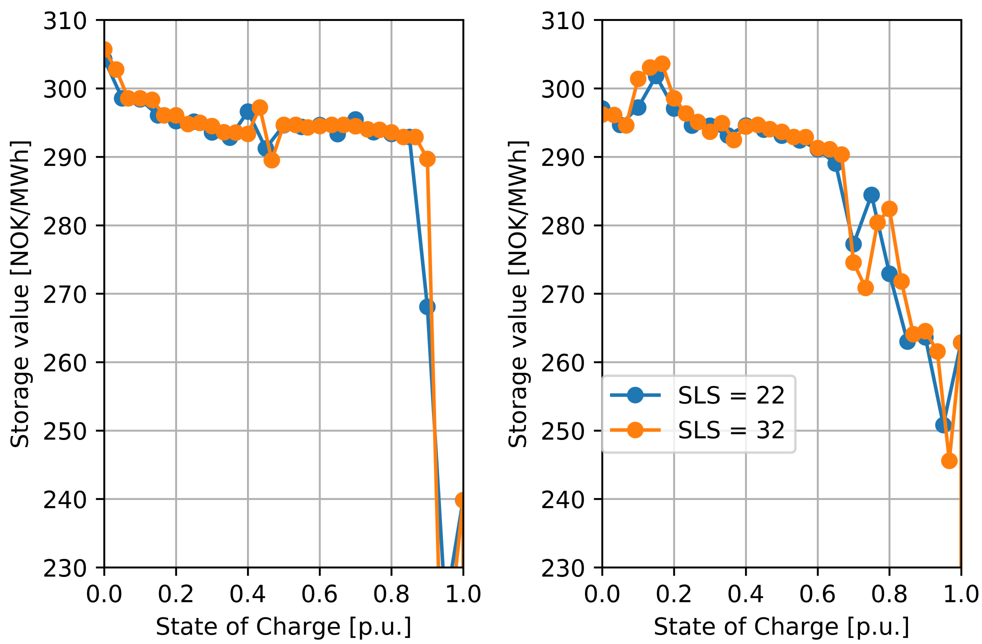

Figure 38: Plot of the storage value curves with different number of SLS for the 15 and 35 MWh storage unit (left and right), using the "high-variance" price curve from Figure 29.

5.3 Test 3: Testing the Simulation Phase for Deterministic Setup with Different SLS

Figure 39 shows a plot of the weekly average value for each test during the simulation phase, for both Case A and Case B. For the simulations done, plots of the state of charge behavior with varying SLS are shown in Figure 40, 41 and 42 for the 1, 15 and 35 MWh storage units, respectively.

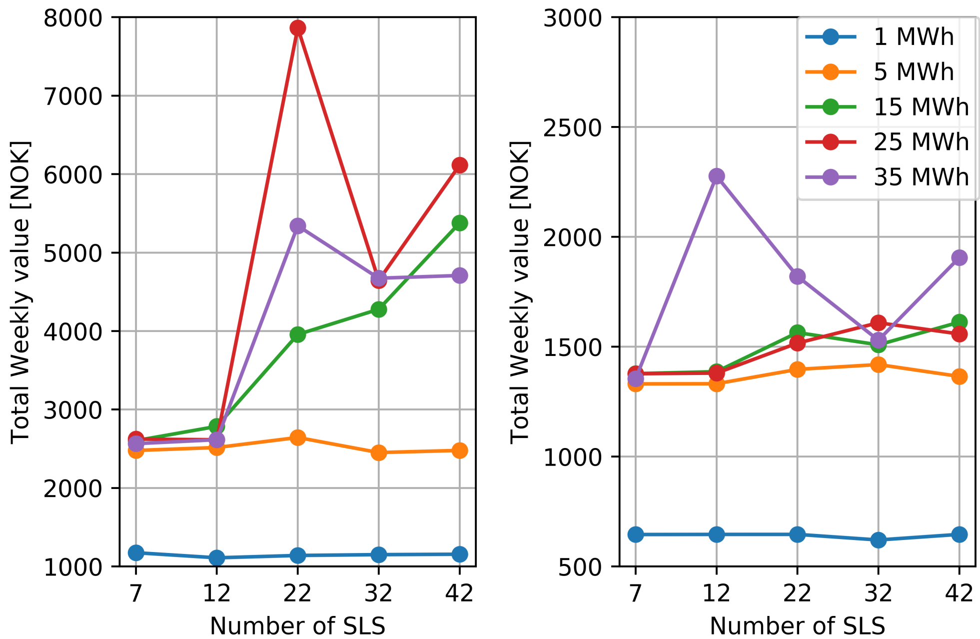

Figure 39: Plot of the weekly value of the storage system with different SLS and capacities for both Case A (left) and Case B (right). The weekly value includes weekly energy sales profit, weekly capacity sales profit, and the value of the stored energy at the end of the week.

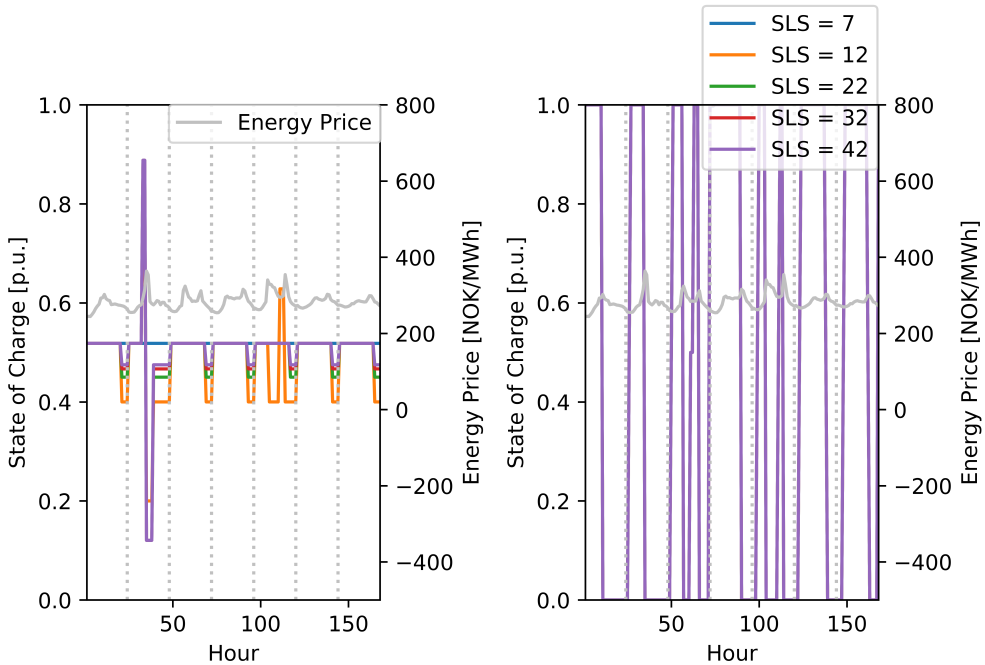

Figure 40: Plot of the state of charge for the 1 MWh storage unit during the whole week, with different number of SLS. Case A is the plot on the left, while Case B is the plot on the right.

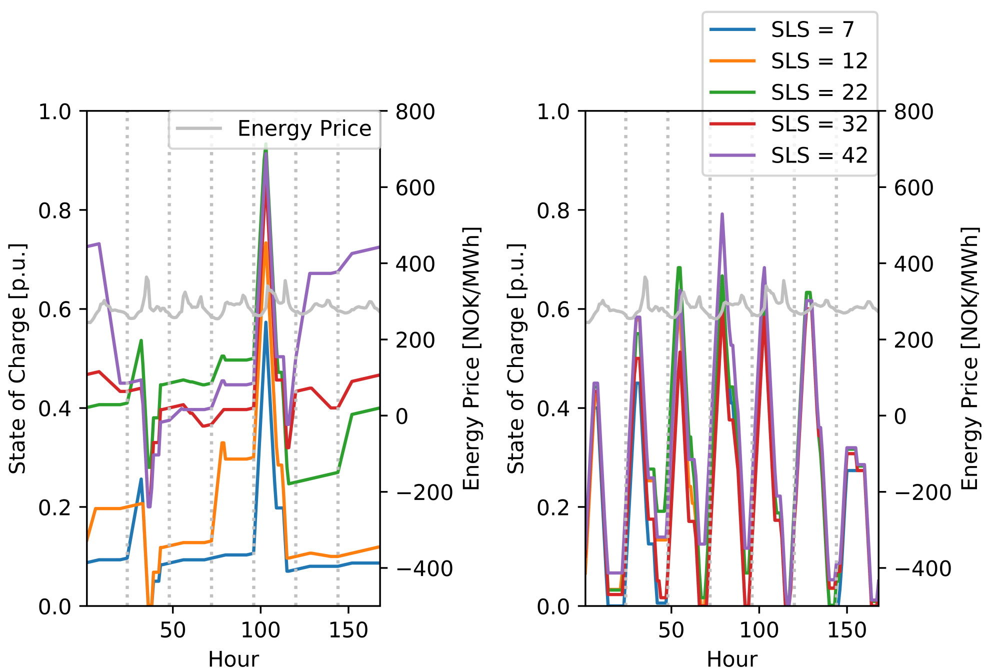

Figure 41: Plot of the state of charge for the 15 MWh storage unit during the whole week, with different number of SLS. Case A is the plot on the left, while Case B is the plot on the right.

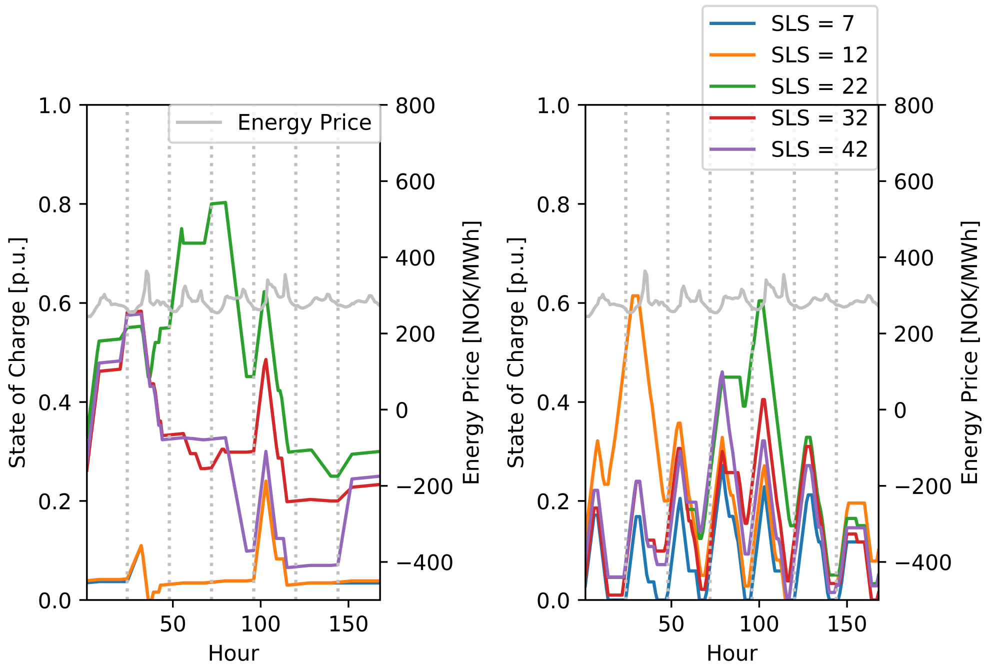

Figure 42: Plot of the state of charge for the 35 MWh storage unit during the whole week, with different number of SLS. Case A is the plot on the left, while Case B is the plot on the right.

