Master's thesis

NTNU
Norwegian University of Science and Technology
Faculty of Information Technology and Electrical Engineering
Department of Electric Power Engineering

Jon Hvideberg Holte

An analysis of energy storage system with wind power for multi-market operation under uncertainty

Master's thesis in Energy and Environmental Engineering
Supervisor: Jayaprakash Rajasekharan
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Problem Description

There is an increasing focus to include more renewable energy sources in the global energy mix. These renewable sources, like wind and solar power, are dependant on weather which make them unregulated sources. This can cause challenges when it comes to securing the supply of power and ensuring the continuous balance of production and consumption. By combining these unregulated sources with energy storage, the production could be balanced. However, with uncertainty in both the power production and the power markets, it can be difficult to optimise the scheduling strategy for such an energy system.

In this thesis, an optimisation model for energy system scheduling based on stochastic dynamic programming has been created and analysed. This model uses concepts found generally in hydropower optimisation and a previous version was originally created in a former master's thesis for energy scheduling of a single storage unit in a multi-market setup. The two main contributions of this thesis are: implementing wind power as an unregulated power source in the optimisation model and analysing the created model in a case study. The created model provide short-term scheduling for an energy system, consisting of a storage unit and wind turbine, which participate in the energy market and reserve capacity market.

In the case study, both deterministic and stochastic setups will be tested. Various seasonal data will be used to test the model in different scenarios based on wind production and prices in the markets. The energy system will also be tested with various storage capacity and wind power ratings. The motivation behind the case study is to investigate what impact the inclusion of wind power have on the behaviour and results of the energy system. An interesting aspect is to see how the storage unit and the wind turbine cooperate and how they participate in the multi-market setup (i.e. how they participate in the energy market and reserve capacity market). Another interesting perspective is to study the effects on the energy system behaviour and profit results from the various seasonal input data and component sizes.

Preface

This master's thesis has been written during the spring semester in 2020 at the Department of Electrical Power Engineering at the Norwegian University of Science and Technology (NTNU). The work consist of both creating and analysing an optimisation model of short term energy system scheduling. The energy system in question consists of both a storage unit and a wind turbine. The model in this thesis is based on an optimisation model used in a previous master's thesis and this work is thus a continuation of that thesis.

This has been an alternative semester because of the Covid-19 outbreak this spring. Even though the pandemic did not affect my work directly, it certainly had its effect on society at large during this project. Therefore, it also had an unintended negative influence on this thesis since working conditions were changed overnight and strict restrictions were imposed which greatly affected us all. However, I hope and believe that this thesis has been as good and competent as possible given the circumstances.

At last, I would like to thank my supervisors Jayaprakash Rajasekharan and Kasper Emil Thorvaldsen for their help and guidance throughout the semester. Both have contributed to good discussions and feedback which have ensured progress in this work. I would like to mention that since this project is a continuation of Thorvaldsen's own master's thesis, he has especially been an inspiration and resource during this work.

Jon Hvideberg Holte
Trondheim June 2020

Summary

With the increasing shares of unregulated renewable energy sources in today's energy mix, balancing energy demand and energy supply over time becomes more challenging. Energy storage is identified as a key technology to overcome this challenge and to ensure power stability. When combining energy storage with unregulated power productions one must consider the scheduling of energy storage operations and interactions with the surrounding systems. An optimal energy scheduling is crucial to obtain a profitable energy system.

In this thesis, an optimisation model was created for an energy system consisting of an energy storage unit and a wind turbine. The energy system is connected to the grid and operates in a multi-market setup, where it participates in both the energy and regulating market with the objective to maximise its profit. The model itself is a short-term model operating at a level that is both multi-stage and multi-scenario stochastic and is based on concepts found in hydropower optimisation. It consists of a two-step process with two phases. Firstly, in the strategy phase, the model uses stochastic dynamic programming to obtain the storage values for the energy system, which is the marginal value of stored energy. Secondly, these storage values are used in the simulation phase to simulate the optimal scheduling strategy.

To analyse the results and behaviour of the optimisation model, a deterministic and stochastic case study is included and seasonal data is used to showcase the model in different situations. The deterministic case study focuses on wind power sizing and system behaviour under an extreme scenario. The stochastic case study has a more thorough analysis of two very different seasonal cases, winter and summer. The price and wind data used in the cases are based on historical data obtained from 2018 and 2012. The model has been tested with different storage capacities in the range of 1-15 MWh and various wind power ratings in the range of 0.5-2.0 MW. To analyse the multi-market feature, the energy system has been tested when only allowed to operate in the energy market, compared to operating in both markets.

The results show that an increase in installed wind power leads to a significant increase in profit. To limit the wind power shed and maximise the wind power utilisation, it is found that a 1.5 MW wind turbine suited this energy system. The model enhances its trade in the energy market when there is an increase in ”free” wind power available. Thus, the multi-market operation decreases as wind production increases. Only when the reserve capacity price is higher than the energy price the capacity market is prioritised by shedding wind power. When wind power production is low, the system operates in both markets due to more available transfer capacity. The seasonal variations have a great impact on the energy system in terms of profit and its multi-market operation. While the winter case with high wind production almost solely operates in the energy market, the summer case benefit from the multi-market opportunity with 12-16 % of total operating profit coming from the reserve capacity market. When participating in both markets, the total operating profit in the winter case with high wind production was 34-38 % higher than for the summer case depending on storage capacity. Note that an installed storage capacity above 3 MWh does not give a significant additional profit in either market. When wind production is high the storage does not contribute to a significantly higher profit, but it provides a more stabilised power exchange. To conclude, the energy storage and wind turbine complement each other in the multi-market setup due to seasonal variations in the wind and would increase the overall yearly performance with different strategies throughout.

Sammendrag

En økende andel av uregulerte fornybare energikilder i dagens energimiks fører til at balanseringen av kraftproduksjon og -forbruk blir mer utfordrende. I den sammenheng identifiseres energilagring som en viktig teknologi for å løse denne utfordringen og bidra til kraftbalanse. Når man kombinerer energilagring med uregulert kraftproduksjon, er det viktig å vurdere hvordan man skal planlegge energilagringen og interaksjonen med de tilknyttede systemene. En optimal energiplanlegging er derfor avgjørende for å få et fungerende og lønnsomt energisystem.

I denne masteroppgaven er det laget en optimaliseringsmodell for et energisystem bestående av en energilagringsenhet og en vindturbin. Energisystemet er koblet sammen med kraftnettet og opererer i både energi- og balansemarkedet med mål om å maksimere overskuddet. Selve modellen er en korttidsmodell som opererer på et nivå som er både flerstegs og multi-scenario stokastisk og er basert på konsepter som brukes i produksjonsplanlegging av vannkraft. Den har to faser som utføres i to steg. Første fase er strategifasen som bruker stokastisk dynamisk programmering for å beregne lagringsverdiene til systemet, som kan defineres som den marginale verdien av lagret energi. Deretter brukes disse lagringsverdiene i simuleringsfasen for å beregne den optimale planleggingsstrategien.

En deterministisk og en stokastisk case-studie blitt brukt for å analysere resultatene og oppførselen til optimaliseringsmodellen. Ulike situasjoner i disse casene ble simulert ved hjelp av data fra ulike årstider. Det deterministiske case-studiet fokuserte på ulike vindkraftstørrelser og modelloppførselen under en ekstrem situasjon. I den stokastiske casestudien ble det gjort en grundigere analyse av to forskjellige årstider, nemlig vinter og sommer. Prisdata og vinddata som er brukt i casene er basert på historiske data fra 2018 og 2012. Modellen er testet med lagringskapasitet på 1-15 MWh og forskjellige vindturbiner i størrelsene 0.5-2.0 MW. For å analysere deltagelsen og oppførselen i markedene har energisystemet blitt testet når det bare opererer i energimarkedet, sammenlignet med å få delta i begge markedene.

Resultatene viser at en økning i installert vindkraft fører til en betydelig økning i profitten. For å begrense overflødig vindkraft og samtidig maksimere utnyttelsen av vindenergien, ble det funnet at en 1,5 MW vindturbin passet dette systemet. Resultatene viser at modellen øker sin prioritering av energimarkedet med mer "gratis" vindkraft tilgjengelig. Så når vindproduksjonen øker minsker deltagelsen i begge markedene. Først når prisen i balansemarkedet er høyere enn energiprisen, blir balansemarkedet prioritert på bekostning av redusert vindkraft. Når det er lite vindkraftproduksjon, deltar modellen mer i begge markedene. Resultatene viser altså at årstidene har stor innvirkning på energisystemet med tanke på den totale profitten og deltagelsen i de ulike markedene. Mens vinter-casen med mye vindkraft nesten utelukkende opererer i energimarkedet, drar sommer-casen fordel av muligheten av å operere i to markeder der 12-16 % av det totale driftsresultatet kommer fra balansemarkedet. Ved deltagelse i begge markedene, var den totale profitten i vinter-casen 34-38 % høyere enn for sommer-casen, avhengig av lagringskapasiteten. Merk at en installert lagringskapasitet over 3 MWh ikke gir en særlig økning av profitt i noen av markedene. Merk også at når vindproduksjonen er høy fører ikke energilagringen til en særlig høyere profitt, men det gir en mer stabil kraftutveksling. Til slutt kan man konkludere med at energilagring i samspill med vindkraft utfyller hverandre når systemet får operere i flere markeder. Systemet vil da kunne øke sin årlige fortjeneste og ytelse ved å ha flere strategier å spille på ved for eksempel variasjoner i vind.

Table of Contents

List of Tables

List of Figures

Chapter 1

Introduction

1.1 Background and Motivation

To reach certain climate goals in the future the current energy system needs to go through a transition by shifting from fossil fuels to renewable energy sources. For instance, the EU has declared ambitious climate goals, which are summarised in Table 1.1, and to reach these goals the energy system needs to become both smarter and include a higher share of renewable energy. The future energy system will thus be characterised by a higher integration of renewable energy.

Goals	**2020**	**2030**
Cut in greenhouse gases (from 1990 levels)	20 %	40 %
Share of renewable production	20 %	32 %
Improved energy efficiency	20 %	32.5 %

Table 1.1: Overview of the EUs climate and energy goals for year 2020 and 2030 [1].

The future includes a transition from power being produced at large centralised power plants and transported to the end-user, to a more decentralised energy structure with distributed generation in the form of renewable power production. However, including more renewable power poses some challenges. Renewable energy sources, such as solar power and wind power, are unregulated sources dependant on the weather. This implies that the sources cannot be turned on and off by choice and have a highly variable power production which is difficult to predict. Balancing energy demand and supply over time then becomes more challenging. Grid stability issues such as inconsistent frequencies could also arise. Another challenge is that constrained transmission and distribution grids could limit the increase in distributed renewable production. To tackle these problems, the energy system needs to be smarter and include new technology to make better use of the energy infrastructure. For instance, energy storage systems are recognised as a key technology to overcome some of these challenges.

Energy storage in cooperation with unregulated power and in connection with the main grid has many possible applications. One objective could be to balance the production from the unregulated power sources, thus increasing the flexibility. If an unregulated power source is connected to an energy storage system, excess power generated in periods with good production conditions can be stored. This stored power could then be used in periods where there is a power deficit or the production conditions are less good. Energy storage could also provide an alternative to grid reinforcements in areas where the transmission grid is weak and constrained by levelling the power output or storing excess energy for other use.

Other grid and market purposes for the integration of a storage system could be to ensure balance in the power system by participating in the regulating market or used for frequency stabilisation. The storage unit could also participate in the energy market and make a profit by buying electricity when it is cheap and selling when it is expensive. An energy storage system is thus capable of multi-market participation.

1.2 Scope and Problem Statement

The main contributions from this work are the following:

- Present a short-term optimisation model for energy system scheduling where it seeks to maximise its profit in a multi-market setup while using a stochastic backwards dynamic programming (SDP) framework.
- Investigate the integration of an unregulated power source, such as wind power, in an energy storage system that operates in a multi-market setup.
- Compare and analyse the results and behaviour of the optimisation model in a case study consisting of both a deterministic and stochastic setup involving two seasonal cases.

This thesis utilises an optimisation model formulated in Python. The whole energy system which the model represents consists of a wind turbine, a converter and a storage unit, e.g. a battery. This system is connected to the main grid and participates in both the energy market and the reserve capacity market, making it a multi-market operation. Within these markets, the model seeks to gain the maximum profit thus making it a model with an economical objective. The motivation for studying a multi-market setup is to see in which market the system chooses to participate and thus in which market it makes the greatest contribution and impact. The model used in this thesis is based on a model from a previous master's thesis from 2018 by Kasper Emil Thorvaldsen [2].

1.3 Thesis Outline

The next following chapter in this thesis, Chapter 2, contains the theory and methodology which are the basis when constructing the model. Chapter 3 gives a description of the model and its elements, while Chapter 4 seeks to explain the setup of the case study analysed in this thesis. In Chapter 5 and 6, the results of the case study are presented and discussed. At last, Chapter 7 formulates a conclusion and Chapter 8 discusses future work related to this thesis. An appendix containing the optimisation model elements, historical data plots, and some of the stochastic input data used in the case study is also included.

Chapter 2

Theory, Background and Methodologies

This chapter includes relevant theory for the master's thesis. The first section, Section 2.1, contains a small overview of academic work and publications concerning energy storage system scheduling. The purpose of this section is to get a general understanding of already investigated areas on this subject and to find out where this thesis belongs in the already existing research work.

The following sections in this chapter consist of relevant theory for this work. It should be mentioned that this master's thesis contains some similarities with previous work done by the author. In 2019 the author analysed an energy system consisting of only a storage unit operating in multiple markets, for various seasons [3]. Since the model that is used in this thesis are an extension of the model used in previous work done by the author, much of the theoretical background is the same. Therefore, Section 2.2 to Section 2.7 are more or less the same as in the previous report mentioned.

Section 2.8 covers distributed generation in the form of wind power, and present theory relevant for the work regarding implementation of wind power in the optimisation model. At last, Section 2.9 covers some of the assumptions made in the creation of the model, as well as some uncertainties that exist in the work.

2.1 Literature Review for Energy Storage System Scheduling

To obtain a sense of perspective of the role that this thesis plays in the already existing academic literature, this section will seek to give an overview on the existing research and literature about energy storage scheduling and management.

In 2018, a systematic literature review of energy management for stationary electric energy storage systems was published [4]. This article reviewed literature that has been published about optimal management of energy storage connected to the power grid or a microgrid. The goal of this framework is to guide future researchers in positioning their work in the literature and also by identifying future research opportunities. In total, 202 publications were reviewed in this article [4].

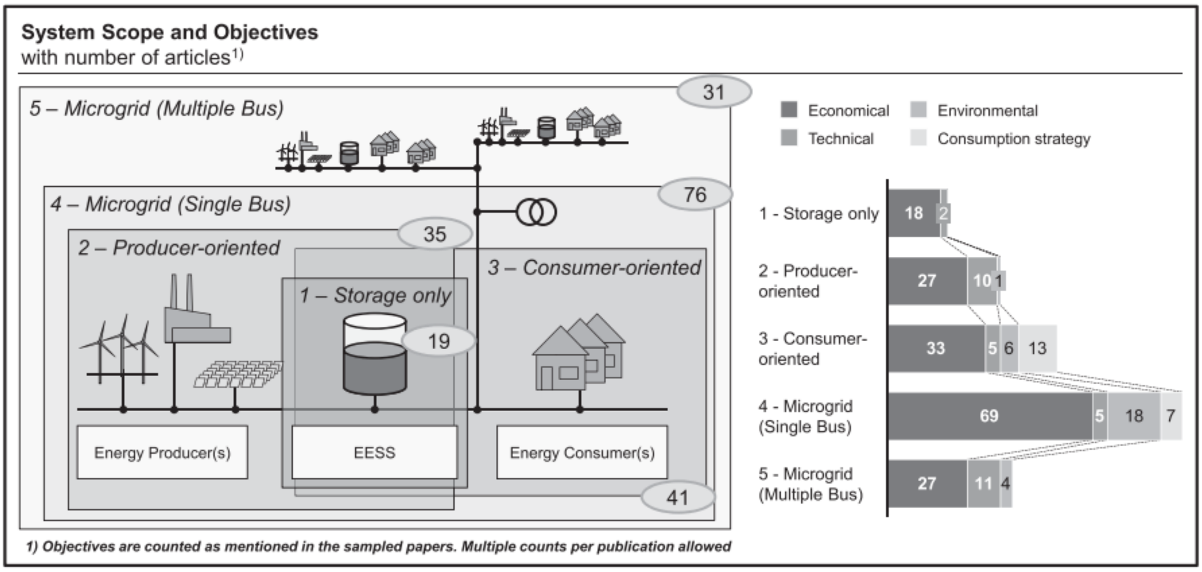


Figure 2.1: The various system scope and objectives in the reviewed publications [4].

As seen in Figure 2.1, the various literature reviewed has different system scope and objectives. The scope of the system refers to the number and type of participants, and the objective is the proposed optimisation focus of the system. It can be seen from Figure 2.1 that most of the objectives have an economic focus where the main intention is minimising costs or maximising profits. Only a handful of the publications have an environmental, technical or consumption strategy objective focus. An interesting aspect in Figure 2.1 is that relatively few publications have the storage only scope or are producer oriented. If the scope is storage only, energy storage systems are considered as independent systems interacting with the grid. When producer-oriented, the case where energy production is combined with a storage system to deliver a combined and improved output is considered. Most of the publications deal with microgrids, either with one bus or several busses.

In the literature reviewed, the type of energy storage system consists primarily of a single unit. The storage technology used can vary and is heavily based on the wanted outcome of the system. However, battery energy storage systems are investigated in around 53 % of these single unit cases [4]. Even though most of the publications feature a load in the system, either uncontrollable or controllable, a significant number of publications did not have a load modelled into the system at all.

When investigating the time horizon which the models in the publications operate within, it could be found that around half of the publications focus on day-ahead scheduling, and then often competing in day-ahead energy markets. The rest of the publications focus on intraday scheduling or optimisation in retrospective form [4]. Few publications were found to be centred around other markets, such as the regulating markets. However, a few publications investigate these subjects and also a multi-market approach. For instance, Kim and Powell had a multi-market approach where they considered a model of a combined wind turbine and battery storage acting in the day-ahead and regulating markets [5].

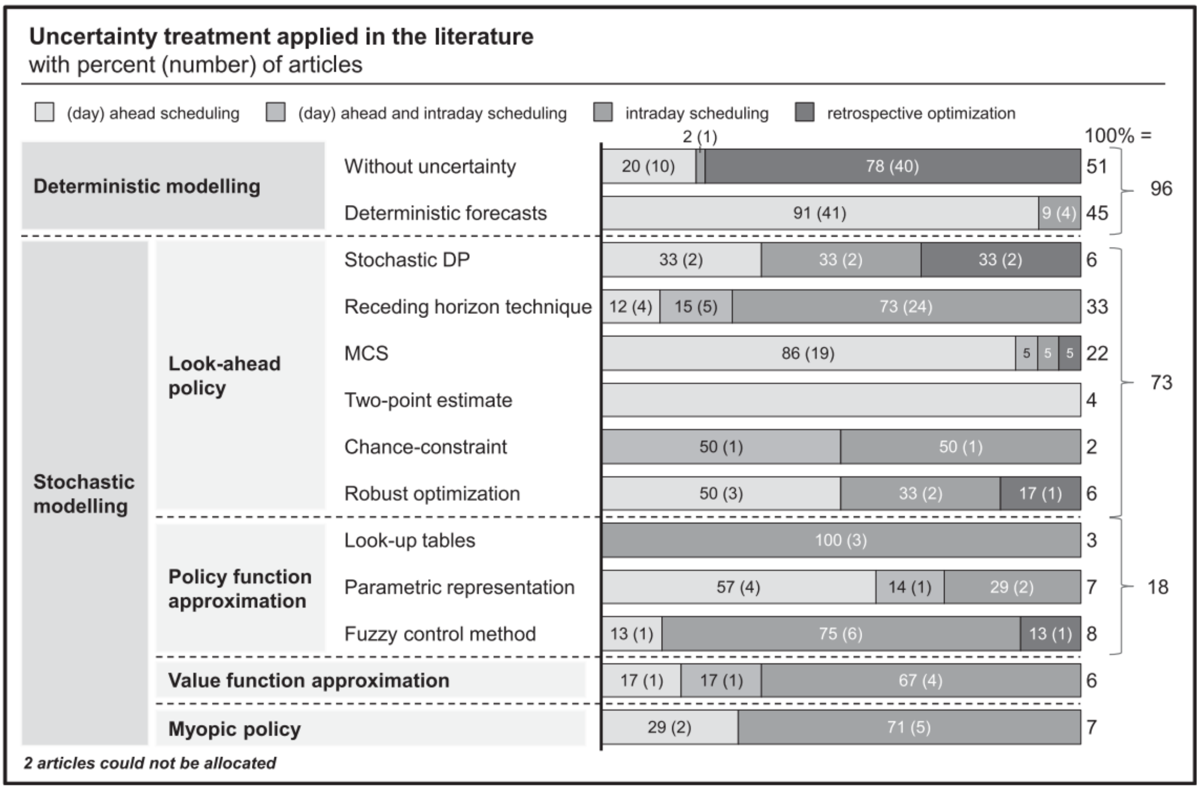


Figure 2.2: The different use of uncertainty handling techniques in the reviewed publications [4].

Scheduling an energy system is a decision-making problem that includes planning for an uncertain future. The uncertainty derives either from technical factors such as unregulated energy production or economical parameters such as electricity price. Seen in Figure 2.2, around half of the publications reviewed did not consider uncertainty at all. Within the deterministic modelling, many of the publications used deterministic forecasts, but this does not include uncertainty since all the data in the forecast is known. When modelling uncertainty, or stochasticity, four policy categories were used to categorise the different approaches. These can be seen in Figure 2.2 and are look-ahead policies, policy function approximations, value function approximations, and myopic policies. When utilising look-ahead policies one makes decisions at the present stage and optimise over a planning period by combining an estimate of future information with an estimate of future actions. The policy function approximations directly return a policy in the current state. The value function approximations use an approach that replaces the value function with an approximation which in turn makes it possible to solve stochastic problems by looking forward instead of a backward iteration. At last, myopic policies optimise for the present time without considering future decisions, although uncertainties are acknowledged.

In the literature review article, it is stated that 19 of the 202 sampled publications applied a Dynamic Programming (DP) approach [4]. In six of these 19 publications uncertainty was included with stochastic modelling, as seen in Figure 2.2. This means that only six out of the 202 publications used Stochastic Dynamic Programming (SDP). The advantage of SDP is that it is a good representation of the probabilistic characteristics. However, the downside is that it often leads to high computational efforts and discretisation can lead to oversimplifications. An example of SDP use in energy storage system scheduling is found in [6]. Here, it was investigated a production-oriented system with a wind power plant and battery participating in both the day-ahead and intraday markets. It was assumed that day-ahead obligations have already been scheduled and the aim was to obtain the intraday position. In this publication, wind power production was the stochastic input. The problem was then solved through full value iteration centred around the forecasted wind power production. Other examples are a paper which describes a stochastic, dynamic programming model that analyse and determine optimal operating strategies for an energy system consisting of diesel sets with optional battery storage and unregulated wind or PV power [7]. Also, a customer-side energy storage system that operates to minimise the electricity bill under a peak-load limitation constraint in demand and price uncertainties [8].

The lack off publications that consider stochasticity in their problems with energy storage scheduling is also discussed in [9]. In this article, energy storage scheduling is considered with distributed generation uncertainties in the form of wind and solar power. The article state that some of the references consider stochasticity in their problems, but none uses stochasticity of wind and solar power in the optimal scheduling of energy storage taking into account the power flow constraints in distribution systems [9].

The authors of the literature review article finish up with presenting propositions for future research. In the bullet points below the propositions are more or less rendered from the article [4]:

- Proposition 1. More publications in the classical management and decision science literature should transfer knowledge from well-known fields of research, such as inventory control, to the discussed application of energy management.

The literature review points out that even though energy management for energy storage systems has been studied frequently in the literature, the combination of known research could be put to better use in the research within this field.

- Proposition 2. The application of a hybrid energy storage system should be investigated further.

Combining different energy storage technology could improve both technical and economical system performance. Thus, more research could be done on this subject.

- Proposition 3. Future research should focus on industrial consumers with controllable loads in energy planning tasks on a detailed level.

In the literature review, only one publication was found to be studying the load of industrial consumers. Therefore, it is proposed more research around this subject.

- Proposition 4. Integrated planning systems should combine the different planning horizons from day-ahead planning to real-time operations and include the possibility of acting in different markets simultaneously.

Since it is acknowledged that most publications reviewed in the article focused on applications for single time horizons acting in single markets only, the proposition is that future research should include participation in different markets at the same time (e.g., regulating market and spot market). It is also pointed out that too few publications address the problems arising from interactions between markets with a different time horizon.

- Proposition 5. Future research should include usage-related model formulations in mathematical models when investigating economic objectives, such as usage-related cost factors.

The lifetime of a storage unit, and consequently the replacement cost, is strongly correlated with the usage. Thus, it is strange that only a handful of publications considered these variable and usage related costs.

- Proposition 6. Investigations on optimal solution properties and closed-form representations should be used more thoroughly in the development of policies for an electric energy storage system.

- Proposition 7. Future research should apply some sort of uncertainty handling technique.

In the aspect concerning the uncertainty, it is found that 51 of the sampled papers focused on day-ahead planning without considering the uncertainty of the input parameters. This is a considerable high number of publications considering that the need for uncertainty to derive realistic planning outcomes is very important. A proposition is therefore that future research should apply some sort of uncertainty handling technique to avoid that the optimisation might lead to unrealistic results.

2.2 Generation Flexibility

With an increase in unregulated energy sources in the energy mix the power system can become more unstable and experience more fluctuation. These problems need to be kept under control so that the power grid and the power system can function well. The main solution to this problem is to have enough flexible power production. In this way, the production can be up- and down-regulated to meet the demand rapidly. Historically, this part has been played by coal and gas plants, but this can also be done by using energy storage units. The storage units can store energy during periods with surplus or cheap energy, and discharge energy when the situation has turned and power is needed.

These energy storage units can be implemented in different levels in the energy system. An example is to help an unregulated power source, such as wind power, to deliver more stable production output. In other words, when the wind blows the storage unit could be charged and then be discharged when there are windless periods. Other usages for the storage unit could be to help with challenges in the power system and power grid. It could improve the security of electricity supply by providing an up- and down-regulation of power. The unit could charge during low-cost periods and discharge under high-cost periods. In this way, high peak-load would be covered by the storage unit, potentially cutting cost. This is called load-shaving and Figure 2.3 illustrate this usage. Also, including a storage unit in the grid could potentially help with congestion problems or if a line is disconnected. To sum up this section, there is plenty of possible uses and benefits of including an energy storage system in the grid.

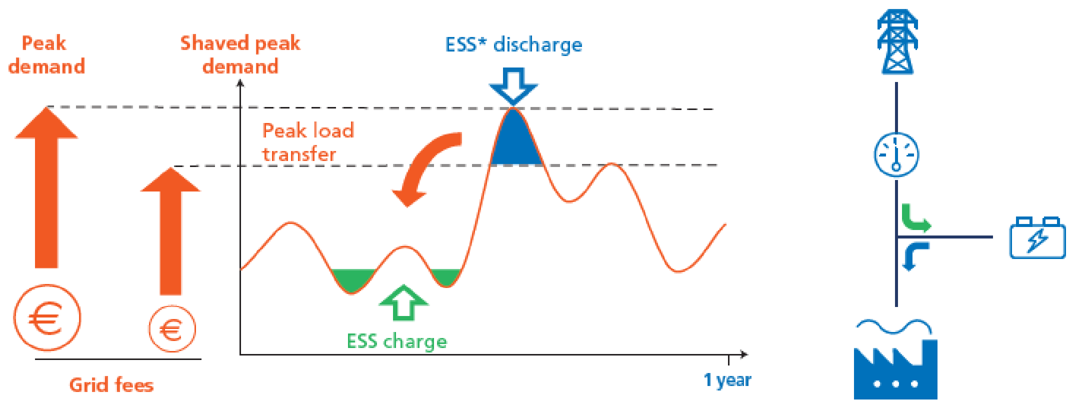


Figure 2.3: An illustration of how an energy storage system could perform load-shaving [10].

2.3 The Power Markets

The power market is an important tool to ensure effective use of power resources and reasonable prices on electricity. This is mainly done through the European power market Nord Pool. This is an exchange for physical power trade, sales, and bids of power, for the Nordic and Baltic countries. Nord Pool consists of both a financial and a physical market. Only the physical market will be described in this thesis, due to the chosen focus.

The power market consists of several markets where bids are submitted and where prices are determined. The Nord Pool exchange is responsible for the day-ahead market (DA) and the intraday market (ID). The TSO in Norway, Statnett, runs the balancing market (BM) and the capacity market (RKOM), also called the regulating market. These markets operate in different time scopes and with different purposes. An illustration of these subjects is shown in Figure 2.4. In the following sections, each of these markets will be described. The information in these sections is obtained from Nord Pool [11], Statnett [12] and a Norwegian energy fact site [13].