5.4 Test 4: Testing the Strategy and Simulation Phase for Stochastic Setup with Different SLS

Table 9 shows the strategy phase performance and the deviation for Case C and D. Also included in this table is the average computation time per iteration. Figure 43 shows the plot of the storage value curve for a given day with different number of SLS for both Case C and D. Figure 44 shows the stochastic performance during the simulation phase, where the average weekly value has been plotted with different number of SLS.

Lastly, Figure 45 shows the variation of the state of charge for the storage unit with different number of SLS, for both Case C and D.

Table 9: Overview of the strategy phase performance for a 20 MWh storage system with stochastic setup. Case C is for participation in both markets, while Case D is only for the energy market.

SLS \Type	20 MWh [Case C]	20 MWh [Case D]
7	True, $t_{avg} = 106.5$	True, $t_{avg} = 80$
12	False, $t_{avg} = 260.3$, $\Delta SV = 3.08$	True, $t_{avg} = 143$
22	False, $t_{avg} = 499$, $\Delta SV = 224.7$	False, $t_{avg} = 266.7$, $\Delta SV = 21.6$
32	False, $t_{avg} = 758$, $\Delta SV = 891.9$	False, $t_{avg} = 393.9$, $\Delta SV = 103.2$
42	False, $t_{avg} = 986$, $\Delta SV = 3571$	False, $t_{avg} = 522.5$, $\Delta SV = 250.3$

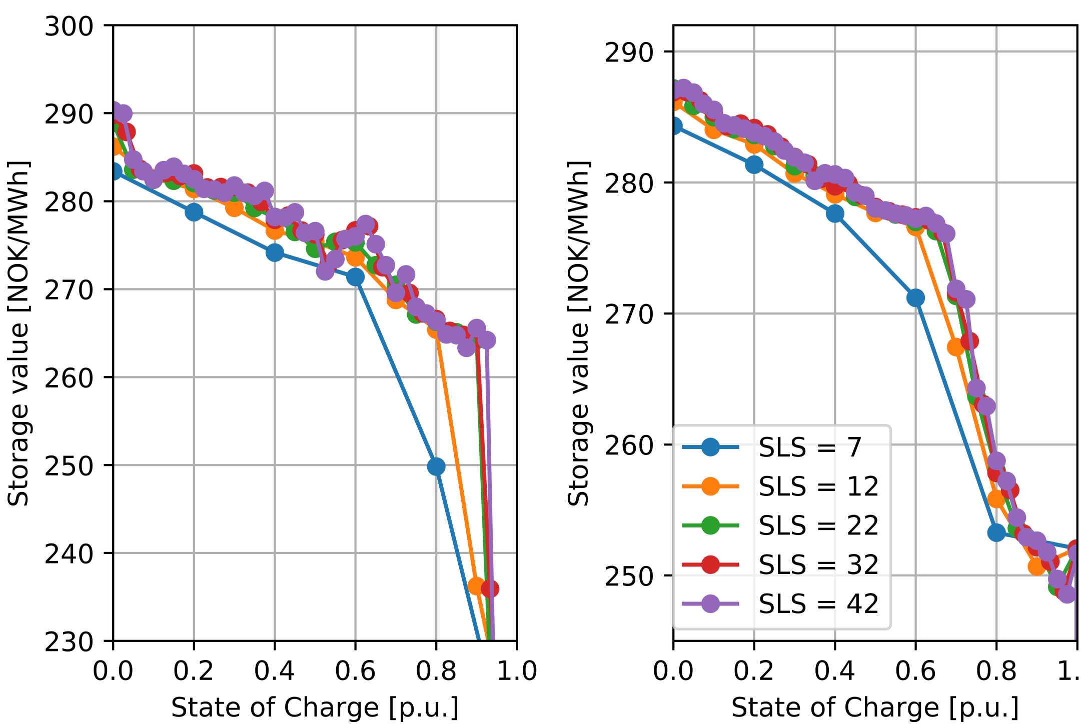

Figure 43: Plot of the storage value curve for both Case C and D with different number of SLS. Case C is on the left, while Case D is on the right.

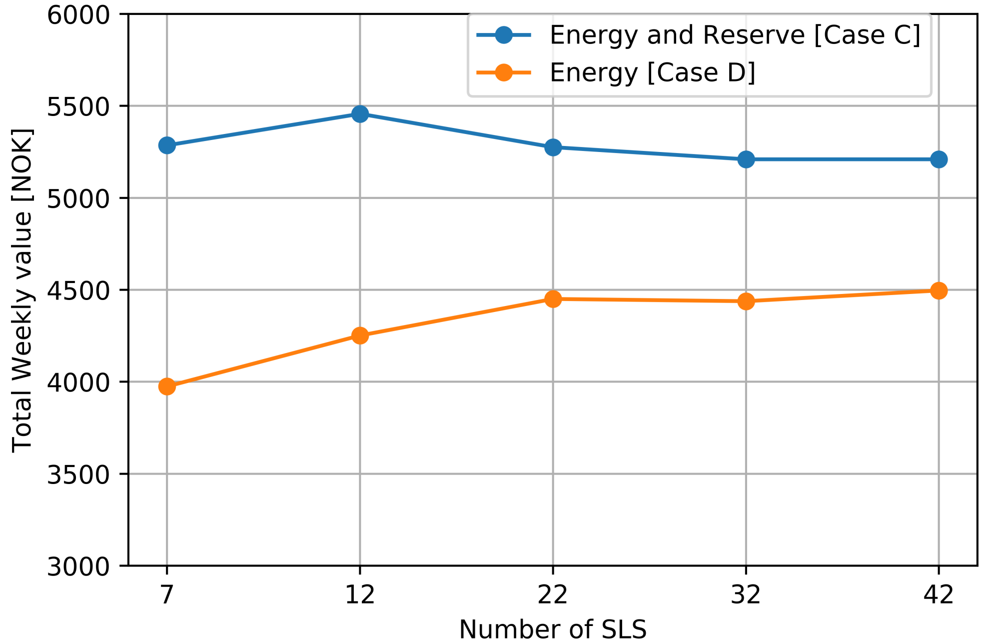

Figure 44: Plot of the weekly value of the 20 MWh storage unit for stochastic setup with different number of SLS.

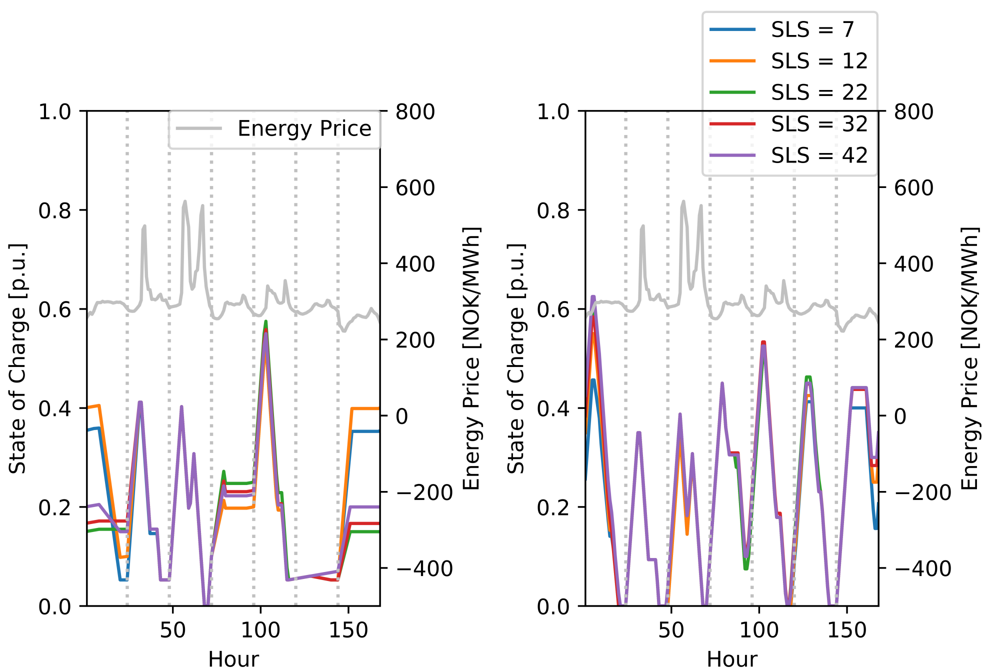

Figure 45: Plot of the state of charge behavior for the storage unit over a week, with different number of SLS. Case C is on the left, while Case D is on the right.

5.5 Case E/EC: Optimal Scheduling With and Without Reserve Capacity Sales for Varying Storage Capacity

Table 10 shows the technical data of the strategy phase performance for Case E and Case EC. Included are both average iteration time usage and deviation result. Figure 46 and Figure 47 show the storage value plotted for both Case EC and Case E, for a 5 and 25 MWh storage unit, respectively. Figure 48 and Figure 49 show the percentile behavior of the state of charge for a 25 MWh storage unit, for Case EC and Case E, respectively. Figure 50 shows the same percentile behavior for a 35 MWh storage unit for Case EC.

Figure 51 shows a plot of the numerous profits for both Case EC and Case E, i.e. the profit from both markets and the total profit. The next plot in Figure 52 shows the profit for each market and the total profit based on each MWh capacity installed.

Table 10: Overview of the strategy phase performance for all storage unit capacities for both Case E and Case EC.

Capacity \Case	Case EC		Case E	
	Strategy Phase result	Time usage per iter	Strategy Phase result	Time usage per iter
0.5 MWh	True	$t_{avg} = 288s$	False, $\Delta SV = 0.83$	$t_{avg} = 290s$
1 MWh	False, $\Delta SV = 0.015$	$t_{avg} = 288s$	True	$t_{avg} = 283s$
2 MWh	True	$t_{avg} = 309s$	True	$t_{avg} = 278s$
3 MWh	False, $\Delta SV = 13.41$	$t_{avg} = 924s$	True	$t_{avg} = 280s$
4 MWh	False, $\Delta SV = 19.64$	$t_{avg} = 2461s$	True	$t_{avg} = 273s$
5 MWh	False, $\Delta SV = 13.12$	$t_{avg} = 2633s$	True	$t_{avg} = 275s$
7 MWh	False, $\Delta SV = 7.59$	$t_{avg} = 1355s$	True	$t_{avg} = 275s$
10 MWh	False, $\Delta SV = 14.3$	$t_{avg} = 915s$	True	$t_{avg} = 267s$
15 MWh	False, $\Delta SV = 84.1$	$t_{avg} = 634s$	True	$t_{avg} = 271.9s$
20 MWh	False, $\Delta SV = 7.12$	$t_{avg} = 503s$	False, $\Delta SV = 24.4$	$t_{avg} = 265s$
25 MWh	False, $\Delta SV = 3743.7$	$t_{avg} = 466s$	False, $\Delta SV = 76.3$	$t_{avg} = 266s$
30 MWh	False, $\Delta SV = 1226.2$	$t_{avg} = 375s$	False, $\Delta SV = 35.4$	$t_{avg} = 265s$
35 MWh	False, $\Delta SV = 364$	$t_{avg} = 407s$	True	$t_{avg} = 266s$

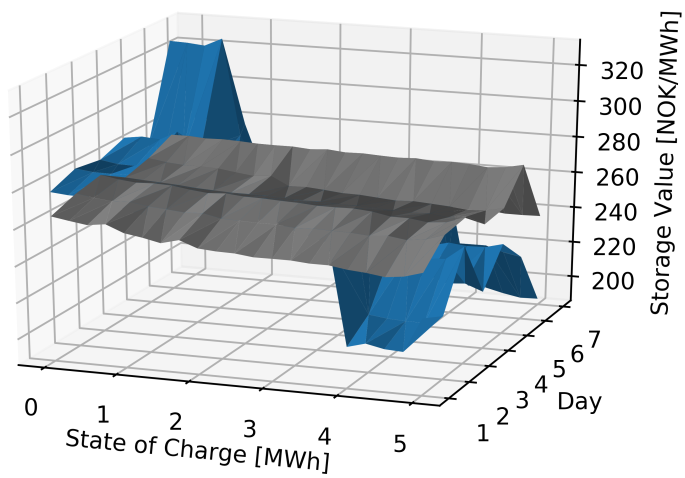

Figure 46: Plot of the storage value curve over the whole week for a given scenario and with varying state of charge for a 5 MWh storage unit. The grey plot is without reserve capacity, while the blue is with both markets available.

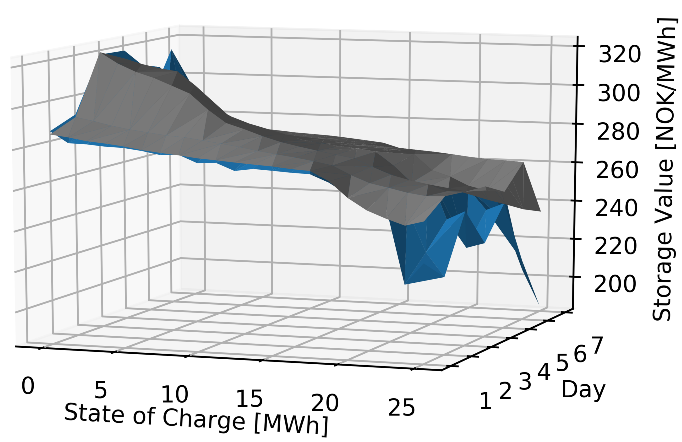

Figure 47: Plot of the storage value curve over the whole week for a given scenario and with varying state of charge for a 25 MWh storage unit. The grey plot is without reserve capacity, while the blue is with both markets available.

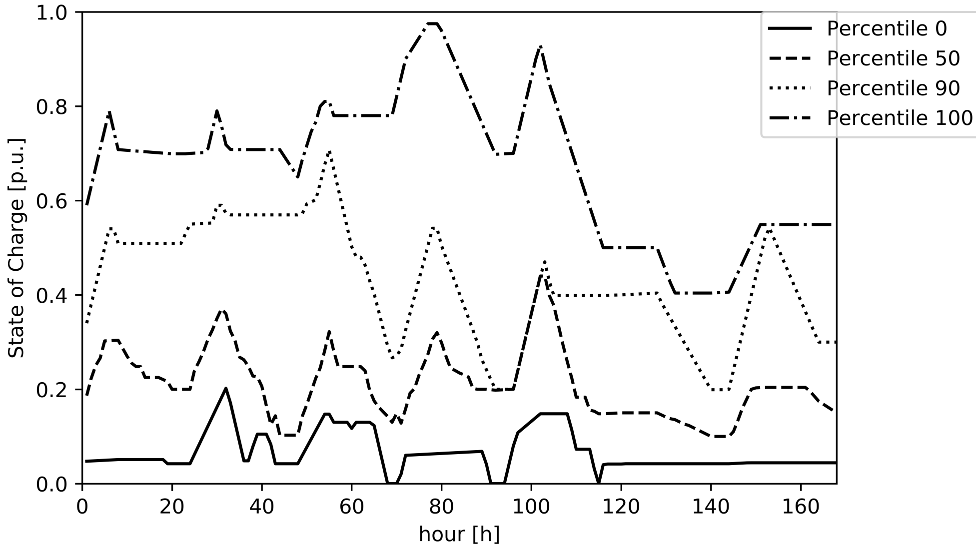

Figure 48: Plot of the percentile state of charge for a 25 MWh storage unit with participation in both markets (Case EC).

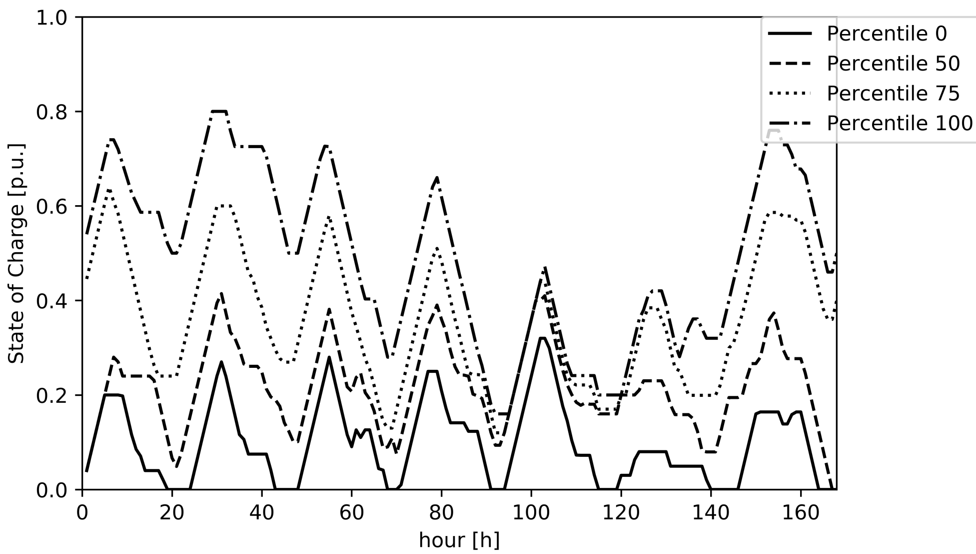

Figure 49: Plot of the percentile state of charge for a 25 MWh storage unit with only energy sales available (Case E).

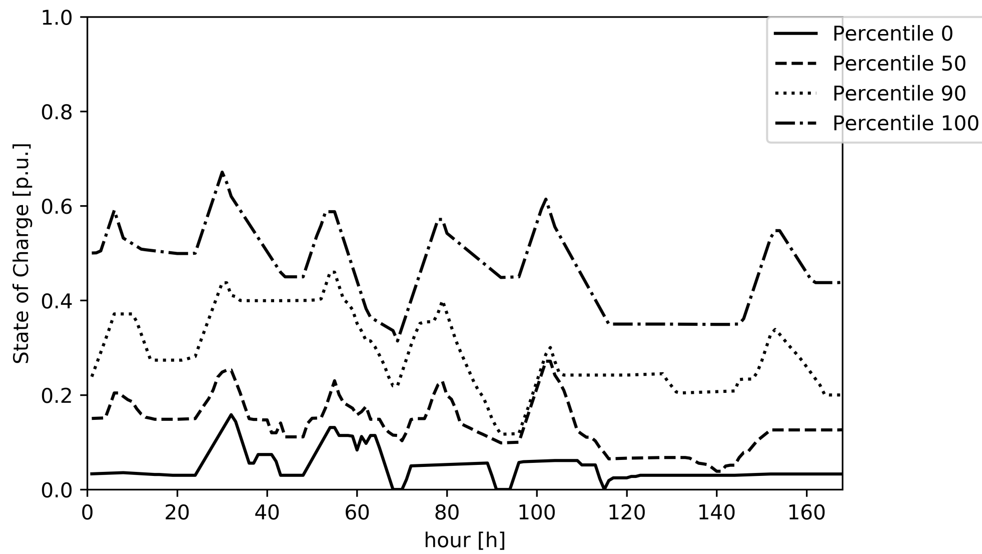

Figure 50: Plot of the percentile state of charge for a 35 MWh storage unit with participation in both markets (Case EC).

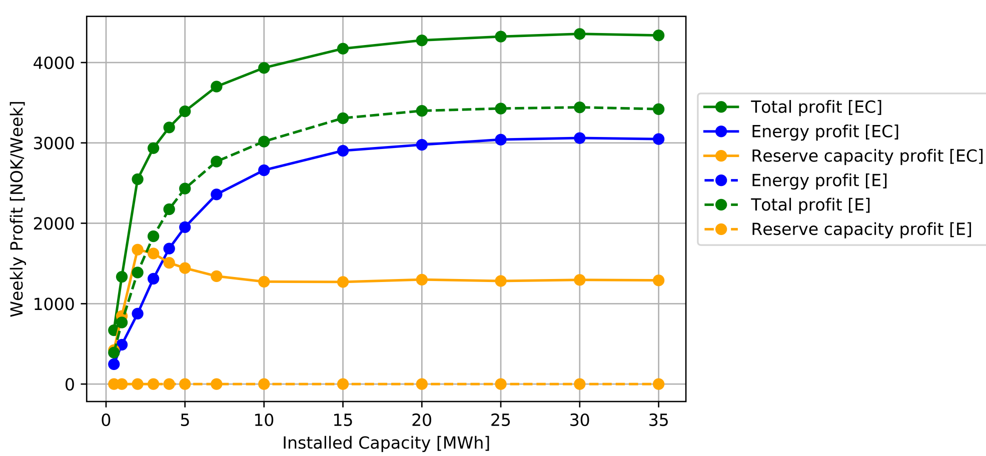

Figure 51: Plot of the weekly profit with increasing storage unit capacity. Includes the total profit, profit from the energy market, and the profit from the balancing market for both with and without reserve capacity sales included.

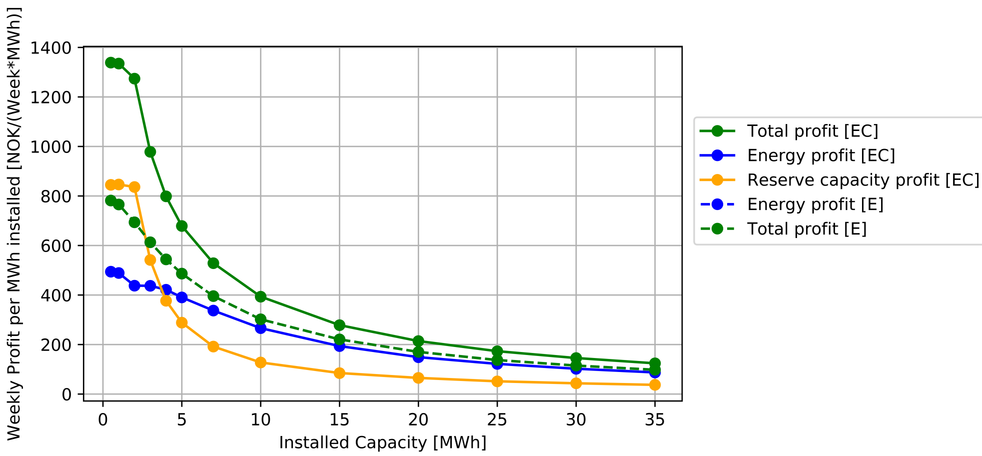

Figure 52: Plot of the expected profit per MWh installed, for all profitable markets. Includes both with and without reserve capacity sales.