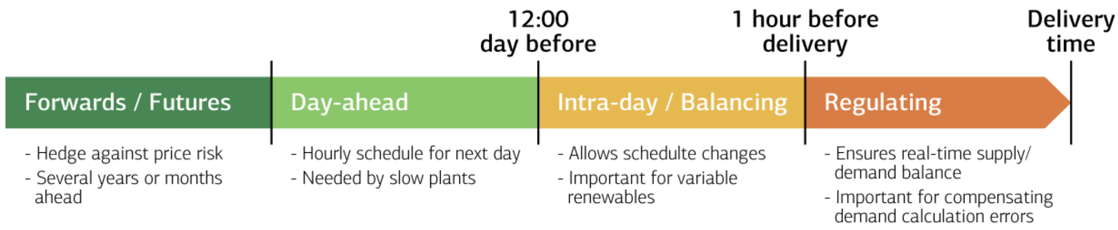


Figure 2.4: Overview of the different operations in the power markets. [14]

2.3.1 The Day-Ahead Market

The primary market for power trading is the day-ahead market, where large volumes of power are traded in Nord Pool. The market consists of contracts for the delivery of physical power hour-by-hour for the next day. Participants submit offers and bids to Nord Pool, specifying the quantity of power they would like to sell or buy, and at what price. The day-ahead market will close at 12:00 each day. Then, the gathered bids will be sorted and separated into supply and demand bid curves. Prices hourly prices for the following day are calculated from the intersection between these two curves. This pricing method is shown in Figure 2.5. The volume of power traded for each hour is also found with this calculation. Note that the market price is the same for all the participants regardless of the bid they have issued.

In an ideal market, all participants would compete against each other and thus the same bidding zone would apply for everyone. However, since the power system has physical transmission constraints, the available transmission capacity must be taken into account. The solution is to introduce several bidding areas with their individual area price. Each area is thus an individual market zone with separate clearing prices. This price is based on the area's supply and demand, but also the transmission capacity to other areas. Therefore, different areas can experience different prices at the same time. It can be noted that the area price and the system price

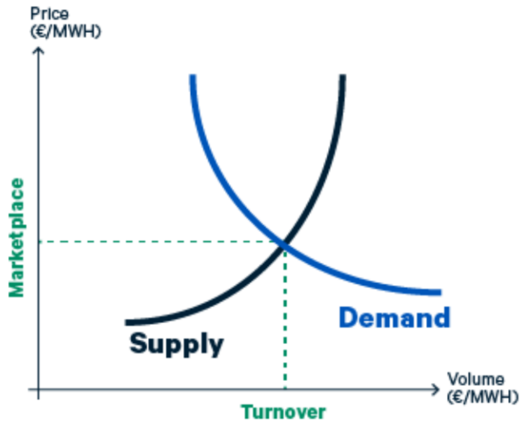


Figure 2.5: Illustration showing how the market price is determined. [11].

also can differ from each other. The system price is calculated based on bids disregarding the available transmission capacity between bidding areas. The system price function as the Nordic reference price. In Norway today there is five bidding areas [11].

2.3.2 The Intraday Market

The day-ahead market tries to ensure a balance between supply and demand. However, there can be events that disrupt this balance after the day-ahead market closes the day before. Such events, like changes in weather or unexpected shutdowns, can influence the actual production or consumption in a way that changes the position from the day before. The intraday market plays an important role to supplement the day-ahead market to ensure balance in the power system. In the intraday market buyers and sellers trade power quantities in the period between clearance in the day-ahead market and up to one hour before the operation. With this market solution, the aim is to achieve a balance through trading.

With more unregulated renewable power sources, like solar and wind, it can be difficult to participate in the day-ahead market because of the uncertainties involving these sources. The intraday market is more suited to handle power trade from these sources because the actual production time is closer. Then, the imbalance between forecast production and actual production decreases. Since it is predicted that the share of these unregulated renewable power sources increases, the share of trading in the intraday market is also likely to increase.

2.3.3 The Balancing Market

Even though the day-ahead and intraday market seek to ensure a balance between production and consumption, there are within a specific hour of operation bound to be some disturbance of that balance. Some examples of possible disturbances could be end-user variations, outage of lines or outage of large consumers or producers. When this imbalance occurs, there must be a system or market that restores the balance in the power system, such that the frequency is kept at 50 Hz. This is the purpose of the balancing market and it is the TSO's responsibility to maintain this market. The balancing market function is to regulate production and/or consumption up or down depending on what is needed to maintain an instantaneous balance. The balancing market can be divided into three regulation reserves: primary reserves (FCR), secondary reserves (FRR-A) and tertiary reserves (FRR-M). The primary and secondary reserves will automatically respond to changes in the frequency, while the TSO needs to manually activate the tertiary reserves.

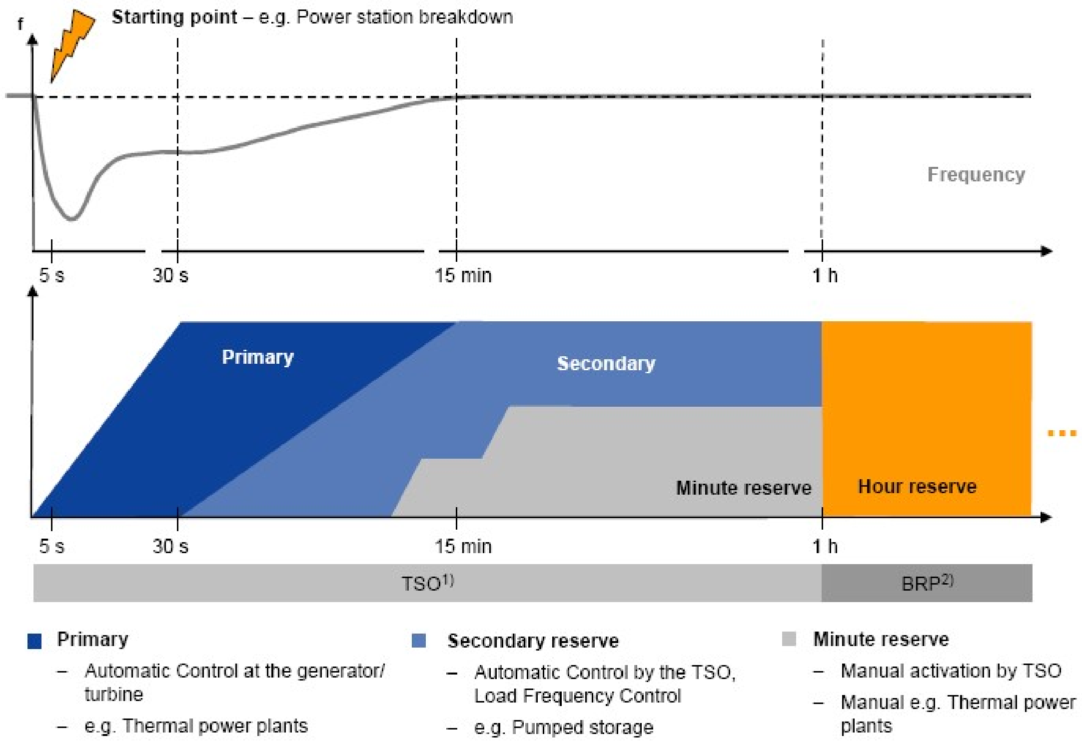


Figure 2.6: Illustration on how the different reserves cooperate to balance the power system [15]. Note that the tertiary reserves is called minute reserve in the figure.

The different regulation reveres will have separate response time, as shown in Figure 2.6. If an imbalance occurs, first the primary reserves automatically try to dampen or stabilise the imbalance. After a few minutes, the secondary regulation is automatically activated. This reserve will affect the power output from the producer, causing either a down- or up-regulation of power to restore the frequency. This frees up the primary resources so it can deal with new imbalances. If the imbalance still causes deviation to the frequency, the tertiary regulation is activated, often called regulating power. This is manually activated by the TSO and the activation can take around 15 minutes after the start of the incident. These reserves will secure ideal frequency and release the secondary reserves. The reserves are traded in different ways. Primary reserves are traded in separate hourly and weekly markets and secondary reserves are traded in a separate weekly market. Tertiary reserves are purchased in the regulating power market (RK). In the Norwegian part of the regulating power market, the TSO ensures enough balancing capacity through the tertiary reserves options market (RKOM). This is discussed in the next section.

2.3.4 The Norwegian Capacity Market

To ensure there exist enough balancing capacity in the Norwegian market, resources for up- and down-regulation, there is a capacity market. This is managed by the TSO and is called

”regulerkraftopsjonsmarkedet” (RKOM) in Norwegian. The bidders in this market get paid an amount to guarantee that they have excess power available to contribute to the balancing power market. This amount is paid in advance and regardless of the resources are actually used or not. However, there will be a penalty to the producer if they cannot meet the demand that has been paid for. Both power production and demand response can participate in RKOM. In this market, there are two options: weekly or seasonal trading. In RKOM-season, options are purchased with duration throughout the expected season, and the producers are required to have their capacity on standby for the entire season. The trades in the RKOM-week are made based on an assessment of the current power situation, such as forecasts of production, consumption, exchange abroad and probable congestion. When traded, the RKOM-week is divided into time sections throughout the week: weekday and weekend. It is also divided into two time segments for each day: day (from 00:00 to 05:00) and night (from 05:00 to 00:00).

2.4 The Norwegian Electricity Price and Load Pattern

The general load pattern for a Norwegian private consumer will vary over the day and year. The typical trend for such a consumer is that there is a high load demand in the morning and evening and these hours are called peak-hours. Even though the peak-hours are not considered long for each day they still require a sufficient grid capacity. The load pattern is reflected in the electricity price, as the price typically rises when the demand is high. Figure 2.7 shows the Norwegian power consumption over the course of one week in the winter and summer season, and the typical load pattern can be seen in this figure.

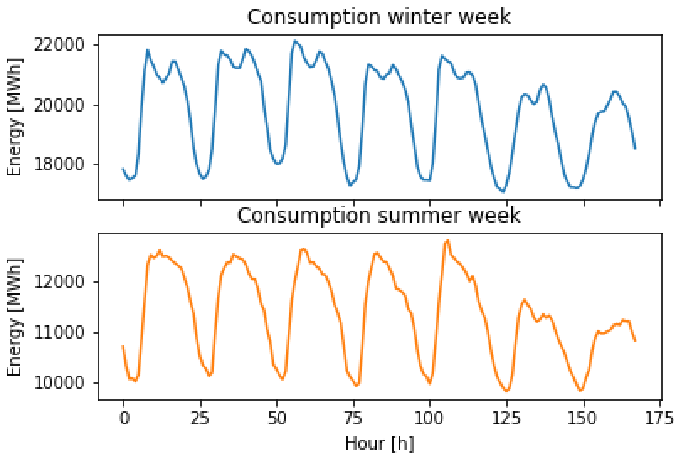


Figure 2.7: The electricity demand for one week in the winter and summer of 2018. The data is obtained from Statnett [12].

Figure 2.7 also illustrate the seasonal differences, and it can be seen that there exist some variations throughout a year. The largest difference is the load quantity. The climate in Norway is cold, especially in the winter, and the main source of heat in Norway is electricity. This adds up to a generally higher load, and thus higher prices, in the winter. This can be seen in Figure 2.7. It can otherwise be assumed that the same pattern structure occurs in all seasons because the consumer behaviour is primarily the same. Holidays and weekends can also affect the load pattern. An example of that can be seen in Figure 2.7 where the peak-load is smaller and occur in a slightly different time scope in the weekends than in the weekdays.

The Norwegian grid needs investment in the coming years because of factors such as an increase of load demand, parts of the grid are old and worn out, an increase in security of supply requirements and new unregulated production in the distribution grid. When upgrading the grid, the grid dimension is decided by the peak-load. However, this peak-load may only occur a few hours every year, so other alternatives may be more economical. One way to tackle this problem is to adjust consumer behaviour to decrease the peak-load. Another way to solve this is by installing storage units in the rural grid. These units can reduce the strain on the grid in the peak-hours by charging when the load is low and discharge when the load is high. In this way, the load pattern will become more levelled and the power transfer from the grid during peak-hours will be decreased. This is called load-shaving or load-shifting and it is mentioned in Section 2.2 and illustrated in Figure 2.3. By investing in a storage unit, the investment in the grid itself can be smaller or it may be kept longer in its current state.

2.5 Energy Storage System

An energy storage system unit capture energy produced at one point in time for future use. For this thesis, the focus will be at energy storage units that operate with electrical energy. Therefore, the function of an energy storage unit described in this report is that it can store and release electricity back and forth depending on the situation and given demand. The applications for such storage units are many, but in this report, there will be a focus on a storage unit that is utilised in connection with the grid at some level. Examples of some large-scale applications are: lowering the peak-demand in the grid, serving as a back-up unit for quick power changes in the grid or storing excess power from unregulated power production such as wind power. Storage units can also be used for small-scale applications, such as for households or small micro-grids.

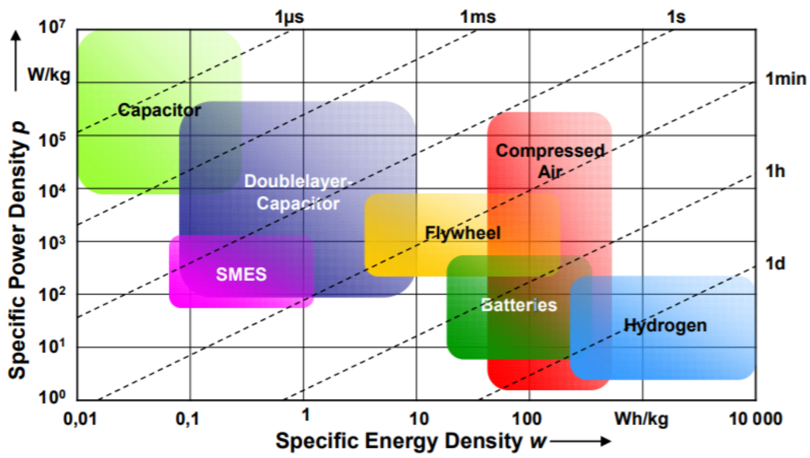


Figure 2.8: A Ragone plot over different energy storage technologies [16].

There are several types of storage units that can store and discharge electricity at request. The different energy storage units have unique qualities in their technologies that make up both advantages and disadvantages and must be chosen based on the wanted purpose. For example, some technologies can provide short-term storage, while others can store energy for longer times. Some storage devices can transfer high power while others must operate at lower power. To help understand the diverse approaches currently of storage systems being used, many of the common storage technologies are illustrated in the Ragone plot in Figure 2.8, which is a plot used to compare the performance of various energy storing units. Even though many vastly different technologies exist for storing energy, this section will focus on two examples of storage technology that are commonly used in grid applications today, which are batteries and flywheels. These two technologies are also used for separate purposes in the grid.