6 Analysis of the Results

6.1 Test 1: Testing the Strategy Phase for Deterministic Setup with Different SLS

The motivation behind this test is to see how the strategy phase performs under different number of storage level segments. Due to high computation time for a stochastic setup, the input data was simplified to only contain a deterministic layout.

6.1.1 Strategy phase time usage

For case A, the average time usage and total number of iterations done are shown in Figure 32. As should be expected, the time usage increases with an increasing number of SLS to calculate. However, when the number of SLS and the storage capacity increased, there were situations where the time limit of 60 seconds for each optimization problem was met, forcing the problem to exit with the present results, which are non-optimal. This was especially the case for SLS of 22 and 42 points. This can be seen in the table by an increase in average time usage. The time limit was introduced to prevent soft locking the operation. This occurs when the model is struggling to find the optimal path, and can give further problems with finding the optimal storage values from the results of the non-optimal performance. This must be taken into consideration to prevent time consuming operations, as time is partly of the essence in these models.

Another concern is the time usage when calculating a stochastic behavior with an increasing number of decision stages. If the model reaches this time limit on multiple occasions, the time usage for each iteration can increase drastically. It is important for a big model like this to have a reasonable time usage, and the time limit for each problem is one way to keep this in check, despite the non-optimal results.

6.1.2 Strategy phase convergence performance with deterministic setup

When comparing the performance in Table 6 and Table 7, one can see that the strategy phase performs decently. For the smaller SLS, there is good performance in both cases, where convergence is obtained. Likewise, smaller storage capacity systems also experience convergence independent of the number of SLS. This shows that the optimal storage values are found for the storage systems, where the strategy phase gives equivalent results for each iteration.

When increasing the storage capacity in Case A, especially at 15 MWh or higher, the increasing number of SLS does not contribute to obtain convergence for the storage values. Actually, the trend is that the total deviation increases with an increasing number of SLS. With an increasing number of discrete points to calculate, there will be an increasing number of points that can cause deviation. However, this should also result in a more accurate storage value plot, giving shorter intervals of the linear approximations made from the piecewise-linear approximation method. The trend can imply that the model struggles to find optimal planning despite more accurate storage value curves. This is the opposite behavior as for a hydropower model, as the increased accuracy in most situations decrease the deviation.

For Case B, this pattern becomes more apparent when the storage capacity reaches 35 MWh. The increasing storage capacity threshold is most likely due to the lesser complexity of Case B, as it only focuses on one market instead of two. The storage values are affected by all profit-seeking options, and therefore should have fewer contributing areas in Case B than Case A. Still, the fact that there are situations where convergence is not obtained with increasing SLS, and that the pattern is exactly the same as for Case A, shows that there are some uncertainties when it comes to acquiring optimal storage values for the system in the strategy phase.

As discussed earlier, the time limit being reached can be a factor to this non-optimal strategy performance. Other possibilities can be weak computational power, or that the number of iterations done are too low. Or, there could be something with the model that makes it difficult to obtain convergence.

6.1.3 Storage value plot for different SLS with deterministic setup

To further analyze the storage values created for the different number of SLS, Figures 33, 34 and 35 were created to study the behavior of the storage value curves. For a 1 MWh storage capacity in Figure 33, where the storage unit can be fully discharged and charged over the course of one hour, the storage value curves experience jumps during the changing state of charge for both Case A and Case B. An interesting point for Case A, is that the storage value hugely drops when the state of charge exceeds 0.5. This is likely due to the sales of reserve capacity, and that the storage unit can sell slightly more reserve capacity if it charges the storage unit slightly, due to the losses during charging. This huge variation in values are to be expected, due to the rapid charge/discharge capability of the storage unit. That the highest storage value is at around 0.5 state of charge shows that the curve promotes keeping energy for maximizing reserve capacity sales.

Further on, the storage value curves experience great change when the number of SLS increases. When there are only 7 segments, the curve does not manage to capture the behavior from reserve capacity sales, and 12 segments only partly manage to capture this. When the segments reach 22 and above, the curve becomes more detailed, and shows how complex the curve actually is. This should result in a more accurate representation and thus a better solution of the potential in storing energy. For Case B on the right, the same can be said about the increasing number of SLS. This shows that an increasing number of SLS does give a more accurate representation of the curve when convergence is obtained.

In Figure 34 with 15 MWh storage capacity, the curves experience some similar overlays in both cases. Some differences are present due to accuracy, but SLS of 32 and 42 show almost the same curves. Also, for Case A, the storage value greatly drops at the end, when the storage unit reaches full storage. This is mainly due to the inability of selling reserve capacity when there is no room for storing energy from down-regulation, which in this plot is considered crucial at the start of the next day. This is especially important due to the constraint on selling equal amounts of reserve capacity for the first 8 hours of the day as has been implemented for this case study.

For Case B, the curve in overall is beginning to form a slow descending form, which is something that is similar to usual water value plots for hydropower systems. The curve without reserve capacity included should have a descending form, as the marginal cost should decrease slightly when the storage unit fills up. This then allows to compare if the stored MWh should be utilized now or stored for the next day.

For the biggest storage system tested, at 35 MWh as shown in Figure 35, the variation between storage value curves begin to become visible. Especially SLS = 22 has a huge variation at the start of the curve for Case A. SLS = 32 and 42 still follow each other, while SLS = 7 and 12 follow their usual paths of underestimating the value compared to the others. The main reason behind these variations could be that the strategy phase did not give converged results, which could explain the unexpected stray path of SLS = 22. For Case B, all SLS follow a nice curve except for SLS = 12, which has a huge over-estimation at around 0.5 state of charge. However, since also Case B experienced non-convergence at 35 MWh, this could be the reason behind.

When analyzing these three plots, the storage value curves seem to be close to identical between each number of SLS, unaffected by the storage value deviation. Of course, they are not identical and equal, there are small deviations in each discrete point, but the curves are close to similar in shape. It shows that the curves do change if the option to sell reserve capacity is present. This usually increases the storage value for the same state of charge for lower values, and decreases it heavily as the storage unit reaches full capacity. The shape of the curves also changes, with reserve capacity giving some higher potential around 0.5 state of charge, but also decreasing the value heavily at the end due to the down-regulation option. So with reserve capacity, the optimal planning seems to imply that having a half-full unit can be beneficial.

6.1.4 Comparing the strategy phase to a hydropower model

When seeing the performance of the strategy phase for this storage unit, the behavior and options the storage unit has compared to a hydropower station could be possibly linked to the failed convergence of the strategy phase. For a hydropower station, the water is stored for future use due to the price variation over several months, but also due to the amount of water flowing into the reservoir. With a natural inflow of energy, the hydropower station is more interested in optimizing the resources received, when they are received. Also, producing power for a hydropower station usually requires a minimum production not equal to 0. As reserve capacity is production flexibility, it can only be sold when there is power production. Another point is that normally, hydropower stations have no ability to affect stored water other than through production regulation. Unless of course, pumps are implemented.

For a storage unit, the natural input of energy is not present, because it has no energy source nearby (at least in this case study). Therefore, it needs to plan every day when to buy and when to sell, to optimize the price differences. The possibility to charge the storage unit could be what makes the convergence criteria harder to achieve. Another point is the reserve capacity sales threshold, which now is not dependent on sales of energy. The storage unit is capable of providing up- and down-regulation of power despite not selling energy at the time of production. This makes the two markets not connected as tightly as for a hydropower station, and creates more options for the producer to allocate resources and priorities in the markets. This added independence could thus impact the convergence criteria in a negative manner.

6.2 Test 2: Testing the Strategy Phase for Deterministic Setup with Different Restrictions

As a deviation in convergence was found between selling and not selling reserve capacity for Case A and Case B respectively in Test 1, this implies that the lack of convergence can be partly due to this extra market participation. This shows that further investigation of reserve capacity impact should be done. However, as Case B did not experience convergence for a 35 MWh storage unit, some other points could impact this optimized strategy planning. This is the motivation behind Test 2, where different options will be analyzed. All 3 different tests here will be discussed separately.

6.2.1 Constant efficiency

With a constant efficiency curve, the strategy phase has acquired convergence for the 15 MWh storage unit, as shown in Table 8. However, for the larger units, the deviation has increased and is higher than the original. This shows that simplifying the efficiency curve, is not what primarily is hindering the model from obtaining optimal storage value curves for the strategy phase. The reason the deviation is higher could be explained by the fact that the efficiency now is the lowest possible value the efficiency curves could obtain, and therefore will have a worse output than the original setup. Also, without the varying efficiency curve, there is no longer an incentive to purchase more power at once instead of continuously purchasing small amounts.

This last observation is shown when analyzing the storage value curves found in Figure 36. For the number of SLS = 32, the curve is flat at several occasions. This implies that there is no extra benefit in trying to vary the state of charge slightly when in the middle of these flat points. This is likely due to the constant efficiency, which now no longer benefits from varying the amount of power bought/sold. Another point is that the curve differences between SLS = 22 and = 32 differ greatly in certain areas, but seem to vary more for the 35 MWh storage unit on the right side of the plot. This can be correlated with the lack of convergence for both curves.

6.2.2 No Reserve capacity block sales

The results in Table 8 show that removing the restriction of selling reserve capacity in blocks does not seem to have a huge impact on the strategy phase performance. For SLS = 22, the results are almost similar to the results of Test 1 in Table 6, while for SLS = 32 the deviations have increased.

When looking at the storage value curves plotted in Figure 37, the lack of convergence can be seen for both storage unit capacities. Especially for the 35 MWh plots, the deviation could origin from the lack of convergence. An interesting observation is that here, the curves are more constantly decreasing with an increasing state of charge, compared to what was the case in Test 1 in Figure 34. There, the middle section could experience varying storage values, decreasing and increasing frequently. This could imply that the variation in these areas in the the plots from Test 1 were due to the constraint on reserve capacity sales. With this restriction, the variation in storage value shows that depending on the state of charge at the end, the potential in profit for the next day is influenced by this end value. That this variation is not present when the restriction is removed, shows that the operator is not so heavily affected by this, due to the added flexibility of options during the morning.

Despite the lack of convergence, this observation could explain why some areas in the original storage value curves behave like they do.

6.2.3 High-variance price data

When using the "high-variance" price data from Figure 29, the results in Table 8 show that 5 out of 6 cases obtained convergence. The only one that failed was the 35 MWh storage unit for SLS = 32. These results imply that the model can find an optimal planning strategy easier when the variation in price is higher, which promotes more active participation to the energy market. Thus, it can seem like the model is struggling more to find this optimal setup when the profit from the energy market are low. Also, it shows that the model can acquire optimal strategy phase results for larger storage unit capacities than for the other variant, which can be the result of a more preferred decision making when it comes to what market to focus on.