2.5.1 Batteries

This section will cover solid-state batteries or more commonly know as conventional batteries. A battery is, on a basic level, a device that stores and converts chemical energy into electricity. One battery consists of one or more electrochemical cells. Each cell consists of two electrodes each with an electrolyte and separated by a separator. With a connection between the two electrodes, a current will be produced. There are many types of these batteries, and these are primarily separated by the type of materials that are used in the cells. Many batteries are rechargeable, and can thus be charged and discharge several times. Figure 2.9 shows a Ragone plot over the different battery attributes based on the materials they are made from. Energy density affects the storage capacity compared to size, while power density affects the power output the storage can provide. It is worth mentioning that the cost of batteries is declining at a quick rate, as they become very popular in electric vehicles and other application such as in connection with the grid or distributed generation. NVE predicts that batteries will play an important role as the world's power system becomes more renewable, and estimates that the costs will decrease further [17]. They point out that recent cost data in Norway shows costs around 4 000 - 6 000 NOK/kWh for stationary batteries.

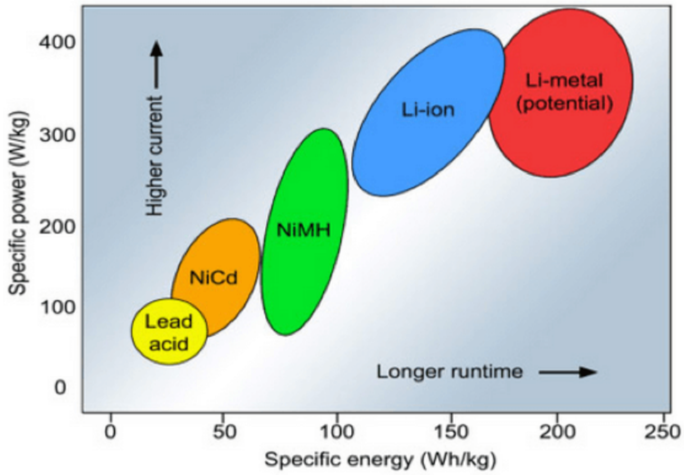


Figure 2.9: A Ragone plot over some of the different battery technology. [18].

Battery type	Advantages	Disadvantages
Lead Acid Battery	• Cheap • Proven technology • Tolerant to overcharging • Can deliver high currents • Many suppliers	• Deficient in cold climate • Not stable capacity • Heavy • Not suitable for fast charging • Possible overheating at charging
Lithium-Ion	• High cell voltage • Low weight • Fast charging • Low self discharge • No memory effect	• Flammable • Degrades at high temperatures • Needs protective circuit • Does not tolerate overcharging

Table 2.1: Some of the advantages and disadvantages for lead acid and Li-ion batteries.

Today, the major types of batteries used for power delivery in the grid are lead-acid and lithium-ion (Li-ion) batteries. In lithium-ion batteries, lithium metallic oxide makes up the cathode, and carbon the anode. Lithium-ion batteries provide a high energy density, as well as low memory effect and low self-discharging effect. A battery's memory effect is a reduction in the storage level in a rechargeable battery, due to incomplete discharge in previous uses. Low memory effect and low self-discharging effect are of great importance to stationary use in the power grid. Li-ion batteries also have a long lifetime and require little maintenance. The major downside to Li-ion batteries is their cost, as lithium is a scarce metal. Lead-acid battery cells are much older technology. These batteries are cheaper, but at the cost of a lower energy density which requires physically bigger batteries compared to Li-ion. They also have a shorter lifetime, higher maintenance costs, and more memory and self-discharging effect. Most of the advantages and disadvantages of these two battery types are summed up and compared in Table 2.1. The information about these two battery types are obtained from [19].

2.5.2 Flywheel

A flywheel is a mechanical device which stores energy in a rotating mass. It stores kinetic energy. The amount of energy stored is proportional to the rotating speed. The losses of the device are mainly frictional. This storage is used for delivering very short-term energy and it has a very fast response time. An application can be to balance the frequency in a power system. The energy from a flywheel is generated from and to electricity by a motor/generator.

2.5.3 Energy Storage Terms

When dealing with energy storage, and especially batteries, some terms are useful to know. In this section, some of those terms will be explained.

State of Charge (SOC)
The state of charge describes at which level (in present) the battery is charged. In other words, how full the battery is. 0 % means that the battery is empty and 100 % means that the battery is full.

Depth of Discharge (DOD)
The depth of discharge describes at which level (in present) the battery is discharged, i.e., how empty. 100 % means that the battery is empty and 0 % means that the battery is full. It can be noted that SOC and DOD are opposite terms of the same measure.

Maximum Depth of Discharge (MDOD)
For some batteries “deep discharge”, which is discharging the battery to 0 %, may be harmful. An example is that lithium-ion batteries typically should only be discharged up to around 80 % before reaching a potentially damaging state [19]. To prevent deep discharge in these Li-ion batteries a battery management system is often included. Unfortunately, some external factors can limit the capacity of a storage unit, where the temperature is the most significant factor. For batteries like lead-acid batteries, the maximum depth of discharge will decrease if temperatures decrease. This means that the usable capacity of the battery is decreased. There is an ideal operating temperature for batteries. This is where they are most efficient. For lead-acid this the recommended operating temperature is 10-25°C. For Li-ion batteries this is the optimum operating temperatures are typically 15-30°C [19]. It is the chemical reactions inside the battery that has a great relationship with the temperature, and it is the chemical reactions that decide the ratings of the battery. This is important to remember when deciding the size of the storage unit. It may not be able to use all its nominal power because of an internal or external factor. It is therefore important to distinguish between the nominal capacity of a battery and the usable

capacity of the battery. To cope with this problem the nominal capacity of the battery can be increased.

Charge Cycle
A charge cycle is a process of completely charging and discharging a rechargeable battery. This term is used to describe how many times a battery can charge and discharge, and is connected to the lifetime of the battery. One cycle often means to drain the battery completely and then charge it fully up, but this can be two half cycles.

Degradation
A battery will over the course of its lifetime degrade. This degradation could lead to lower energy capacity, power output and efficiency. The implications of this degradation influence the return on the investment or can represent a cost called degradation cost. The degradation will vary according to how the battery is used, and factors that drive this includes temperature, current- and power-rate, average state of charge and depth of discharge. Note that other storage units could also have this degradation, but it is mostly common for batteries.

2.5.4 Converters

An important device in an energy storage system is the converter. This device is the link between the storage unit and the outside system that can be the grid (AC system), a private household or a DC system. The converter can provide the needed voltage, frequency and/or correct current form, DC or AC, for each connected system. Both the storage unit and the outside system will have requirements for these parameters. This could be as simple as changing the voltage of AC power just like a transformer, but specialised converters can also handle more complex scenarios. Since the converter is the link between the storage unit and the outside system and has limitations for both power input and output, this device could potentially create a bottleneck. Usually, they are rated by their maximum output level. It is therefore important to use a converter that is scaled for the wished outcome of the system. An additional problem is that the efficiency of the converter also can vary and depend on the output power. This can create a non-linear situation.

2.5.5 Storage Unit and Converter Sizing

When planning an energy storage system, two of the main components are the storage unit and the converter. Choosing the right size for these two components are critical to achieving the wanted function of the system. When discussing the size of these two components it is the capacity of the storage unit and the power transfer capacity of the converter that is the focus. This could be called the power:energy ratio and limits the flexibility in the system and the duration of the output/input power flow. The dimension and ratio between these two limitations must fit the wanted purpose of the energy storage system. To take an example, to contribute to frequency regulation in the grid it is needed a high flow of power in short time periods. When scaling a storage system for this purpose, the capacity of the storage unit can be small, but the converter must have a high rated power. In the case of a storage unit that should be used in load balancing, higher storage capacity is needed so it can store enough energy in off-peak-hours and discharge energy throughout the duration of the peak-hours. Then, the converter needs to be sized accordingly to cover the wanted parts of the peak-hour demand.

2.5.6 Seasonal Impact on Storage Technology

As discussed in Section 2.5.3, the temperature has an effect on the storage units. The consequence of this is that the units may behave differently in the winter compared to the summer. Batteries function best at normal room temperature, around 20 °C. High temperatures negatively affect a battery, often with a shorter lifetime, while cold temperatures will typically reduce the capacity and performance of the battery. With this in mind, it can be important to ensure an acceptable temperature range when installing a storage unit, such as a battery, in the grid. This unit will often be affected by weather and climate, and its ratings may not be optimal if not the right conditions are ensured. This could be done by protecting the storage unit from the weather conditions and installing temperature sensors to keep track of the operating conditions.

2.5.7 Seasonal and Weekly Variation

All the electricity that goes through the storage unit originates from charging and discharging the unit. When the unit is charged or discharged is based on prices and power availability from the wind turbine. In conventional hydropower, which the model used in this thesis is built on, it is the weather that causes the ”charging” of the reservoir. Therefore, strong seasonal variations are common and the reservoir usually experience ”charging” (filling) in the summer and ”discharging” (depletion) in the winter. For an energy storage unit in connection with the grid and wind power, there are other criteria for when the storage unit should charge and discharge. An example is that the storage unit should store energy when there is cheap electricity, and use energy when the electricity price is high. Since the energy system modelled and described in this thesis experience significant weekly and hourly price and wind variations, it makes sense to do short-term scheduling. This section will explore these weekly variations and also point out some of the seasonal variations that can occur.

From the Norwegian load pattern, discussed in Section 2.4, it was shown that the consumers typically have peak-hours in the morning and the evening during weekdays. In the weekend, the load pattern is flatter and the peak-hours have smaller amplitude. This ”weekend” pattern is similar to the load pattern in holidays. In other words, there are strong variations over the course of a week, from hour to hour and from night to day. The seasonal load variation will in simple terms affect the amplitude and not behaviour. The same load curve shape is seen in the summer and winter. The difference is that in the winter there is higher demand caused by heating needs. To compare this to a hydropower model, the changes cannot be seen from hour to hour, or day to day, so it makes more sense to do a scheduling model over a long period such as a year. The load pattern is heavily reflected in energy prices. The energy price, and to some degree the reserve capacity price, have thus strong weekly patterns. When creating the price input data used in the model it is very important that this weekly pattern is represented.

If the energy storage is connected to an unregulated power source, seasonal weather changes will have an impact on the behaviour of the system. An example could be in a wind power plant in connection with a storage unit in Norway. In this energy system, the wind turbines will not produce as much electricity in the summer because of seasonal variation in the wind speed. This may cause the battery to buy more electricity from the grid if it should stay operational in this season, and thus increase the operational cost in the summer season. In other words, if energy storage and unregulated power sources are combined, the seasonal variations are intensified.

2.6 Hydropower Scheduling

The optimisation model used in this thesis was created on the basic concepts of long-term hydropower scheduling. Here, the water value concept is used, and this concept is also used in the model for this thesis. Note that this is referred to as storage values (SV) because this model operates with a storage unit, not a hydropower plant. This section is based on information from the compendium in the course ”TET4135 - Energy Systems Planning and Operation” [20] and literature given in an old course named ”ELK-15 - Hydro Power Scheduling” [21].

Ideally, the operational planning process for hydropower should have been a large integrated optimisation model that issued the right approach for ongoing operational decisions. However, because of the complexity and uncertainty of the planning problem, operational scheduling must be divided into smaller segments. This is to get the right level of detail and at the same time be able to limit the models so that they do not become too large. Keep in mind that the main objective behind the hydropower operation scheduling is to maximise the profit. From Figure 2.10 it can be seen that the scheduling is divided into long-term scheduling, seasonal scheduling, short-term scheduling, and detailed simulation. In this figure every planning segment has stated its time horizon, the model applied and the output result. The time horizon and information flow between the levels will vary from a power plant to another power plant. Note that, in relations to the model described in this thesis, only the long-term scheduling will be described further.

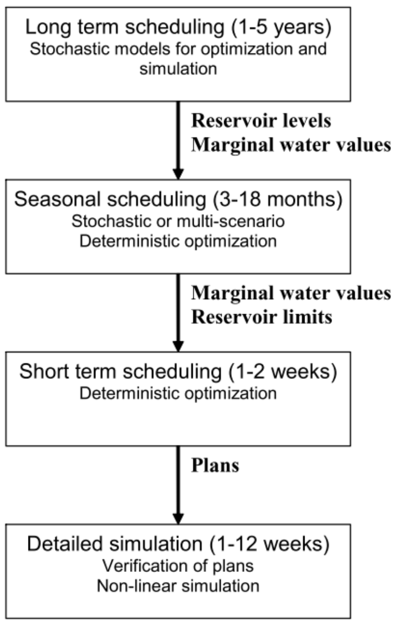


Figure 2.10: The hydropower production scheduling hierarchy [21].

2.6.1 Long-Term Scheduling

The purpose of the long-term scheduling is to ensure a reasonable allocation of resources over time, with a typical time horizon of 1-5 years. To ensure this, stochastic models for simulation and optimisation are used. Long-term scheduling is based on meteorological and hydrological statistics and other forecasts of decision factors such as power demand, power prices, inflow, and plans of new facilities that could influence the operation. The detailed picture is left out since it is necessary to take into account uncertainty, aggregate and big picture descriptions of the system. The long-term scheduling is divided into two phases: a strategy phase and a simulation phase. Firstly, water values are calculated in the strategy phase. Next, the simulation phase will simulate the operation scheduling for the system for a given set of years based heavily on the water values.

Some assumptions are done in these sections discussing hydropower scheduling and water value method. For practical reasons, only one hydropower plant is taken into consideration, with price variables assumed known and not affected by the volume produced. The connections or impacts from other areas or plants are not considered. With this in mind, the optimal water values created in the strategy phase will only apply for this hydropower plant alone.

2.6.2 Water Value Method

Conceptual
In hydropower production, water is obviously an important resource. Water is often considered ”free”, but for a hydropower plant, the water itself has value since it could be used for power production. With this value quantified the power plant could schedule their production since it is possible with a reservoir to choose between producing now at the current prices or store the water for later production at different prices. This water value is thus an important tool when scheduling production over a period of time. By definition, the water value is an expression for the expected marginal value of the energy stored in the reservoirs [21]. This value will become small if there is much water in the reservoir and there is a risk of spilling. However, when the water level is low the water value will be high. So, an operational strategy with water value will minimise the risk of spillage and empty reservoirs. The water value can be considered as a function of time and reservoir level.

Mathematical Derivation
Assuming a weekly planning period from week t to week T, the expected total operation dependent revenue for this period is $K(v,t)$. This revenue is a function of the reservoir level, v, and time step t. This is illustrated in Figure 2.11, and the equation for this revenue is given in Equation 2.1

$$K(v,t) = \sum_{i=t}^{T} R(v,q,i) - K^{end}(v) = R(v,q,t) + K^{end}(v,t+1) \tag{2.1}$$

From Equation 2.1 it can be shown that $R(v,q,i)$ is the operation dependant revenue when moving from time step t to $t+1$ and q is the energy of quantity drawn from the reservoir to produce power. $K^{end}(v)$ is the value of the remaining water as a function of the reservoir level, v, at the end of the planning period T. As seen from the equation this is the same as operation revenue the first week, $R(v,q,t)$, plus the total operation revenue from time step $t+1$ to the end of the period, $K(v,t+1)$.

There can be many different revenues from the operation for a given week, $(R(v,q,t))$. These will depend on how much energy that is produced from the reservoir, q, in that given week. The

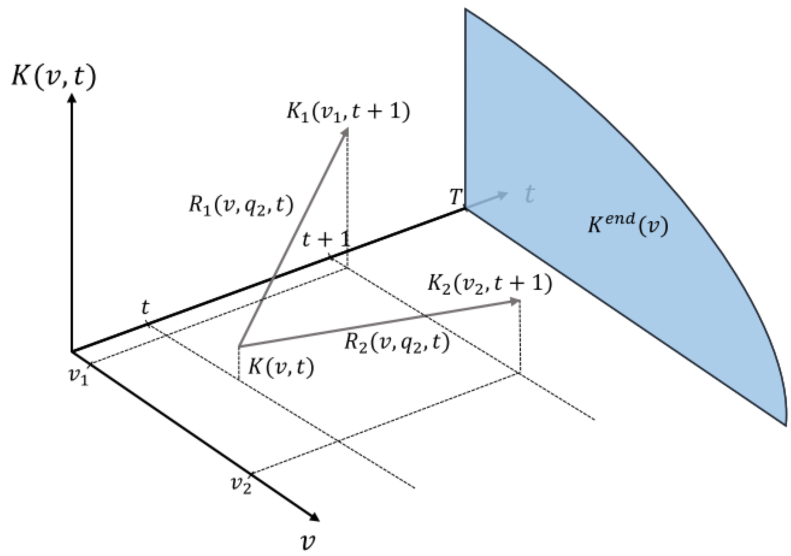


Figure 2.11: Illustration of the mathematical explanation of the water value [20]. The reservoir level, time period and the operation dependent revenue is represented on the different axis.

optimal operation is to maximise the total operation revenue $K(v,t)$ regarding to the energy produced, q, at time step t:

$$\max_q K(v,t) = \max_q [R(v,q,t) + K^{end}(v,t+1)] \tag{2.2}$$

To find this optimal value for Equation 2.2, the equation is deviated with respect to the used water for energy production, q, at time step t, and set to zero. This gives Equation 2.3.

$$\frac{dK}{dq_t} = \frac{dR}{dq_t} + \frac{dK}{dq_t} = \frac{dR}{q_t} + \frac{dK}{dv_{t+1}} \cdot \frac{dv_{t+1}}{dq_t} = \frac{dR}{q_t} + \frac{dK}{dv_{t+1}} \cdot (-1) = 0 \tag{2.3}$$

From this equation, the optimal operation for time step t is found:

$$\frac{dR}{dq_t} = \frac{dK}{dv_{t+1}} \tag{2.4}$$

Where $\frac{dR}{dq_t}$ is the marginal operation dependant revenue at time step t and $\frac{dK}{dv_{t+1}}$ is the marginal total future operation dependant revenue depending on the reservoir level, v, at time step $t+1$. This is called the water value at time step $t+1$, (or $WV(t+1)$).

Stochastic Inflow

In a real situation, it is very difficult to predict future inflow. However, the inflow can be represented in many scenarios with different probability of occurring. Then the inflow is represented stochastic. The water value needs to reflect on all possible scenarios, and thus reflect uncertainty. Assuming one week of operation and I inflow scenarios with an individual probability, p_i. First, all water values for each reservoir point given the inflow is calculated, ($WV(i)$). Then the wanted water value is the sum of these water values multiplied with each weighted probability, as shown in Equation 2.5.

$$WV_0 = \sum_{i=1}^{I} p_i \cdot WV(i) \tag{2.5}$$

Backward Dynamic Programming

The method used when doing water value calculations is called backwards dynamic programming. This is a method used to find the initial optimal value and the optimal path to get there when the end value is known. Thus, when water values are calculated above it is assumed that the water value for week *t+1* is known. In this way, the water value could be calculated at each time step throughout the whole planning period by beginning at the end of the period and trailing backwards. However, the value at the very end of the planning period must be estimated. The water value at the beginning and end of the year should be equal and if there is a deviation the iteration will continue until the wanted precision is reached. So, this is an iterative process and it is done with stochastic inflows.

2.6.3 Defining Reservoir Segments

As stated in the previous section, the water value method is reliant on the reservoir level. This value will, in reality, be continuous and can take any values between an empty reservoir and a full one. However, when modelling this setup, some simplifications must be made. To solve this, the reservoir is divided into a quantity of segments. Each segment will in this way represent a given reservoir level. The total number of segments are not fixed and can be defined by the user. A high number will give good accuracy, but rise the complexity and computation time. Mathematically, the total number of segments is NR, where n is the given segment. The water value model can then limit its computation to $n \in NR$ points.

2.7 Scheduling a Short-Term Storage Unit

The model used in this thesis uses short-term scheduling for a storage unit and a wind turbine when operating in both the energy market and the capacity market. The basis of this model is highly inspired by the long-term scheduling model described in Section 2.6 and many concepts explained in that section are used. The model itself is described in detail in Chapter 3. However, some concepts and notes about the model will be described in this section.

In terms of modelling the energy scheduling, it makes more sense to talk about short-term planning than long-term which is the planning period in the original long-term scheduling (LTS) method. This is because of the appearance of short-term variations present in the input data. For example, the storage unit will experience a variation in usage over the course of a week, mainly due to demand and price variations discussed in Section 2.5.7. Furthermore, wind production can experience a vast variation in output over the course of a week because of fluctuating wind speed. For a hydropower plant that utilises the LTS method, this variation is seasonal, and the use of a long-term period is therefore reasonable. The short-term planning period for the model used in this thesis is one week. With this in mind, the method used in short-term scheduling for this system is the same as for the LTS, only that the time horizon is shorter.

One other small difference from the LTS method is that this model schedule a energy storage system and thus the marginal cost of stored energy will be referred to as ”Storage Value” (SV). The reason for this is that there is no water present in this system, so it makes no sense of describing the marginal value of stored energy as water value which is done in the original method.

2.7.1 Modelling Optimal End Value of State of Charge

The model considers multiple sequential days or weeks, and must therefore also take into account the potential of storing energy for future use. In this model, a storage value curve has been implemented to model the marginal value of stored energy. This method is commonly used in hydropower modelling and may be an unusual choice when it comes to a short-term planning period. There are also other ways to include this future potential. An example of deciding the optimal endpoint is to simply set a required end value for the state of charge at the end of the decision stage. The main problem with this method is to choose the right end value, which should be close to the optimal end value.

2.8 Distributed Generation (DG)

Distributed production is increasingly being implemented in the power system, especially since the share of renewable energy sources must increase to meet future climate goals. Distributed generation, hereby referred to as DG, is a collection of technology that enable electricity production and storage close to the end-user, often in small-scale. One could say that distributed generation is electric generation located in the distribution grid. There are multiple benefits with DG. In many situations, this technology can produce electricity at both lower cost and fewer environmental consequences than the traditional power supply. This is because the technology often uses renewable power sources. The power production with these sources are unregulated and can thus have low power security. This problem can be solved by combining these generation units with an energy storage system. In this way, higher power reliability can be ensured. The trend is to shift from a few large-scale power plants located far from the costumers to DG systems that consist of numerous small plants or generators. Figure 2.12 illustrate this power system transition.

The individual technologies used for distributed generation is often referred to as a distributed energy resource (DER). This includes both small-scale power generation and storage technologies. Examples of such technology can be a diesel generator, fuel cells, photovoltaics (solar) power systems and wind power systems. The DG technologies typically have a power generation capacity that ranges from one kilowatt to about 100 MW [22]. To compare this to the utility plants, they often have a power capacity above 1 000 MW. In this section, the focus will be on wind power and how to model that renewable power source.

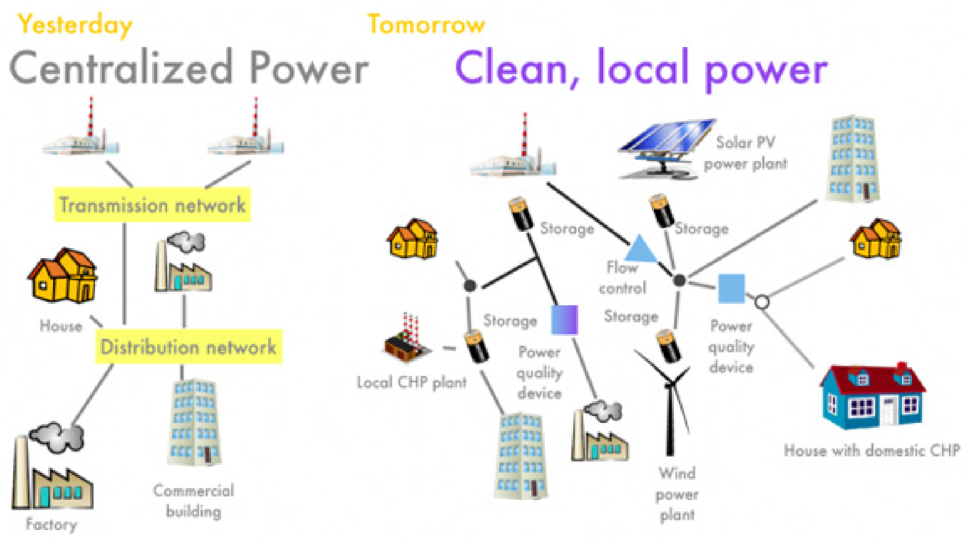


Figure 2.12: An illustration of the traditional power system and the smart power system with DG [22].

2.8.1 Wind Power

Wind power is harnessing the kinetic power in the wind into electricity. This is done by having wind turbines that transform the kinetic wind energy into rotational energy. This rotational energy is furthermore converted into electrical energy by a generator. To produce enough energy, it is often required a number of wind turbines. Their maximum possible efficiency based on the wind energy is 59.3 % (Betz limit), but the more common efficiency of a wind turbine is around 40 % [22]. Suitable places are often coastal areas, plains or on high ground such as mountains with little obstruction of the wind. Thus, placement is one of the key challenges with wind turbines. The downside of wind power is that it has some significant environmental problems such as noise, aesthetics, and interactions with animals such as birds.

Wind power, which offers a stochastic, variable distributed generation is an unregulated power source and therefore introduces some challenges. For example, there could be high power production when there is a surplus in the market and low production when power is needed. There could occur stability issues when introducing much wind power. Fluctuations in wind power production also make it challenging for owners of wind power plants to compete in electricity markets. Because of these challenges, the maximum implementation of wind power in electricity networks could be limited. Flexible distributed energy resources, such as energy storage systems, could offer levelling of wind power because of the ability to store energy over time. This could provide the necessary flexibility and help to solve some of these challenges. Both technical issues and market operation could be improved. Furthermore, many potential wind power sites are located in areas with a weak electrical connection point. Hence, energy storage could provide an alternative to grid reinforcements.

Wind Power Output

The theoretical power output from the wind energy by the wind turbine is given by:

$$P_{wind} = \frac{1}{2} \cdot \rho \cdot A_w \cdot C_p \cdot v^3 \tag{2.6}$$

As seen from Equation 2.6 the power output, P_{wind}, given in watt, for a wind turbine depends on many parameters. Some of the parameters depends on natural conditions at the specific site which make them uncertain and variable, such as the wind speed, v, in $[m/s]$ and to some degree, ρ, which is the air density given in $[kg/m^3]$. Other parameters are defined by the manufacturer and the given wind turbine. These include A_w which is the area swept by the rotor blade $[m^2]$ and C_p which is the power coefficient of the given wind turbine. The power coefficient is in turn decided by variables such as the tip speed ratio and the pitch angle of the turbine.

When considering the effects of all the influencing parameters to get the proper power output of a wind turbine, the problem can become very complex. Hence, it could be difficult to calculate the output power using the theoretical Equation 2.6. Another way to solve this is to use a power curve which is given for a particular wind turbine. The power curve gives the output power of the turbine at a specific wind speed. This provides a useful tool to model the performance and power output of wind turbines. A typical power curve for a pitch regulated wind turbine is shown in Figure 2.13.

In the first region in Figure 2.13 there is no power production. The wind speed is below the minimum speed required to produce any energy. When the speed reaches the cut-in speed the wind turbine start producing energy, this is the threshold minimum for the wind turbine. Then, in region two there is a steep growth in power production. When the wind speed reaches the rated wind speed value, the wind turbine could produce the rated maximum power. A power production beyond this rated maximum cannot be achieved. Therefore, in region three a constant power output is produced until the cut-off speed is reached. When the cut-off wind speed is attained in region four, the turbine is shut down to protect its components from the high wind speeds. Thus, it produces zero power in region four.

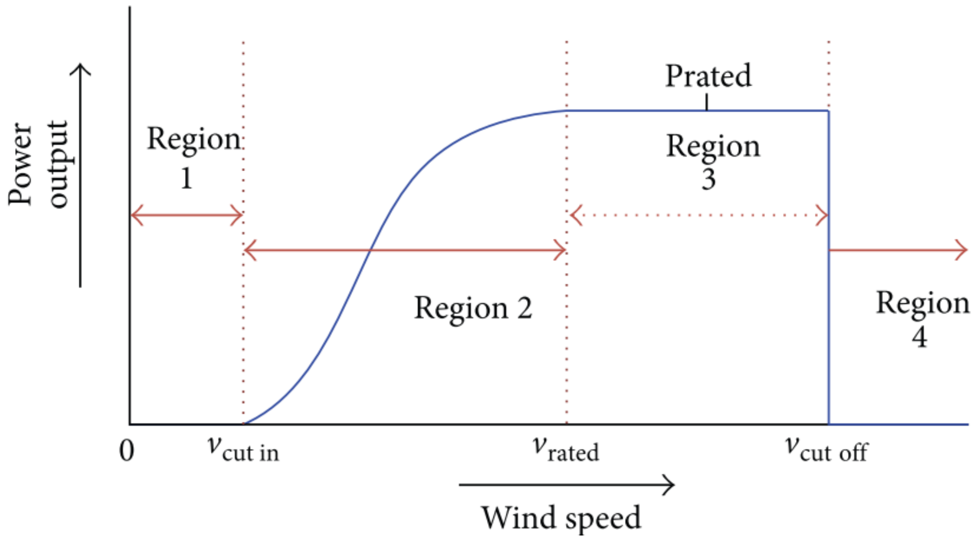


Figure 2.13: Typical power curve of a pitch regulated wind turbine [23].