The storage value curve plots in Figure 38 show a similar pattern for both SLS cases in both plots. Especially for the 15 MWh, there are only small differences across the whole curve. This is good news as both of them acquired optimal results from the strategy phase, showing that the main difference when changing SLS is the number of points, as well as small differences in some areas of the curve. However, the shapes stay the same.

When comparing this to the "low-variance" results, it shows that the model is struggling during the strategy phase to obtain optimal planning and storage value curves when the profits from the energy market are low. For the "low-variance" scenarios, there will be higher profit from participating in the reserve capacity market, and thus the storage level during the decision stage will experience low variation. As the profit from each market are low, there will be more flexible variations in participation for each market, which makes optimal planning more complicated. This will occur for each iteration, where the small changes in storage value curve seem to impact the objective function and keep it non-equal for each iteration.

However, as seen with this "high-variance" price data, the higher the participation is in the energy market, the more exact storage value curves the model creates and the lower the deviation gets between iterations. This shows that the increasing participation in the reserve capacity market makes it more difficult to obtain optimal storage value curves when the storage unit increases in capacity, as it increases the potential profit it can obtain from the energy market.

6.3 Test 3: Testing the Simulation Phase for Deterministic Setup with Different SLS

6.3.1 Simulation phase performance for different SLS with deterministic setup

Having achieved optimal storage values or not, the main objective of the strategy phase is to find the most accurate storage values for the storage unit at the end of its decision stage. This will help plan the forecast for tomorrow today, and store necessary energy to supply the next day to achieve a higher profit. If the storage value curves vary, the amount of stored energy for the next day will vary and a change in profits will be expected.

Over the course of a week, there are three economical considerations that are necessary when comparing weekly profits and value. The first two are the profits from selling energy and reserve capacity, and the third is the value of the stored energy at the end of the week. This is to include the future estimated profits that the storage unit will consider for the next week.

Based on these factors, Figure 39 shows the weekly economical performance for the different storage capacities, the different number of SLS, and between Case A and Case B. For Case A, the weekly value does not increase majorly with the increasing number of SLS for 1 and 5 MWh stored capacity, but with higher storage capacities the weekly value has a rapidly increasing trend with the increasing number of SLS. For storage capacities of 15 MWh and higher, the increase in value is vastly higher when the number of SLS exceeds 12. The storage value plots show that the curves were very simplified when the number of SLS were 12 and 7, which shows that the model is unable to accurately pinpoint the future value curve from the storage values, and lowers the weekly value significantly. Therefore, "perfecting" the curve seems to imply giving a more accurate prediction.

For Case B, without reserve capacity, the variation is more flat than for case A, with the exception of the 35 MWh storage capacity system. As it was the only one not obtaining convergence, that is probably the reason for the unexpected behavior. This shows that the number of SLS does not greatly impact the performance during the simulation phase, however there is still some increase for larger storage units. If the strategy phase fails to converge, it can seem as if the system becomes more inaccurate in the simulation phase with varying SLS.

When comparing Case A and Case B, the weekly value is considerably higher with reserve capacity sales enabled than without. This is to be expected as the contribution from multiple markets results in more areas to optimize, which should give a higher benefit. Also, the storage values usually tend to be higher for Case A than for Case B at low state of charge, due to the added future profits from the reserve capacity market being possible at those levels, which also contribute to a higher weekly value if that state of charge is frequently met. This shows the increased profitable potential in utilizing both markets.

6.3.2 Simulation phase weekly storage level behavior with deterministic setup

Analyzing the value of each week shows how the model considers the benefits of participating in the market, but does not give any information regarding the performance of the storage unit. Analyzing the state of charge of the storage unit during the week will help explain the considerations the model makes and what is seen as optimal performance. Also, as the change in state of charge is directly coupled with participating in the energy market, this enables to analyze the planning for this market.

Figure 40, 41 and 42 plot the performance of the storage units' state of charge during the deterministic weeks, including the weekly price curve. For 1 MWh, as shown in Figure 40, both Case A and Case B have similar state of charge levels during the week for the different SLS. Case A, however, has some small deviations, typically due to trying to participate in the energy market by buying and selling energy. This figure shows that for such a small storage unit, there is more profit in selling reserve capacity, which explains the almost constant state of charge.

For a 15 MWh storage unit, as illustrated in Figure 41, Case A has massive differences in optimal planning. Every scenario has its own optimal strategy for seeking profit, which results in different optimal state of charges for each hour. From the starting hour to the last hour of the week, the state of charge for all scenarios are different. However, all versions participate in the energy market when the prices are high, as is seen around hour 45 and 100, where the state of charge is decreasing. So for areas with preferred participation in the energy market, the model manages to optimize this situation for all scenarios. However, it is the planning of optimal storage level during the rest of the week that is widely different.

This same trend is shown in Figure 42 for the 35 MWh storage unit. The variations in the state of charge strategy are present. However, here, SLS = 7 and SLS = 12 have almost equal optimal planning strategy, and SLS = 32 and SLS = 42 have similarities in certain areas of the plot. This is quite interesting, as this is a situation where almost none of the storage value curves experienced convergence.

One thing that all these plots have in common for Case A, is that the lower the SLS value is, the lower the optimal state of charge planning is, at least for SLS under 22. SLS = 7 and SLS = 12 are in all cases very low when it comes to their state of charge, which can be linked to the approximated modelling of the storage value curve. By having lower values in the plots and not having a detailed representation of the variations, the strategy seems to underestimate storing energy in the storage unit for future use. With these low values, it is most likely that the storage unit is mostly participating in the reserve capacity market, which explains the lack of variation in the state of charge.

For Case B, all plots show peaks and bottoms, which is due to the charging and discharging of the storage unit to participate fully in the energy market. This is an expected behavior, as it is the only way to make profit. Another observation is that there is low variation in optimal state of charge for the different storage capacities and the different number of SLS. Since Case B had convergence for all capacities except for the 35 MWh capacity, this shows that the increasing SLS value leads to small adjustments in optimal planning. However, Figure 42 does show what happens when the convergence criteria is not met, as different optimal state of charge paths are shown here.

This shows the importance of having a high number of storage level segments for plotting the storage value curve, but also the importance of obtaining convergence. if the number of SLS is too low, the model seems to underestimate the potential of storing energy for the future, and without convergence, the optimal strategy can vary greatly. This implies that having a balance between these two setups could be optimal, where one could sacrifice some detailed storage value curve for less deviation.

However, in a deterministic layout, this pattern will repeat itself every week, and thus the extra stored energy will never be used for an unknown future day. As the system knows the future outcome based on the storage value curve, the stochastic uncertainty is not present. These situations are important as this is where storing extra energy for the next day can result in much more profit. As such, analyzing with a stochastic setup will be necessary to see the impact and confirm the theory.

6.4 Test 4: Testing the Strategy and Simulation Phase for Stochastic Setup with Different SLS

6.4.1 Strategy phase for a stochastic setup with different SLS

Table 9 shows the performance of the strategy phase for both with and without reserve capacity sales. Also included is the average time usage for each iteration depending on the number of SLS. The number of converged cases were pretty low, and none present for a high number of SLS. This shows that with the current setup, reaching a converged case for the full test will be difficult and not possible for every test. Therefore, it is important to choose an accurate representation of the storage value curve with low deviation. The time usage must also be considered, as it increases when the number of SLS increases. This is as expected, due to the increasing number of decision stages that must be computed.

For the deviation between with and without reserve capacity sales enabled, the trend stays the same, as Case C has a higher deviation than Case D, while having a higher time usage. Thus, disabling the reserve capacity market does affect the storage value curves and their accuracy in terms of deviation.

When comparing the results from Case C in this table to the results from the deterministic setup in Table 6, the deviation between the non-converging cases are not that far off. With the exception of SLS = 42, the deviations for the 20 MWh storage unit are close to the deviations that the 15 and 25 MWh storage units experienced with their deterministic behavior. As the stochastic setup has 16 price possibilities for every day, the total number of decision stages to compute are 16 times higher than the deterministic. With the increasing amount of computations to do, the deviation is affected by far more scenarios and thus could experience much more deviation. The fact that this is not the case for most of these tests in Table 9, can be due to two factors.

The first factor to consider is that the different price possibilities are varying in behavior, which has an effect on finding the optimal planning strategy. The deterministic price setup in Test 1 used the "low-variance" energy prices, which made the potential profits from the energy market less opportunistic. This made reserve capacity sales favored for parts of the week. When comparing this to Test 2, where a "high-variance" energy price was tested, the "high-variance" obtained more often a converged strategy phase. This was most likely due to the high potential in profit from the energy market. Therefore, these two situations show that the model can struggle to find optimal planning depending on the input data, and thus can give varying and non-optimal solutions. As the stochastic setup consist of many different scenarios, some of these can give a clear accurate result while some can struggle to find the optimal planning.

The other factor that must be mentioned is the fact that all storage value curves are dependent on all future possible price scenarios. As is shown in Equation 10, the weighted objective function for a given scenario is based on all the possible futuristic objective functions and their probability. This is because the present day decision scheduling should be based on all possible scenarios that can occur tomorrow. Thus, the storage values calculated will be based on both decision stages with low price variation and high price variation, their contribution depending on their probability. This impacts two things. The first is that each storage value will be influenced by low variation decision stages, and the second is that they will only impact based on their probability. Therefore, the decision stages present in Test 1 will only impact the stochastic setup partly, which also holds true for the decision stages in Test 2.

As this is true for both Case C and Case D, this explains the deviation obtained. This can also be used to argue that the model is struggling more to find optimal consistent planning strategies for low energy prices. However, the fact that the deviation for the stochastic setup is low compared to the expectations from the deterministic tests, implies that the stochastic analysis should provide more accurate and similar planning strategies.

6.4.2 Storage value curves for stochastic setup

The storage value curve for a given day shown in Figure 43, shows what was discussed in the previous section, that the weighted probability gives less variation for each storage value. Both cases show that the increasing number of SLS gives a more accurate representation of the storage value curve, especially that SLS = 7 is underestimating the potential in storing energy. For the other SLS, the curves are almost equal in shape. What is lacking in both cases is that there are no abnormal jumps in the curves, which could be the case for some of the deterministic tests. This is the result of having each storage value point being determined by the weighted future profit, which helps negate stray paths.

For Case C, the curves are almost equal for all cases except SLS = 7. An interesting observation is the small decrease and sudden increase in storage value at around SOC = 0.6, which as was tested in Test 2 is due to the reserve capacity sales being done in blocks. The sudden decrease when the storage unit is approaching full capacity is due to the lack of reserve capacity sales, but the varying number of SLS impacts when this slope is starting, due to the detailed points.

Case D has the same shape as shown in Test 1, with a continuously decreasing curve for increasing state of charge. An interesting point is at around 0.6-0.7 SOC, where the slope is much steeper than before. This is probably due to the discharge capacity of the storage unit. At this point, the storage unit is at around 12-14 MWh, which is enough energy to fully discharge the storage unit for almost half a day. Having more energy than this, serves little purpose when only participating in the energy market, as the rest of the day can be used to charge the storage unit. Therefore, the energy price must be much lower to promote further storage of energy.