Typically, in normal operations, the objective of a wind turbine is to maximise its power production. The wind turbine would then operate on the power curve slope based on the given wind speed. However, wind turbines in a wind farm are often restricted or down-regulated to stabilise the power grid or improve the efficiency of the wind farm [24]. This down-regulation could be obtained by adjusting the turbine control input, namely the generator torque and the blade pitch [24]. Therefore, the wind speed sets the limit for maximum power production, but the real output power for the wind turbine could be controlled by an operator or control system.

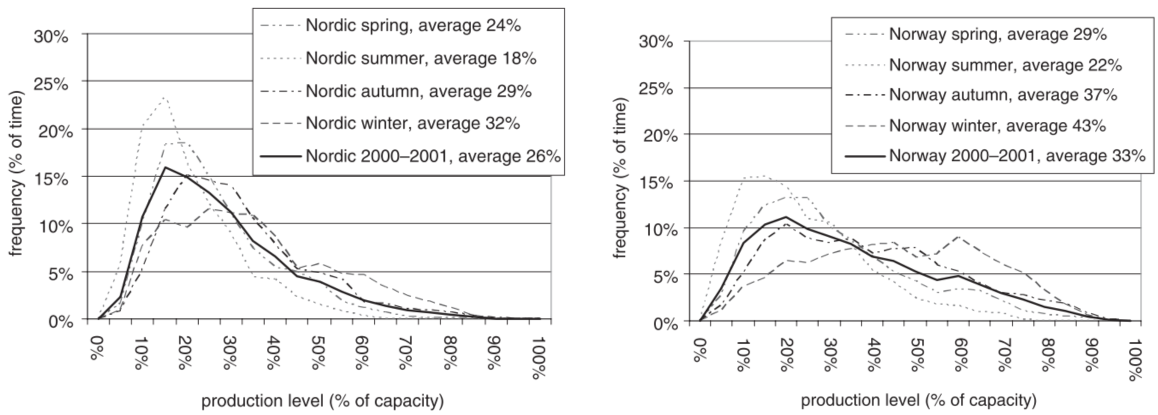


Figure 2.14: Difference in frequency distributions of wind power production for the Nordic and Norway in the four seasons [25].

In terms of production, wind power is also affected by the season. In Central and Northern Europe, there is a distinct seasonal variation with most wind in winter, and least wind in summer. The production during the summer months is around 60%–80% of the yearly average, while the production during the winter months can reach 110%–150% of the yearly average, according to data for the years 2000–2002 [25]. During spring and autumn, the production is somewhere in between. This is highly relevant for the Nordic countries and Norway as well and is illustrated by the frequency distributions for the four seasons presented in Figure 2.14.

Wind Power Sizing

Wind power could be easy to implement as distributed generation since wind turbines can be bought in multiple sizes after the specific need. However, in terms of wind power in combination with energy storage, these two components need to cooperate and complement each other. Both the capacity size of the storage unit and wind turbine must be chosen to meet possible challenges in the system, such as bottleneck. Various sizes can be tested to find the most beneficial size given the limits in the system. However, when there is a high mismatch between low installed storage capacity and a high power rating for the wind turbine it would mean that the storage capacity is utilised very quickly when the wind turbine produces at maximum. On the other hand, a high installed storage capacity versus a low power rating for the wind turbine will suggest that not all the energy storage capacity is utilised. Both of these scenarios are not economically beneficial.

When examining similar models in other publications, it could be found that in reference [26] the storage capacity tested was significantly larger than the rated power of the wind turbine. However, the power rating was more in line with the maximum charge/discharge capacity of the storage unit and the maximum exchange with the grid. It should be noted that in this case study a load had to be covered by the wind turbine and storage unit and a dump-load for excess power was implemented. The size of the wind turbine was thus chosen to be in the same range as the transfer capacity in the system so that the load is covered and the dump-load is used as little as possible. In the model in this thesis, no load or dump-load are included. Therefore, the power produced by the wind turbine must be exported to the grid or stored in the storage unit. An excessively large wind turbine will thus create excess power since the bottlenecks towards the storage unit and towards the grid do not have the capacity to transfer all the energy generated. On the other hand, a too small wind turbine will not have a significant effect on the system since it often does not produce at its maximum. To summarise, it makes the most sense to have a wind turbine that corresponds to the size of the bottlenecks against the storage unit and the grid. The size of the energy storage unit may well be considerably larger, but at one point the bottleneck towards the storage unit makes sure that an increase in storage capacity is redundant.

2.8.2 Wind Power Modelling

The main goal of the implementation of wind power in the model used in this thesis is not to model wind power in a very technical manner, it is to study the impact from an unregulated power source on the already existing storage model. The model has an economic objective as it participates in two markets to obtain maximum profit. In that sense, the most important part of the implementation of wind power is to model the power source such that it will contribute with a stochastic and variable flow of power into the system. Therefore, the main implementation focus is the uncertain power flow, which may have different values in separate time steps. Another way to look at the wind power implementation is that the wind turbine is a black box. This box then produces a variable and uncertain power flow based on wind speed and the physical and technical elements inside the box are not considered. While not explicitly stated, this is the approach done in similar publications such as [26] and [9].

In both [26] and [9] a wind turbine is included in the model with a power flow that is based on the power curve output with an associated time series for wind speed. These publications have an economic objective of energy storage scheduling and thus have implemented wind power with a focus on the power flow it provides into the system. In [9], the stochasticity and uncertainty of the wind speed plays a great role in modelling, while in [26] there are other focuses. Power flow from a wind turbine based on various and continuous wind speeds is also modelled into an energy storage system with connections to the grid in [6].

Based on solutions found in the literature and mentioned above, the wind power flow is modelled with a power curve approach in this thesis. The power curve data is often given in power output points given specific wind speeds. Then, a continuous power curve is created in a simplified way by linearise between the points. In this way, the power curve becomes a piecewise linear curve. This is a simple and common way to model a power curve [23]. The power curve is divided into segments based on wind speeds and the coherent power output value is linearised value between those segments. An example: if the power curve segments state that the power output is 80 % with a wind speed of 12 m/s and 20 % with a wind speed of 8 m/s, the power output at 10 m/s is 50 %.

The wind speed data itself could be the input data used in the model, however, to avoid making the model too complicated the input data can be the wind power output. In that case, the wind speed data must be converter to power output data, e.g. with the help of a power curve. In the publication mentioned above the wind speed are the input data, but in this thesis, the use of wind power output data in per unit as input data is the approach chosen. However, the approaches are very much the same, only that using the power output data the wind speed data is converted beforehand. It is still the wind speed data that is the foundation for this input data.

Furthermore, schematically the wind power should be integrated on the AC-side of the converter in the storage system. This is because the output power for a wind turbine is AC. Also, this is the methodology used in the literature found, e.g. [6]. The power from the wind turbine could then be stored in the energy storage unit or sold to the grid. This could potentially happen in the same timestep, with some of the wind power being stored while some are being sold. To avoid that all the wind power is being sold in the model, there should be a transfer limit on the gird connection. In this way, a weak grid connection is implemented into the model, which is a real problem with wind power installations in rural areas as discussed in Section 2.8.1.

2.9 Assumptions and Uncertainties

Even though this model of an energy storage system with wind power strives to simulate realistic behaviour, some assumptions must be made and some uncertainty is bound to arise. This applies for close to all models, also the hydropower model, since perfect modelling is almost impossible to achieve. However, the model can still be relevant and realistic as long as these potential weaknesses are been made aware of. This section will thus cover some uncertainties and assumptions that are made in this model.

2.9.1 Input Data, Wind Data and Price Data

To create reliable behaviour and realistic results it is important to have precise, decent, and consistent input data for the whole scheduling process. If the model should produce accurate reactions and decisions of what one could expect, it is very important with detailed data of what the system is exposed to. To solve this in the best way possible, the stochastic input data is based on historical data. This data could include both extreme scenarios and more likely scenarios, but will depend on what historical data set that is used. In this way, the model could be tested in many possible scenarios. Yet, it is not desirable to analyse too many scenarios, so to make this comprehensible the data input is divided into a defined number of discrete stochastic variables that represent the possible scenarios that can occur at the given stage. Some of these variables could be extreme points, but their impact will be based on the given probability for that specific scenario. In this way, all historically possible scenarios could be included and then weighted after their probability.

Historical price data from the markets are used in this model. When using such price data, the user is not aware of the time of bidding. This represents uncertainty. Furthermore, one must assume that the participation of the wind and storage system will not influence the prices. In other words, the prices are fixed, and the markets can be considered inelastic. The price data is used in the model for every decision stage and is at that point known. However, the stages of the future decision are still unknown, so if one is scheduling for Tuesday the prices and wind production on Wednesday are still kept unknown. It can also be added that the price and wind data must be extracted into multiple discrete stochastic variables. These are named wind and price nodes in this model and thesis.

The wind input data is chosen to be presented in power production output given in per unit of the wind turbine rating, but it is essentially given by the wind speed data. While the historical price data is often presented in an hourly way because of the bidding process, the wind production data is a more continuous data set in reality. This is because the wind speed which dictates the power output is a continuous element and can vary within each hour. However, an hourly time series is not uncommon for wind data either. Such hourly based data is used in this model and simplifies the conversion into wind and price nodes since the standard way of scheduling in the model is also on an hourly basis.

2.9.2 Wind and Price Node Probability

Each of the wind and price nodes in a decision stage, created with the historical data, has a specific probability of occurring. This is the basis of the stochastic model. The challenge is to find solid and reliable probabilities for each wind and price node. The future nodes are usually dependent on the decisions and previous nodes. This challenge is maybe even more difficult for backward dynamic programming since the previous stage is never determined before the current stages.

To solve this in a simple way, it is assumed that the historical data sets have a normal distribution. This will allow for the simple creation of nodes based on the mean value of the data set and the standard deviation. When using this method, it can be assumed that 68 % of the data is within one standard deviation of the mean, 95 % of the data is within two standard deviations of the mean, and so on. This is illustrated in Figure 2.15. This approach simplifies the creation of probability data since it can be modelled by using the probabilities in the normal distribution.

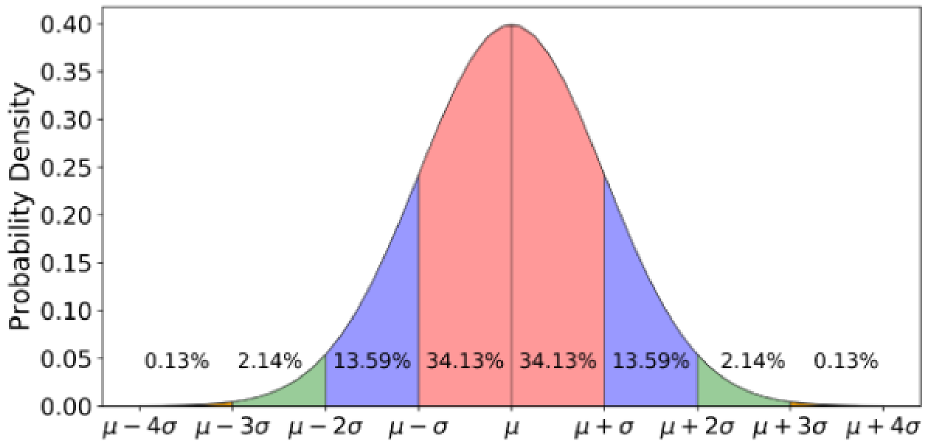


Figure 2.15: The normal distribution curve [27].

It should be mentioned that this is not a perfect setup, but adequate since the main focus of this thesis is not to create a probability model, but to study the behaviour, performance and decision making of the model. A better way of model this probability could be by using a Markov Chain, which is a mathematical system that experiences transitions from one state to another according to certain probabilistic rules [28]. This system allows future probability decisions to be made regardless of the decisions made in the past.

2.9.3 Modelling Piecewise Linear Curves

When implementing the storage values in the optimisation model this is done with piecewise linear curves and by using so called SOS2 variables to generate a piecewise linear approximation. The method involves taking the non-linear curve and divide it into discrete points where each point has a specific performance. Then, there are drawn lines between the individual point to create a curve. In this way, the non-linear curve becomes piecewise linear. It is the lines between the discrete points that are modelled with SOS2 variables. These require that no more than two neighbouring points have a non-zero value of their SOS2 variables and that they equal 1 when summed up. So, if the wanted point is between two discrete points, the value is found by doing a linearisation of the adjacent discrete points. The benefit of such a method is that a non-linear curve could be integrated into the model in a decent approximation. However, this could potentially increase the computation time, especially when there is a high number of discrete points.

Chapter 3

Model Description

In this chapter, the model used in this thesis will be explained in detail. This includes the structure of the system and how the model works in whole, and in its two phases, to provide energy storage scheduling with distributed generation included. The chapter includes an explanation of the optimisation problem which is the underlying problem in both phases and the core of the model. It will describe its structure, but also discuss the motivation behind some of the choices made and some of the different options within. Also, an explanation of the algorithm in the two phases could be found in Section 3.2 and Section 3.3.

The basis for the model used and studied in this thesis is an optimisation model made by Kasper Emil Thorvaldsen for his master's thesis at NTNU in 2018 [2]. The main difference in these two models is that the original model did not include a form of distributed generation. The inspiration for the original model is gathered from hydropower scheduling in the energy and reserve markets. The inspiration for the extension with unregulated power generation is gathered from literature found in similar literature. This theory is discussed in Section 2.8.

The model in this thesis is made to study the performance of an energy system consisting of a storage unit and a wind turbine which operates in both the energy market and the reserve capacity market. It is a short-term stochastic model that can be characterised as both multi-scenario and multi-stage. Since the system scheduled contain uncertainty in energy prices and power generation, stochasticity has been included in the model. This model is made with Pyomo in Python.

The model is divided into two different phases. The motivation behind the two-phased approach is based on models used in long-term hydropower scheduling, which are described in Section 2.6. The first phase is the strategy phase, where a strategy for storage unit scheduling is conceived through the creation of the storage values. The storage value can be defined as the marginal cost of storing one more kWh of energy in the storage unit, which means it is a marginal opportunity value. It is these values that are the criteria used in the scheduling strategy and they are created by using Stochastic Dynamic Programming (SDP). A storage value is calculated for each possible scenario based on the energy prices and power production and then weighed with a stochastic probability. When the SDP-phase is complete, and the storage values are obtained, the second phases can begin. The second phase is the simulation phase. Here, the storage values are included to simulate the performance of the storage unit for numerous possi-

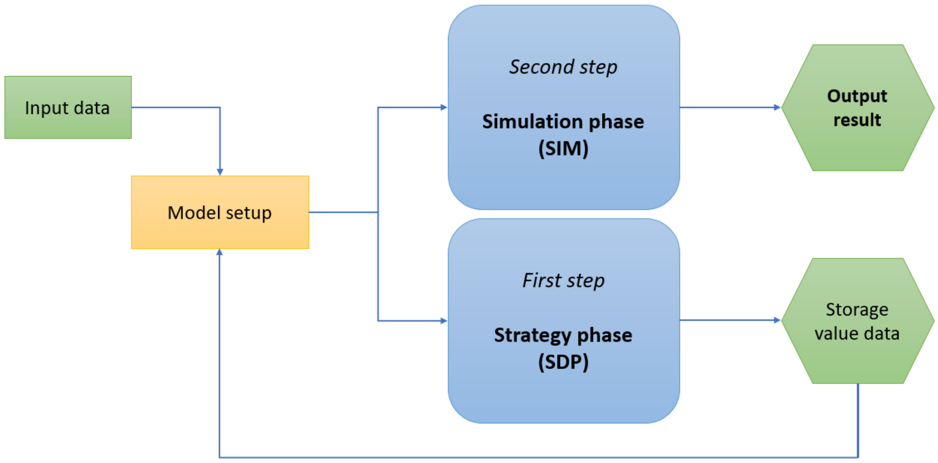


Figure 3.1: A general overview of the model as a whole and its two steps.

ble scenarios. By doing this, the system behaviour for various stochastic scenarios is simulated with the optimal strategy given in these storage values. The general overview of the model and the two phases are illustrated in Figure 3.1. It is important to note that the strategy phase needs to be completed first to obtain the storage values since the simulation phase is dependant on these values. In that sense, this is a process with two steps. Each phase uses the optimisation problem described in Section 3.1 for computation.

As discussed in the paragraph above, the output values for the strategy phase is storage values for a given model setup. The output values for the simulation phase, and hence when the entire model has been operated, are the optimal values for the variables in the optimisation problem for a given scenario. This includes, among other things, the optimal charging and discharging of the storage unit in each time step and the optimal power flow to and from the grid in each time step. In general, these output values illustrate the optimal power flow in the system as well as the optimal trade in the two markets for each time step. Thus, the resulting profit values in the markets are obtained in this phase.

3.1 Optimisation Problem

The optimisation problem is the most central part of the model. The optimisation problem is used in both phases, strategy phase and simulation phase. An abstract optimisation problem is created in ”Model setup” in Figure 3.1. This abstract model goes into use in the next phases when it creates multiple individual instances of the optimisation problem based on the input data and different scenarios. In the strategy phase, the problem is used to find the storage values and in the simulation phase, it is used to simulate a given set of situations with storage values. Since the optimisation problem is the main part of the model itself, this section will focus on explaining the problem and its functions. Section 3.1.1 will give a general overview of the problem and clarify the system it should represent. Section 3.1.2 to Section 3.1.4 explain the problem structure in its objective function and constraints.

Note that the whole overview of the model formulation is found in Appendix A. However, a presentation of the main aspects of the optimisation problem is described here in this section.

3.1.1 General overview

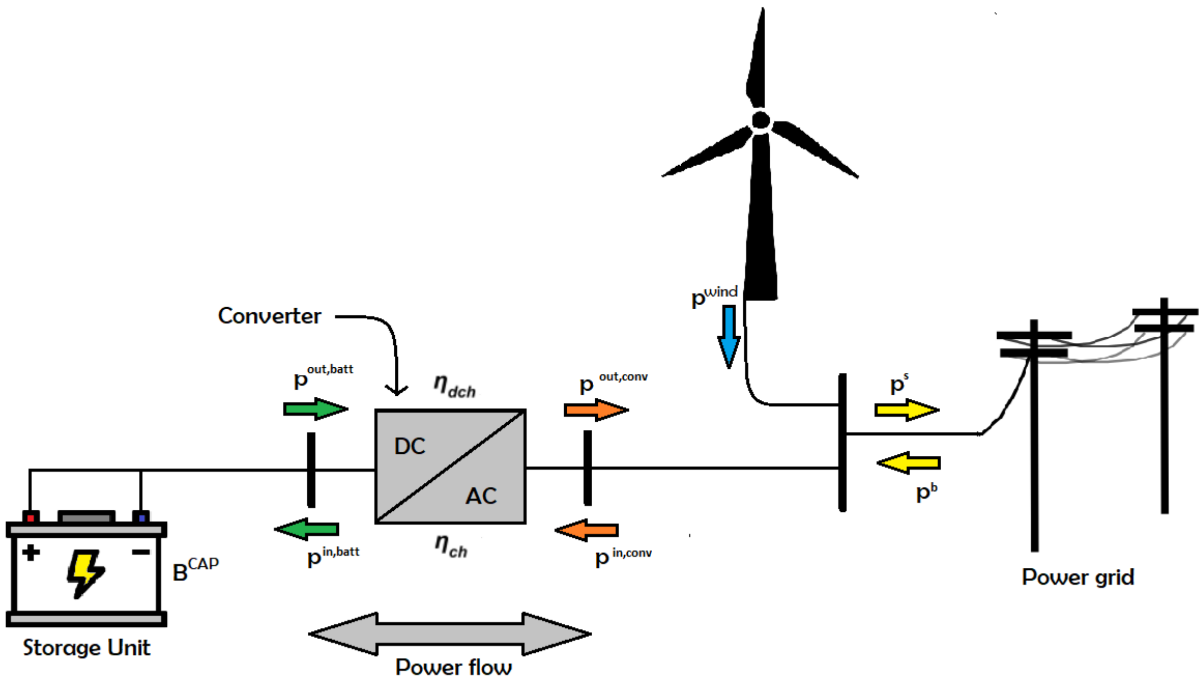


Figure 3.2: A sketch of the layout of the storage system with wind production used in the optimisation problem. Note that the storage unit does not need to be a battery.

Figure 3.2 illustrates the system represented by the optimisation problem. It is a single energy storage unit in connection with a wind turbine and the grid via a converter. The storage unit does not necessarily need to be a battery as shown in Figure 3.2, but are used for visual purposes. However, a battery could be a good option for a grid connected storage unit, as discussed in Section 2.5. A battery is also a viable option of energy storage in connection with unregulated generation such as wind power.

The energy system is considered placed in a rural area with limited transmission capacity to the grid. This creates two potential bottlenecks in the system, in the converter and in the connection to the grid. Both of these limitations will create constraints in the optimisation problem. Since the storage unit is considered to store energy over potentially several hours, the power:energy ratio of the storage system is regarded low. The power capacity of the chosen converter will thus create a bottleneck to and from the storage unit because of this low power:energy ratio. The power can flow in both directions through the converter as well as to and from the grid. When power passes through the converter it charges or discharges the storage unit. When the power flows through the converter, it will become affected by the converter efficiency. Thus, the level of power going into the converter is not the same as the level of power coming out of the converter. This can be explained from Figure 3.2 in the way that the orange power flows at the power grid side will not have the same values as the green power flows at the storage unit side.

The power flow from the wind turbine could either be stored, $p^{wind,store}$, or be sold to the grid, $p^{wind,transf}$. Thus, the power sold to the grid, p^s, is the sum of the sold wind power, $p^{wind,transf}$, and the power from the storage unit affected by the converter, $p^{out,conv}$. In the same way, the power going into the converter, and then the storage unit, is the sum of the power bought from the grid, p^b, and the stored wind power, $p^{wind,store}$. There is no limit on the wind power other than set by the production premises and power rating of the turbine. Note that the power from the wind turbine will vary and be unpredictable. When passing through the converter, the input power, $p^{in,conv}$, will be affected by the efficiency, η_{cha}, and become the power flow that charges the storage unit, $p^{in,batt}$. The same process happens when discharging. The output power from the storage unit, $p^{out,batt}$, gets influenced by the discharging efficiency, η_{dcha}, and become the output power which is being sold, $p^{out,conv}$. This can be summed up in these equations:

$$p^{in,batt} = \eta_{cha} \cdot p^{in,conv}$$
$$p^{out,conv} = \eta_{dcha} \cdot p^{out,batt}$$

The main purpose of the optimisation problem is that it will determine the optimal power flow, i.e. how much power flowing in and out of the storage unit and how much power bought and sold to the market. This is calculated in time steps that are defined by the user. In this way, there is calculated an optimal power flow for each time step, *t*, in the total number of time steps, *TS*, i.e. for $t \in TS$. It is assumed hourly time steps in this thesis.

3.1.2 Objective Function

The objective of the optimisation problem is to try to maximise its total profit from the storage system and wind turbine. This is achieved when the system operates in the markets, and simultaneous utilise the accessible wind power, in an ideal way. In the model, this is accomplished by maximising the objective function, which can be found in the Equations A.1 to A.5 in the Appendix A. Also, the objective function is repeated on the next page.

$$OBJ = \sum_{t \in TS} E_{price,t} \cdot p_t^f \cdot T_t \tag{A.1}$$

$$+ \sum_{t \in TS} C_{price,t} \cdot cap_t \cdot T_t \tag{A.2}$$

$$- \sum_{t \in TS} A_{price,t} \cdot p_t^{art} \cdot T_t \tag{A.3}$$

$$+ \sum_{t \in TS} Shed_{value,t} \cdot p_t^{wind,shed} \cdot T_t \tag{A.4}$$

$$+SV + DVal \tag{A.5}$$

Equation A.1 is the total profit from the energy market. Here the energy price in time step *t* is multiplied with the net power traded in *t* and the length of time step *t*. The same goes for Equation A.2 which refers to the total profit from the capacity market. Therefore, it is the price of reserve capacity multiplied with the capacity traded and the length of the time step, all in time step *t*. Note that the energy profit in Equation A.1 can be negative in some time steps. This is because when the system participates in the energy market it exploits the price difference that occurs over the planning period. Therefore, the profit can in some time steps become negative if purchasing power for later stages. Equation A.2 can never be negative because the power traded in the reserve capacity market, cap_t, is never negative. The variable operates with only positive values since the system either sells reserve capacity, or it does not.

The only negative part of the objective function is Equation A.3. This represents the penalty cost of storing power in the storage unit that can be considered artificial. Since this part of the objective function reduces its maximum potential, the artificial power bought in a given time step, p_t^{art}, is only utilised when absolutely necessary. It should not normally occur and is used more as a fail-safe in the model. There has been added a small value for shedding wind power. This is shown in Equation A.4. The power shedded in time step t is represented in $p_t^{wind,shed}$, and the parameter $Shed_{value,t}$ is the value or reward for that shedded power. This is included to prevent the model from discarding excess power in the converter and instead reduce the wind power going into the system, p_t^{wind}. Therefore, to give the model an incentive to shed the excess power a small reward was introduced. Note that the value for shedding is set so low that it will not have an impact on the results. Equation A.5 includes the value of the remaining stored energy in the storage unit and therefore the future profit. In total, all these equations represent the total net profit of the energy storage system.

3.1.3 Variables

All the variables in the model can be found in appendix A, but since they are frequently used in the optimisation problem explanation in this section, they are also presented here. Note that it is only the continuous variables that are included in this section, not the other variables.

$p_t^{in,batt}$	=	The power charged into the storage unit on the storage unit side of the converter in time step t (energy stored in unit) [MW].
$p_t^{out,batt}$	=	The power discharged from the storage unit on the storage unit side of the converter in time step t (energy released from unit) [MW].
$p_t^{in,conv}$	=	Power flow into the converter on the grid side in time step t (energy intended to be stored) [MW]
$p_t^{out,conv}$	=	Power flow out of the converter on the grid side in time step t (energy to be sold from the storage) [MW]
p_t^{b}	=	The power bought from the grid on the grid side in time step t (Power going into the system from the grid) [MW].
p_t^{s}	=	The power sold to the grid on the grid side in time step t (Power going into the grid from the system) [MW].
p_t^{f}	=	The net power exchange to the grid in time step t [MW].
cap_t	=	The reserve capacity sold in time step t [MW].
p_t^{art}	=	The artificial power bought in time step t [MW]
SV	=	The energy storage value in the storage unit at the end of the decision stage [NOK].
p_t^{wind}	=	The total power flow from the wind turbine going into the system in time step t [MW]
$p_t^{wind,store}$	=	The power flow from the wind turbine which is stored in time step t [MW]
$p_t^{wind,transf}$	=	The power flow from the wind turbine which is transferred to the grid in time step t [MW]
$p_t^{wind,shed}$	=	The power shed from the wind turbine in time step t [MW]
soc_t	=	The state of charge for the storage unit at the end of time step t [p.u.].

3.1.4 Constraints

To get a realistic behaviour and accurate decision making in the storage and wind system, it is important that relevant constraints are implemented in the model and that they are expressed correctly. This section will explore the different constraints that exist in the model.

Constraints for the Energy Storage Unit

The energy storage unit considered in this model is ideal. This means that the storage unit has no losses and it does not have an efficiency related to storing and discharging electricity. Thus, no constraints to express the power loss in the storage unit have been included. However, when modelling this storage unit other constraints are needed.

The storage unit needs an initial balance in the first time step. This is created in Equation A.6 which ensures that the storage level at the end of the first time step is equal to the initial storage level and the energy stored and discharged during that time step. In this equation, the parameter T is the length of the given time step and the parameter B^{MAX} is the maximum capacity of the storage unit.

$$soc_0 \cdot B^{MAX} - p_0^{in,batt} \cdot T_0 + p_0^{out,batt} \cdot T_0 - p_0^{art} \cdot T_0 = SOC^{Start} \cdot B^{MAX} \tag{A.6}$$

Equation A.7 ensures the energy balance in the storage unit for the rest of the time steps. It makes sure that the storage level the start of the time step plus the energy stored and minus the energy discharged during the time step, must be equal to the energy at the end of the time step.

$$soc_{t-1} \cdot B^{MAX} + p_t^{in,batt} \cdot T_t - p_t^{out,batt} \cdot T_t + p_t^{art} \cdot T_t = soc_t \cdot B^{MAX}, \quad t \in TS \backslash [ord(t) > 0] \quad \text{(A.7)}$$

The variable for artificial power, p_t^{art}, is included in Equation A.6 and A.7. As mentioned earlier, this artificial power source is not used if not utterly needed, because it is implemented in a costly way in the objective function.