6.4.3 Simulation phase for stochastic setup with different SLS

The values shown in Figure 44 illustrate that there are not much difference in expected value for the different number of SLS. For Case C, the deviation is small and shows that the model does not differ greatly in actual performance during the simulation phase. Note that the values here are the average values for 100 weeks. Thus, small deviations could be the result of a continuous difference in optimal planning. However, it seems like this is marginal. For Case D, the same pattern is not found. Here, one can see that the expected value is increasing at first, until stabilizing at around SLS = 22. This shows that without reserve capacity sales, the strategy is more dependent on optimal and detailed storage value curves, as this directly affects the starting values for the next day.

The performance of the simulation phase for a given week is illustrated in Figure 45, and shows that for Case C the state of charge during this week differs noticeably. However, during high energy price peaks, all scenarios have almost exactly the same scheduling, from start to finish. It is during days with low variation that the deviation is present, which is shown both at the start and the end of the week. Looking at these end points, one can see that for SLS = 7 and = 12 the state of charges are noticeably lower at the end of the first day, but higher at the end of the week. For these scenarios, the lower the number of SLS, the more it seems to overestimate and underestimate the potential for future profits compared to higher accuracy of the curve.

Another observation is that this storage unit never utilizes its full capacity. The storage unit is at max 60 % full, which can imply that the storage unit is over-dimensioned for these market trends. However, as this is only for 1 given week, it does not tell anything about the behavior in total. But due to a high energy price variation, it does show that even those peaks do not encourage full capacity.

For Case D, the continuous variation in state of charge is almost constant for all scenarios. As it can only gain profits from buying and selling energy, it needs to plan this optimally, which the storage value curves seem to indicate almost perfectly. Despite some small deviations between them at the start and the end of the week, the scheduling is almost identical. As the change in energy price is quite high at times, this shows the model manages to plan these occurrences very well.

6.4.4 Optimal SLS and time usage

When discussing how detailed the storage value curve that will be used for the full test should be, where this stochastic setup will be analyzed for varying storage unit capacities, the factors that should now be considered is time usage and expected acceptable storage value deviation. Based on Table 9, the number of SLS = 22 or 32 will meet both requirements, and also provide good accuracy for the simulation phase for both with and without reserve capacity sales, as was previously discussed. For future use, SLS = 22 will be used as it will cut down the time usage to an acceptable amount, and will result in 2464 decision stages to compute per iteration. This will also give a time buffer in case the decision stages should struggle to obtain optimal planning and meet the time limit set. As a time limit of 60 seconds could result in high computation time if met numerous times, it has been shortened down to 20 seconds. As not many decision stages will use up all the time allotted, it is preferred to have a semi-high time limit to give more time to find the optimal decision, especially with a computer with decent computational power.

6.5 Case E/EC: Optimal Scheduling With and Without Reserve Capacity Sales for Varying Storage Capacity

6.5.1 Strategy Phase computation comparison

When comparing the performance of the strategy phase for both Case EC and Case E in Table 10, one can see that the majority of capacities for Case EC did not obtain convergence. This deviation is small for the lower storage capacities, but increases noticeably when the capacities are at 25 MWh and higher. For these storage capacities, the storage unit will need to use more than a whole day to fully charge or discharge the unit, which means one would need to plan for multiple days in advance to fully utilize the whole storage unit. This planning seems to make it complicated for the strategy phase to acquire optimal storage value curves, which explains the deviation here. As there are 2464 discrete states for each iteration, the average deviation varies considerably between each capacity, especially the 25 MWh storage unit that experiences big deviation per state. For the others, the deviation per state is relatively small, which indicates that the difference in storage value curves are marginal. However, as was tested in Test 4 for the varying storage value curves, deviation in curve pattern does affect the performance somewhat, and thus the profit. Case E sees many situations where convergence was obtained, meaning that optimal storage value curves were found. The deviation and failed convergence occurs when the storage unit reaches high capacities, however with much smaller deviations than Case EC. This implies that the reserve capacity market increases the complexity of this model, making the strategy phase encounter difficulties.

For the time usage per iteration, Case E sees almost the same computation time across all capacities. This shows that the complexity of simulating is not heavily affected by varying capacities. However, this cannot be said for Case EC, which sees much variation in computation time. For small capacities, the time usage is pretty low, and for high capacities it is somewhat higher. The interesting point is for capacities around 4-7 MWh, where the time usage almost reached 45 minutes per iteration, compared to around 4 minutes for Case E. This is mainly due to the complexity these capacities experience when it comes to what market to optimize in. This is probably the threshold where there are small margins between choosing to optimize in reserve capacity sales or energy sales, which requires much more comparison and calculation for the given decision stage. Therefore, many of the computations will be affected by high computation time that will be limited by the time limit.

6.5.2 Storage Value curve comparison

As shown in Figure 46, the storage value curve for the 5 MWh storage unit varies between Case EC (blue) and Case E (grey). Case EC has a more up and down variation in storage values, which can be seen when the state of charge is close to empty and close to full capacity. This shows that the curve does consider the optimal point, depending on the expected scenario for the next day. The end points have higher variation due to the reserve capacity constraint of having enough capacity for up- and down-regulation, as discussed earlier.

For Case E, the storage value curve is almost flat for all days and for varying state of charge. This is probably due to the low storage capacity, in this case a capacity that can be fully charged in 5 hours. As each day usually starts with low energy prices compared to the expected pattern throughout the day, there is plenty of time to charge the battery. And since it cannot participate in the reserve capacity market during this period, there is nothing else that the storage unit can do, and the dependency on the previous day is much less present. Therefore, storing energy for the next day when it can be charged up so fast is not so important, which is reflected by the almost flat curve.

For the 25 Mwh storage unit in Figure 47, Case E now shows variation in the storage value curve and thus promotes planning for the future. It would take more than a full day to fully charge/discharge the storage unit, which means there is potential in charging it for future discharge. This is why the curve has such high storage value at low state of charge, and low value at high state of charge. The change in storage value from day to day is due to the expected scenarios each day brings, showing that some days have higher or lower potential in utilizing stored energy. This curve is almost identical for Case EC in this plot, which shows that the same scheduling is occurring here. The fact that Case EC in general has a lower storage value curve than Case E is mainly due to the ability of participating in the reserve capacity market. However the deviation between them is small across the curve except for high state of charge, where Case EC drops in value to promote reserve capacity sales at the start of the next day.

6.5.3 Storage capacity utilization during simulation phase

The larger the storage unit gets, the more energy can be stored for the future and thus give more incentives to plan for the future with the intention of higher profits. For smaller capacities, the storage unit can be charged quickly before high energy prices occur and then discharged during these periods. However, for larger storage units, it is important to check how the stored capacity is utilized, and to check if they are fully charged or discharged during their operation.

Figure 48 shows the percentiles of the state of charge for the storage unit in Case EC. This 25 MWh storage unit is rarely at a high state of charge, having only 2 short peaks where it almost reaches a full state of charge for the 100 % percentile. Another observation is that the 90 % percentile is far lower, showing that the high state of charge occurs very rarely during the simulation phase. The fact that the 50 % percentile never exceeds 0.5 state of charge, indicates that the storage unit is almost never operating with high amounts of stored energy, and that it usually stays around 10-40 %, which is around 2.5-10 MWh. So the total installed capacity does not seem to give the output that is wanted, and this can imply that the installed capacity is over-dimensioned for the market and the converter size. Also, as the percentiles experience low variation in state of charge during each hour, it shows that reserve capacity sales are happening and that it is participating in both markets. As the reserve capacity sales hinder high energy sales, the flat parts in the plot are a result of this.

For a bigger capacity, as shown in Figure 50 for the 35 MWh storage unit in Case EC, it is now very visible that the whole storage unit is never utilized. As the state of charge even for the 100 % percentile does not exceed 0.7 p.u., or 24.5 MWh, there is no added profit to gain for this extra installed capacity. This shows how big the installed storage unit should be compared to the rated power output. Of course, this is also based on the market prices that the storage unit experiences, but as the storage unit is storing for short-term use, this plot shows that the short-term use is usually not more than a couple of days in the future.

For Case E, as shown in Figure 49, one can see that all percentiles experience huge variation in state of charge during the week. This is as earlier mentioned due to the energy market interaction. An interesting observation is that as with Case EC for the 25 MWh storage unit, there are also low periods where the storage unit is fully utilized based on its installed capacity. In fact, Case EC seems to experience higher state of charges for the 100 % percentile than Case E. This is mainly due to the short peak-hours, which does not seem to justify fully charging the storage unit beforehand. The 50 % percentile also shows the same as Case EC, that the typical state of charge is at around 10-40 %, resulting in low utilization of the extra capacity.

6.5.4 Expected weekly profit

From Figure 51, one can see the expected weekly profit for both Case EC and E with an increasing installed capacity. As expected, Case EC experiences higher total profit for all capacities than Case E. This is due to the ability of optimizing resources in multiple markets at the same time. This impacts the profits earned from the energy market separately, which alone is lower for Case

EC than for Case E. However, this sacrifice does contribute to the total profit. The highest difference between the two cases in terms of expected profit is at 2 MWh storage capacity, where Case EC has 83 % more profit than Case E, which equals to 1160 NOK.

For Case EC, the total profit increases rapidly at the beginning for low installed capacity, and starts to stagnate at around 15-20 MWh. At this point, the increase per installed MWh is much less, which as discussed in the previous subsection is mainly due to not having much storage capacity issues. For reserve capacity sales, the curve experiences a high increase at low capacities, while decreasing slowly before stagnating at around 1200 NOK/Week, when it exceeds 7 MWh. The high increase in the beginning is due to the ability of participating heavily in the reserve capacity market, which is a resource-free market in this model, only constrained by the converter and the leftover energy stored in the storage unit. At smaller capacities, the need to store energy for future use is not necessary and cannot be utilized for many hours, and thus it manages to draw more profit out of the reserve capacity market. The peak is at 2 MWh because this is where it can sell maximum reserve capacity, due to having 1 MWh stored and 1 MWh free space. The decrease it experiences for bigger capacities is due to the increased potential in the energy market. With this increase in storage potential, it sees more profit in increasing energy market participation, and the reserve capacity market is now restricted by the converter rated power. Thus, the reserve capacity is decreasing to a steady point, while the energy profit increases rapidly due to the added storage potential.

For Case E, as it only can gather profit from the energy market, it follows the same trend as Case EC for energy profit. However, it does have a higher profit from that market because it cannot balance resources between multiple markets, and therefore tries to make use of every price difference. But even here the increased total profit stagnates because it struggles to utilize the installed capacity fully.

Analyzing the performance based on the strategy phase results from Table 10, a positive remark is that the model seems to capture the increased profit with increasing capacity. Despite the failed convergence, the total profit curves follow the expected pattern and have no visible strays. This shows that the model is able to plan this in a detailed manner despite not obtaining convergence.

Comparing Case EC and Case E shows that participating in both markets gives a higher total profit than only selling energy in the energy market. From an optimizer's point of view, this is the expected result as disabling the reserve capacity market is constraining the model more. As is a typical experience, each constraint either results in a decreasing or an equal objective function (for maximizing). This shows that by enabling reserve capacity sales, one constraint is removed or relaxed and also gives an increasing potential.

6.5.5 Expected weekly profit per installed MWh

When planning on installing storage units, it is important to analyze the expected increase in profit per MWh installed. Figure 52 shows how much profit each MWh installed capacity provides for the different storage capacities. All curves are slowly decreasing with increased capacity, which is as expected as each MWh installed will yield less profit. One interesting thing about the curve is when analyzing the lower capacities. For Case EC, the reserve capacity profit per MWh is almost constant for the first three capacities tested. A behavior like that shows that in these areas of the curve, the storage unit cannot make full profit on the most profitable incidents, which can be solved with higher installed capacity. This is as described earlier, because the reserve capacity is not fully utilized at these small capacities due to the stored energy constraint. For the energy profit, the curve is not so flat at the start as it manages to sell energy at the peaks from the beginning, and will for each additional MWh sell on the next-highest peaks as well.

6.5.6 Benefit of using storage units for reserve capacity participation

This model and especially Case EC and Case E have shown that the storage unit can increase its participation by selling reserve capacity to further increase profits. A storage unit has a high flexibility in power input/output, helping to contribute to the change in demand on the grid despite not participating in the energy market, as it can both charge and discharge power when prompted. For other dispatchable energy sources, they do not have the same flexibility when not participating in the energy market. Usually, they need to be operating and generating power to be able to participate in the reserve capacity market with their generation flexibility, giving them lesser possibilities on optimal strategy for a given hour. This holds true for a hydropower station without pumps installed. The storage unit can bypass this by using the limit on the converter for only reserve capacity sales. And as the storage unit contributes in the energy market during high variance in energy prices, the storage unit can participate in the reserve capacity market between these periods, increasing the total participation in the power market.

6.6 Summing Up Key Points

As this analysis is quite extensive and covers a lot of ground, this section was made to compile most of the findings and observations, which are presented in the following bullet points:

- The strategy phase managed to obtain convergence for various installed capacities with a deterministic setup, creating storage value curves that forecast potential future profit. However, this was found to be affected by the installed capacity, which struggled more when the capacity increased.
- The storage value curves became more detailed as the number of SLS increased. At a lower number of SLS, the curve would underestimate or overestimate the value of storing for the future.
- Increasing the number of SLS did not give better results in the strategy phase when convergence was not obtained originally, something that usually is the case for hydropower systems. In this analysis, it gave a higher deviation in most cases.
- The storage value curves for a stochastic setup varied between enabling reserve capacity sales or not. Without reserve capacity sales, the curve slowly decreased with an increasing state of charge, showing a changing benefit based on the amount of stored energy. With reserve capacity sales, the same pattern was found, but the restriction on reserve capacity sales made the curve drop at almost full capacity to prioritize some free space.
- The strategy phase performance struggled more when reserve capacity sales were enabled than without. Also, comparing two deterministic setups with different energy price pattern, the strategy phase performed better when higher energy price variation was present.
- The strategy phase performed better with a stochastic setup, due to the weighted contribution of each stochastic possibility that affected all storage values. The deviation for the non-converging scenarios did not increase heavily despite the increased number of decision stages to analyze.
- When testing the strategy phase for a stochastic setup with different number of SLS, the optimal number was found to be 22, which gave a detailed representation of the curve while having acceptable deviation and computation time.
- The simulation phase managed to plan and simulate the behavior of the storage unit for several weeks, while using the storage value curves to successfully consider the future potential. This was the case with both deterministic and stochastic setup.

- Depending on the storage value curve provided, the storage unit had different scheduling during the day and different end level on the state of charge. This shows the importance of accurate storage value curves.

- With higher increased capacity, the simulation phase showed that it became more difficult to fully utilize the complete storage unit. Especially at 25 MWh and above, the extra capacity was almost never used and thus gave no additional profit.

- For all storage capacities, the storage unit had a higher total profit when reserve capacity sales were included. Due to the possibility of participating in both markets, the storage unit managed to optimize in both markets and give a higher total profit. However, for higher installed capacities, the increased profit became smaller because the storage unit struggled to fully utilizing the extra capacity.

7 Conclusion

This report has analyzed a new method of considering the future potential of storing energy for a storage unit scheduling model participating in both the energy and reserve capacity market. The method is based on hydropower long-term scheduling, using stochastic dynamic programming to find a marginal cost of opportunity curve for the end level of the storage unit based on the future possible outcome. To be able to also consider uncertainty in forecasting the next day, it is required that the marginal cost of opportunity is influenced by all possible outcomes. The presented results from the strategy phase showed that generating these curves impacts the end storage level to promote the expected future profitability. However, with an increasing storage unit capacity, it proved to be a challenge to obtain optimal curves, which lead to the use of non-optimal results. This was observed both with and without enabling reserve capacity sales, however this problem was more apparent when enabling this market. Increasing the accuracy of this curve, which improves the deviation for hydropower models, gave no better results and instead increased the deviation. This opposite outcome favors as further investigation of this part of the model.

The presented results from the simulation phase showed that the storage unit balanced participation in both markets when enabled to, while also taking into account the optimal end storage level based on the storage value curve provided. With different curves, the end storage level would change, promoting good accuracy in the strategy phase to have optimal performance.

A profitability analysis of a storage unit located near Trondheim, Norway, has been carried out using this model to find the increased profitability with increasing installed capacity. For this case study, the addition of participating in the balancing market increased the total profit compared to only operating in the energy market. The increased profitability reached 83 % at the highest, giving an increase from 766 to 1334 NOK per week for a 2 MWh storage unit. However, the increased profitability decreased for higher storage capacities. The study showed that for storage units above 15 MWh, this additional MWh gave almost no increase in profitability, showing a saturated participation in the markets with the given rated power of the converter. This is a useful analysis, as this can help study the optimal installed capacity to prevent installing a too small or a too large storage unit.

In overall, the storage unit scheduling model has shown good performance and can be a useful option for analyzing storage units from a stochastic point of view when considering multiple markets.

8 Future Work

During this thesis, multiple tests have been performed to observe the strengths and weaknesses of the model. One of the observations was that the model does struggle to perform an optimal strategy phase run for large storage units, which is something that could be analyzed further to find the reason behind this.

Another interesting point could be to investigate the reserve capacity constraint regarding available energy storage. With the current restriction, the storage unit must be able to provide the up- and down-regulation for the whole time step, which potentially can be considered too strict. It could be interesting to further study the impact from adjusting this parameter. Also, trying to implement actual reserve capacity utilization in the model would change how it operates in this market, as it currently only sees this as a resource-free profit, except for available stored resources.

As this model utilizes stochastic dynamic programming that usually is found in hydropower models, comparing the performance of this modelling setup versus another modelling setup typically used for storage units, would help analyze the accuracy of its performance. An example could be to implement Rolling Time Horizon to the same optimization problem and see how the optimal scheduling varies.

Implementing energy producing sources into this model could be another interesting thing to analyze, as this would make the storage unit not only focus on energy price variation, but also production variation from e.g. a wind turbine. How it would operate in both markets with this extension could be interesting to investigate. The same goes for adding loads or other energy dependent objects into the system, as this changes the scheduling and objective of the storage unit.

References

[1] Nord Pool AS. *Balancing market*. Accessed 4.12.2017. URL: http://www.statnett.no/Kraftsystemet/Markedsinformasjon/.

[2] Nord Pool AS. *The power market*. Accessed 4.12.2017. URL: https://www.nordpoolgroup.com/the-power-market/.

[3] Energy Storage Association. Accessed: 19.05.18. URL: http://energystorage.org/energy-storage/energy-storage-technologies.

[4] Energy Storage Association. Accessed: 19.05.18. URL: http://energystorage.org/energy-storage/technologies/lithium-ion-li-ion-batteries.

[5] EUROPEAN COMMISSION. *A policy framework for climate and energy in the period from 2020 to 2030*. 22.1.2014. URL: http://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:52014DC0015&from=EN.

[6] European Council. *Electricity interconnection targets*. Accessed 8.12.2017. URL: https://ec.europa.eu/energy/en/topics/infrastructure/projects-common-interest/electricity-interconnection-targets.

[7] Gerard L. Doorman. *Hydro Power Scheduling*. 1st Edition. Department of Electric Power Engineering, NTNU, 2017.

[8] epec Engineered Technologies. Accessed: 19.05.18. URL: http://www.epectec.com/batteries/cell-comparison.html.

[9] ENTSO-E. *ELECTRICITY IN EUROPE 2015*. Accessed 8.12.2017. 6.2016. URL: https://www.entsoe.eu/Documents/Publications/Statistics/electricity_in_europe/entsoe_electricity_in_europe_2015_web.pdf.

[10] THEMA Consulting Group. *Teoretisk tilnærming til en markedsløsning for lokal fleksibilitet*. Version ISSN 1501-2832. Norges vassdrags- og energidirektorat, 2016.

[11] Gurobi. Accessed: 19.05.18. URL: http://www.gurobi.com/company/about-gurobi.

[12] Arild Helseth, Marte Fodstad, and Chiara Bordin. *A Stochastic Dynamic Programming Model for Scheduling Energy and Reserve Capacity*. Version 1.0. This report is confidential. SINTEF Energy Research, 1.02.2017.

[13] Arild Helseth et al. *Assessing Hydropower Operational Protability Considering Energy and Reserve Markets*. Version ISSN 1751-8644. SINTEF Energy Research, Lyse Produksjon AS, 2017.

[14] Worranat Pakornrat Henry Maltby. Accessed: 14.12.17. URL: https://brilliant.org/wiki/markov-chains/.

[15] IEA. *Nordic Energy Technology Perspectives 2016*. International Energy Agency, 2016. URL: http://www.nordicenergy.org/wp-content/uploads/2016/04/Nordic-Energy-Technology-Perspectives-2016.pdf.

[16] Sandia National Laboratories. Accessed: 19.05.18. URL: https://software.sandia.gov/downloads/pub/coopr/CooprGettingStarted.html#.

[17] NVE. Accessed: 19.05.18. URL: https://www.nve.no/reguleringsmyndigheten-for-energi-rme-marked-og-monopol/sluttbrukermarkedet/ams/.

[18] Pyomo. Accessed: 19.05.18. URL: http://www.pyomo.org/about.

[19] Pyomo. Accessed: 19.05.18. URL: http://pyomo.readthedocs.io/en/latest/library_reference/kernel/piecewise/piecewise.html.

[20] Python. Accessed: 19.05.18. URL: https://www.python.org/about/.

[21] Satcon. Accessed: 20.05.18. URL: http://www.satcon.com/uploads/products/en/1MW-PG-US-UL.pdf.

[22] Javier Silvente et al. *A rolling horizon optimization framework for the simultaneous energy supply and demand planning in microgrids*. Version 1.0. 25.05.2015.

[23] John Wiley Sons. *Renewable and Efficient Electric Power Systems*. Version ISBN 0-471-28060-7. 2004.

[24] SSB. *Fakta om energi*. page 28. SSB, 03.2013.

[25] Statnett. *Langsiktig markedsanalyse, Norden og Europa 2016-2040*. Stanett, 2016.

[26] Statnett. *Systemdrifts- og markedsutviklingsplan 2017-2021*. Stanett, 2017.

[27] Kasper Emil Thorvaldsen. *Profitability of a Hydropower Producer Operating in Two Different Markets*. Version 1.0. Department of Electric Power Engineering, NTNU, December 2017.

[28] Battery University. Accessed: 19.05.18. URL: http://batteryuniversity.com/learn/article/bu_210b_flow_battery.

[29] Bolun Xu et al. *Factoring the Cycle Aging Cost of Batteries Participating in Electricity Markets*. 28.07.2017.

A Mathematical Model Description

A.1 Model functions

A.1.1 Sets

TS	Time steps for sales of energy and reserve capacity within decision stage
NR	Steps for piecewise-linear approximation of storage values
K	Steps for piecewise-linear approximation of power production
C	Total number of reserve blocks. What time steps in TS split the blocks.

A.1.2 Indexes

t	Time step for sales of energy and reserve capacity
n	Step for piecewise-linear approximation of storage values
k	Step for piecewise-linear approximation of power production using an efficiency curve
c	Reserve block

A.1.3 Parameters

$E_{price,t}$	Energy price for time step t $[NOK/MWh]$
$C_{price,t}$	Reserve capacity price for time step t $[NOK/MW]$
A_{price}	Price for purchasing artificial energy $[NOK/MWh]$
$DVal$	Offset in value function $[NOK]$
T_t	Length of time step t $[h]$
B^{MAX}	Capacity of the energy storage unit $[MWh]$
$MDOD$	Maximum depth of discharge for the storage unit $[p.u]$
B^{Start}	Storage unit capacity at the start of the decision stage $[p.u]$
C^{Max}	Maximum reserve capacity sales $[MW]$

P_{ch}^{max}	Maximum power output from converter during charging $[MW]$
P_{dch}^{max}	Maximum power output from converter during discharging $[MW]$
$P_{ch,in}^{max}$	Maximum power input to the converter during charging $[MW]$
$P_{dch,in}^{max}$	Maximum power input to the converter during discharging $[MW]$
η_{ch}^{max}	Highest efficiency for the converter during charging $[p.u]$
η_{dch}^{min}	Lowest efficiency for the converter during discharging $[p.u]$
$P_{ch,t}^{max}$	Maximum power output from converter during charging at time step t $[MW]$
$P_{dch,t}^{max}$	Maximum power output from converter during discharging at time step t $[MW]$
$P_{ch,in,t}^{max}$	Maximum power input from converter during charging for each time step t $[MW]$
$SOC_{pts}[n]$	1-Dimensional list containing piecewise linear points for SOC $[p.u]$
$SV_{pts}[n]$	1-Dimensional list containing piecewise linear points for Storage Values based on SOC $[NOK]$
P_{k}^{pts}	Output power from converter on each point k, for both charging and discharging $[MW]$
P_{k}^{cha}	List containing input power to the converter during charging, given as a piecewise-linear list. power input for each point k $[MW]$
P_{k}^{dis}	List containing input power to the converter during discharging, given as a piecewise-linear list. power input for each point k $[MW]$
R_{c}^{list}	list containing reserve sales blocks for each time step c

A.1.4 Variables

Continuous variables

soc_t	State of Charge for the storage unit at the end of time step ts $[p.u]$
p_t^{in}	Power stored to charge the storage unit in time step ts $[MW]$
p_t^{out}	Power discharged from the storage unit in time step ts $[MW]$
p_t^b	Power bought from grid in time step ts $[MW]$
p_t^s	Power sold to the grid in time step ts $[MW]$
p_t^f	Power overview on the grid side in time step ts $[MW]$
cap_t	Reserve capacity sold in time step ts $[MW]$
p_t^{art}	Artificial power bought in time step ts $[MW]$
SV	Value of stored energy in the the storage unit at the end of the decision stage $[NO$

Binary variables

$\delta_{t,k}^1$	SOS2-variable for power flow through converter during charging for each time step ts and each discrete point k
$\delta_{t,k}^2$	SOS2-variable for power flow through converter during discharging for each time step ts and each discrete point k
δ_n	SOS2-variable for end-value of stored power in the storage unit at the end of the decision stage for each discrete point n

A.2 Objective

$$OBJ = \sum_{t \in TS} E_{price,t} \cdot p_t^f \cdot T_t \tag{A1}$$

$$+ \sum_{t \in TS} T_t \cdot C_{price,t} \cdot cap_t \tag{A2}$$

$$- \sum_{t \in TS} A_{price,t} \cdot p_t^{art} \cdot T_t \tag{A3}$$

$$+ SV + DVal \tag{A4}$$

A.3 Constraints

A.3.1 Initial storage balance

Description: Storage level at the end of the first time step is the initial storage level + stored energy - discharged energy.

$$soc_0 \cdot B^{MAX} - p_0^{in} \cdot T_0 + p_0^{out} \cdot T_0 - p_t^{art} \cdot T_0 = SOC^{Start} \cdot B^{MAX} \tag{A5.1}$$

A.3.2 Storage balance

Description: Storage level deviation between start and end of the time step must be equal to energy stored and energy discharged.

$$soc_{t-1} \cdot B^{MAX} + p_t^{in} \cdot T_t - p_t^{out} \cdot T_t + p_t^{art} \cdot T_t = soc_t \cdot B^{MAX}, \quad t \in TS \backslash [ord(t) > 0] \tag{A5.2}$$

A.3.3 Upper capacity Limit [flow]

Description: Limits up-regulation of reserve capacity based on available power increase in the converter. Going from charge -> discharge and backwards is allowed. There are two possibilities, based on user-specification: A6.1 is with hourly charge limit, A6.2 is without.

$$-p_t^f \geq cap_t - P_{dch,t}^{max} \quad t \in TS \tag{A6.1}$$

$$-p_t^f \geq cap_t - P_{dch}^{max} \tag{A6.2}$$

A.3.4 Lower capacity limit [flow]

Description: Limits down-regulation of reserve capacity based on available power decrease in the converter. Going from charge -> discharge and backwards is allowed. There are two possibilities, based on user-specification: A7.1 is with hourly discharge limit, A7.2 is without.

$$-p_t^f \leq -cap_t + \frac{P_{ch}^{max}}{\eta_{ch,t}^{max}} \quad t \in TS \tag{A7.1}$$

$$-p_t^f \leq -cap_t + \frac{P_{ch}^{max}}{\eta_{ch}^{max}} \tag{A7.2}$$

A.3.5 Higher capacity limit [storage]

Description: Limits down-regulation of reserve capacity based on remaining storage potential in the storage unit. The maximum charging efficiency is also taken into consideration, allowing to sell more down-regulation capacity that would be lost in the conversion.

$$cap_t \cdot T_t \leqslant (1 - soc_t) \cdot \frac{B^{MAX}}{\eta_{ch}^{max}} \quad t \in TS \tag{A8}$$

A.3.6 Lower capacity limit [storage]

Description: Limits up-regulation of reserve capacity based on remaining energy stored in the storage unit. The maximum depth of discharge is included to limit the lower boundary. Minimum discharging efficiency is also taken into consideration, avoiding to sell more capacity than the storage unit will be able to give on the output side of the converter.

$$cap_t \cdot T_t \leqslant (soc_t - (1 - MDOD)) \cdot B^{MAX} \cdot \eta_{dch}^{min} \quad t \in TS \tag{A9}$$

A.3.7 Power flow

Description: Connects the variable p_t^f to p_t^s and p_t^b.

$$p_t^f \cdot T_t = p_t^s \cdot T_t - p_t^b \cdot T_t \quad t \in TS \tag{A10}$$

A.3.8 Power flow [charging]

Description: Sets the relation between energy bought and energy stored in the storage unit. The converter efficiency is vital in this conversion. There are two possibilities, based on user-specification: A11.1 is for a constant efficiency, A11.2 and A11.3 are for a piecewise-linear efficiency curve based on power flow.

$$p_t^{in} \cdot T_t = \eta_{ch} \cdot p_t^b \cdot T_t \quad t \in TS \tag{A11.1}$$

$$\sum_{k=1}^{K} \delta_{k,t}^1 = 1, \quad \delta_{k,t} \quad \epsilon\{0,1\}, \quad t \in TS, SOS-2 \tag{A11.2}$$

$$p_t^{in} = (\sum_{k=1}^{K} \delta_{k,t}^1 \cdot P_k^{cha}(p_t^b)), \quad t \in TS \tag{A11.3}$$

A.3.9 Power flow [discharging]

Description: Sets the relation between energy discharged from the storage unit and energy sold. The converter efficiency is vital in this conversion. There are two possibilities, based on user-specification: A12.1 is for a constant efficiency, A12.2 and A12.3 are for a piecewise-linear efficiency curve based on power flow.

$$p_t^s \cdot T_t = \eta_{dch} \cdot p_t^{out} \cdot T_t \quad t \in TS \tag{A12.1}$$

$$\sum_{k=1}^{K} \delta_{k,t}^2 = 1, \quad \delta_{k,t} \quad \epsilon\{0,1\}, \quad t \in TS, SOS-2 \tag{A12.2}$$

$$p_t^{out} = (\sum_{k=1}^{K} \delta_{k,t}^2 \cdot P_k^{dis}(p_t^s)), \quad t \in TS \tag{A12.3}$$

A.3.10 End value of stored energy

Description: Sets the value of remaining energy in the storage unit at the end of the decision stage. The use of piecewise-linear approximation is active here.

$$\sum_{n=1}^{NR} \delta_n = 1, \quad \delta_n \epsilon\{0,1\} \tag{A13.1}$$

$$SV = (\sum_{n=1}^{NR} \delta_n \cdot SV_{pts}[n, soc_{TS}]) \tag{A13.2}$$

A.3.11 Reserve blocks

Description: Sets the reserve capacity time steps that should have equal value. Enables reserve capacity sale blocks.

$$cap_t = cap_{t-1}, \quad t \in TS \backslash [ord(t) > 1, t \neq R_c^{list} for c \in C] \tag{A14}$$

A.3.12 State-of-charge boundaries

Description: Limits the state-of-charge area for the storage unit. This is based on the user-defined parameter MDOD, which limits lower boundary.

$$(1 - MDOD) \leq soc_t \leq 1, \quad t \in T \tag{A15}$$

A.3.13 Buying and selling power limit

Description: Shows the limit of the amount of power to buy or sell. Note that the selling quantity is limited by the converter.

$$0 \leq p_t^b \leq \infty \tag{A16.1}$$

$$0 \leq p_t^s \leq P_{dch}^{max} \tag{A16.2}$$

A.3.14 Input and output power to storage unit limit

Description: Shows the limit of the amount of power going in and out of the storage unit. The limit for input power is set by the converter limit.

$$0 \leq p_t^{out} \leq \infty \tag{A17.1}$$

$$0 \leq p_t^{in} \leq P_{ch}^{max} \tag{A17.2}$$

A.3.15 Reserve capacity sale limit

Description: Limits the amount of reserve capacity that can be sold in each time step.

$$0 \leq cap_t \leq C^{Max} \tag{A18}$$