As discussed in Section 2.5.3 some storage units have a maximum depth of dispatch. This is also implemented into this model with the use of the parameter $MDOD$ in Equation A.8. This constraint sets the state of charge in a given time step to be less or equal to the maximum depth of dispatch of the storage unit.

$$(1 - MDOD) \leq soc_t \leq 1 \ , \quad t \in TS \quad \text{(A.8)}$$

Constraints for the Converter

The converter's purpose is to be the link between the DC power side and the AC power side. The storage unit is connected to the DC side and the power grid and wind turbine are connected on the AC side. All power flowing in and out of the storage unit must go through the converter. However, the converter has a rating for maximum power transfer. This capacity value can be different for charging and discharging, or it can be the same values. Equation A.16 and A.18 shows these constraints. Here, the parameter P_{dch}^{max} is the maximum power transfer through the converter during discharge of the storage unit. In the same way, P_{ch}^{max} is the maximum power transfer through the converter during charging. Note that there is no limit on the amount of power going *out* of the storage unit or power that comes *into* the converter from the grid side. The reason for this is that these power flows has not interacted with the converter yet and thus not affected by the transfer limit. The constraints for this can be seen in the equations A.15 and A.17 in the appendix.

$$0 \leq p_t^{out,conv} \leq P_{dch}^{max} \quad \text{(A.16)}$$

$$0 \leq p_t^{in,batt} \leq P_{ch}^{max} \quad \text{(A.18)}$$

In contrast to the storage unit, the converter has an efficiency that represents losses. The quantity of power going into the convert is not the same as the quantity of power going out. In this model, the converter efficiency can either be represented by non-linear efficiency curves with varying efficiency output affected by the given power level or it can be constant. A constant efficiency has been chosen in this thesis because it reduces complexity. However, the non-linear representation can be found in the appendix. The constant converter efficiency has been included in the model through Constraint A.19 and A.22. These equations show how the power flows between the converter and storage unit are affected by this constant efficiency.

$$p_t^{in,batt} \cdot T_t = \eta_{ch} \cdot p_t^{in,conv} \cdot T_t \ , \quad t \in TS \quad \text{(A.19)}$$

$$p_t^{out,conv} \cdot T_t = \eta_{dch} \cdot p_t^{out,batt} \cdot T_t \ , \quad t \in TS \quad \text{(A.22)}$$

Constraints for the Power Grid

Through the connection with the grid, the wind and storage system can buy and sell power. To simplify power traded with the grid, one constraint has been made to collect the power sold and bought into one variable, p_t^f. This is the net power transfer to the grid. The constraint in Equation A.9 ensures this net balance in the given time step t.

$$p_t^f \cdot T_t = p_t^s \cdot T_t - p_t^b \cdot T_t \ , \quad t \in TS \tag{A.9}$$

There is a transfer capacity in the connection with the grid. This is a situation that could occur in rural places with wind power, as discussed in 2.8.1. When implementing this in the optimisation problem, the net power flow to and from the grid needs to be within the transfer limit, $P^{transf,MAX}$. This net power flow is defined by the sold and bought power in Equation A.9. The constraint that limits the net power transfer is illustrated in Equation A.12. Note that the variables for bought and sold power also must be within the limits of the transfer capacity as shown in Equation A.13 and A.14.

$$-P^{transf,MAX} \leq p_t^f \leq P^{transf,MAX} \tag{A.12}$$

$$0 \leq p_t^s \leq P^{transf,MAX} \tag{A.13}$$

$$0 \leq p_t^b \leq P^{transf,MAX} \tag{A.14}$$

Constraints for Power Flows in the System

In the system containing both a storage unit and a wind turbine, there are a handful of power flows. It is important that these power flows are balanced to each other and interact deliberately. The power that is sold can either come from the wind turbine and/or the storage unit. Thus, Equation A.10 is a constraint that defines the variable for net power sold, p_t^s, by the variables for power from the wind turbine and power from the storage unit. In a similar way, the power flow into the converter can come from the wind turbine and/or the grid. Equation A.11 is therefore a constraint that define the variable for net power going into the converter on the grid side, $p_t^{in,conv}$. This power flow is made up by the power from the wind turbine and the bought power from the grid.

$$p_t^s \cdot T_t = p_t^{out,conv} \cdot T_t + p_t^{wind,transf} \cdot T_t \ , \quad t \in TS \tag{A.10}$$

$$p_t^{in,conv} \cdot T_t = p_t^b \cdot T_t + p_t^{wind,store} \cdot T_t \ , \quad t \in TS \tag{A.11}$$

Constraints for the Reserve Capacity

When selling reserve capacity, it includes flexibility in both directions, up-regulation as well as down-regulation. In other words, if selling a reserve capacity of 1 MW, the unit must be able to provide both 1 MW increase and 1 MW decrease in the power output. There are mainly three limiting factors to the quantity of reserve capacity that can be provided: the converter, the power grid connection and the storage unit.

One limitation to the reserve capacity that can be provided is the converter. This is one of two bottlenecks in the system that limits the reserve capacity. The power flow through the converter must be restricted to its maximum limit at any time. The sold reserve capacity is therefore restricted to the available capacity in the converter. In the model this is implemented in the constraints in Equations A.25 and A.26. This shows the limits of down- and up-regulation of reserve capacity based on available power decrease/increase in the converter. Note that the expression inside the parenthesis determines the direction of the power flow through the converter. Only one of the variables inside the parenthesis should be active in a given time step.

$$-(p_t^{out,conv} - p_t^{in,conv}) \geq cap_t - P_{dch}^{max} \tag{A.25}$$

$$-(p_t^{out,conv} - p_t^{in,conv}) \leq -cap_t + \frac{P_{ch}^{max}}{\eta_{ch}^{max}} \tag{A.26}$$

In this setup, the parameters P_{ch}^{max} and P_{dch}^{max} is the maximum power output for the converter during charging and discharging. When charging, the efficiency for the maximum power output, η_{ch}^{max}, must be included, as seen in Constraint A.26. This is because the power must pass through the converter and thus introduce losses, while in Constraint A.25 this efficiency is already considered. Since this efficiency is included in the charging constraint, the down-regulation limit can be slightly higher when seen from the grid side because there will be losses in the converter.

As seen from the Constraints A.26 and A.25 the reserve capacity sold is limited by the power flow through the converter in time step t. If this is low, the reserve capacity potential is higher and vice versa. For instance, if it is assumed 1 MW maximum power output from the converter with an efficiency of 1, and a power flow of 0.4 MW going out of the converter at the given time step, the potential reserve capacity in that time step is limited to 0.6 MW. The down-regulation potential is 1.4 MW, but the up-regulation potential is only 0.6 MW, and therefore the up-regulation potential becomes the dominant constraint for the reserve capacity. The calculations for this example are shown below:

$$-0.4 \geq cap_t - 1 \Rightarrow cap_t \leq 0.6 \quad \text{and} \quad -0.4 \leq -cap_t + \frac{1}{1} \Rightarrow cap_t \leq 1.4$$

The other bottleneck in the system that limits the available reserve capacity is the power transfer capacity to the grid. This limits the available reserve capacity in the same way as the converter. The constraints for this limit are shown in Equations A.27 and Equation A.28.

$$-p_t^f \geq cap_t - P^{transf,MAX} \tag{A.27}$$

$$-p_t^f \leq -cap_t + P^{transf,MAX} \tag{A.28}$$

The reserve capacity will also be limited by the storage unit. The remaining storage capacity in a given time step must be large enough to offer both the up- or down-regulation throughout the entire time step. In simple terms, the storage unit must have energy stored to provide up-regulation and available storage capacity to provide down-regulation. This is implemented in two constraints shown in Equations A.29 and A.30. The parameters in these constraints concerning the storage unit are B^{MAX} which is the maximum capacity and $MDOD$ which is the maximum depth of dispatch. Also, the parameter for maximum efficiency for charging in the converter, η_{ch}^{max}, and the parameter for minimum efficiency for discharging, η_{dch}^{min}, are used.

Both efficiencies are included since the power must pass through the converter when charging and discharging the storage unit. The minimum power efficiency is taken into account to avoid the possibility of selling more reserve capacity than the storage unit can deliver to the grid side. Note that the reserve capacity potential in Constraint A.29 will increase because of the efficiency losses in the converter.

$$cap_t \cdot T_t \leq (1 - soc_t) \cdot \frac{B^{MAX}}{\eta_{ch}^{max}} \ , \ \ t \in TS \tag{A.29}$$

$$cap_t \cdot T_t \leq (soc_t - (1 - MDOD)) \cdot B^{MAX} \cdot \eta_{dch}^{min} \ , \ \ t \in TS \tag{A.30}$$

Constraints for the Power Markets

For trade in the energy market, the only constraint is the power transfer limit. This restriction is implemented in Constraint A.12. When within the limits, the profit that can be gained from this market is exemplified by Equation 3.1. Here, the energy price for a given time step is $E_{price,t}$, while p_t^f is the net power transfer that was established by Constraint A.9. Note that the profit can be negative for a given time step if the power transfer is negative. Then power is bought from the energy market. The optimisation problem will try to maximise this profit from storing or buying energy when prices are low (low $E_{price,t}$) and selling energy when prices are high (high $E_{price,t}$).

$$E_{profit,t} = E_{price,t} \cdot p_t^f \tag{3.1}$$

The profit from the reserve capacity market can be calculated in a similar way. This is presented in Equation 3.2. Here the reserve capacity price for a given time step is $C_{price,t}$, while cap_t is the reserve capacity sold in this time step. In contrast to the profit from the energy market, this value will always be zero or larger. This is because reserve capacity is either sold or not, and there does not exist an option to *buy* reserve capacity from other participants.

$$C_{profit,t} = C_{price,t} \cdot cap_t \tag{3.2}$$

It can be mentioned that the participation in the reserve capacity market will limit the participation in the energy market because storage capacity in the storage unit must be reserved for up- and down-regulating and not used. This is also true the other way around. When participating in the energy market, storage unit capacity is used to store energy and thus cannot be reserved for use in the reserve capacity market. The model will try to optimise the participation in both markets so that the total profit is maximised.

When participating in the reserve capacity market the capacity is sold in blocks, as mentioned in Section 2.3.4. Therefore, the same reserve capacity has to be sold throughout the entire block period. The length of the period could be one hour or several consecutive hours. This is implemented in the model with the constraint shown in Equation A.31.

$$cap_t = cap_{t-1}, \ \ t \in TS \setminus [ord(t) > 1, t \neq R_c^{list} \ for \ c \in C] \tag{A.31}$$

The capacity sold in time step t must be the same as the capacity sold in time step $t-1$, as Constraint A.31 shows. This holds true for all time steps not included in R_c^{list}, which is a list with C inputs and where each input is the start of the next equalised reserve capacity period.

Constraints for the Storage Value

The optimisation problem will strive to maximise the participation in both the energy market and the reserve capacity market, but it will also need to consider the value of storing energy from one decision stage to another. In other words, storing energy in the storage unit for use at a future decision stage that is not known at this point. This is ensured through the constraint in Equation A.33. The implementation of this storage value at the end of the decision stage has been done with piecewise linear approximation.

$$SV = \sum_{n=1}^{NR} \delta_n \cdot SV_{pts}[n, soc_{TS}] \tag{A.33}$$

Constraint A.33 sets the total value of the remaining energy in the storage unit at the end of the decision stage, which is SV. In this constraint SV_{pts} is a list containing piecewise linear points of storage values. These values are dependent on the storage level, n. This list of storage values is created based on possible future scenarios which have been simulated by a stochastic dynamic programming method. Note that soc_{TS} is the storage level at the end of the decision stage and that the storage level n is a specified storage value contained in the set NR, i.e. $n \in NR$.

$$\sum_{n=1}^{NR} \delta_n = 1 \ , \quad \delta_n \in [0, 1] \tag{A.32}$$

The variable δ_n is the SOS2-variable related to the end value of stored power at the end of the decision stage. The constraint in Equation A.32 ensures that the sum of all the SOS2-variables has the value of 1 in the entire set of storage levels, NR.

Constraints for the Wind Turbine

The power flow from the wind turbine can flow in two different directions in the system. It can be stored in the storage unit or it can be sold to the grid right away. These two power flows need to be connected to the total wind power going into the energy system from the wind turbine. Therefore, it is created a constraint that connects the variable for total utilised wind power from the wind turbine, p_t^{wind}, with the variables for stored wind power and transferred wind power from the wind turbine. This constraint is showcased in Equation A.34.

$$p_t^{wind} \cdot T_t = p_t^{wind,store} \cdot T_t + p_t^{wind,transf} \cdot T_t \ , \quad t \in TS \tag{A.34}$$

The maximum produced power from the wind turbine in a given time step is defined by the power rating of that specific turbine, $P^{wind,rated}$, and the power output in that time step. Furthermore, the power output is based on the wind speed in that time step and the turbine's power curve. This power output is given in p.u. and are illustrated in the parameter, $P_t^{wind,output}$. The power output takes a value between 0 and 1, where 0 is no power production and 1 is production at the rated power level.

The wind turbine can either produce at this maximum power output, or it can choose to produce at a lower production level. Thus, the turbine can be throttled to produce at a wanted power level as long as it does not exceed the maximum possible power production at that time. This was briefly discussed in 2.8.1. It can, for instance, be beneficial to produce a smaller amount of wind power if the reserve capacity market is very profitable in a certain time step and the transfer capacity must be reserved for that purpose. The wind power production must also be contained within the limits of the bottlenecks in the system. If the utilised wind power going into the system is less than the total available wind power, some of the wind power is shedded. To represent this power shed, a variable, $p_t^{wind,shed}$, is introduced. In the optimisation problem a constraint that limits the variable for total wind power going into the energy system, p_t^{wind}, and the wind power shed, $p_t^{wind,shed}$, to the maximum available power output from the wind turbine has been included in Equation A.35.

$$p_t^{wind} \cdot T_t + p_t^{wind,shed} \cdot T_t = P^{wind,rated} \cdot P_t^{wind,output} \ , \quad t \in TS \tag{A.35}$$

3.2 Strategy Phase

The strategy phase is the first phase that must be simulated in this two-phased model. This phase develops the scheduling strategy in the system. The strategy is based on finding the storage values or the marginal values of stored energy. Thus, the main purpose of this phase is to obtain these storage values. This is done through stochastic backward dynamic programming, which is very similar to how it is done in some models in hydropower scheduling. This was discussed in Section 2.6. This section will include an explanation of the strategy phase and the SDP method used in this phase.

$j \leftarrow 0, \Delta \leftarrow \infty, SV^j \leftarrow 0$
while $\Delta > \epsilon$ **do**
  $j \leftarrow j + 1$
  for $d = Days - 1..0$ **do**
    for $n = 1..NR$ **do**
      for $pr = 1..PR$ **do**
        $\{E_{price}, C_{price}, Wind_{power}\} \leftarrow StochVar(d, pr)$
        $SV(n) = SV^j(n, pr, d+1)\ ,\ for\ n = 1..NR$
        $B^{Start} = SOC(n)$
        $\alpha(pr, n) \leftarrow Optimise$
      end for
      for $pr = 1..PR$ **do**
        $\alpha_w(pr, n) = \sum_{pr' \in PR} prob_{pr}(pr, pr', n) \cdot \alpha(pr', n)$
        if $n = 0$ **then**
          $DVal = \alpha_w(pr, d)$
        else
          $SV^j(d, n-1, pr) = \frac{\alpha_w(pr,n) - \alpha_w(pr,n-1)}{SOC(n) - SOC(n-1)}$
        end if
      end for
    end for
  end for
  $\Delta \leftarrow \sum_{d \in Days} \sum_{n \in NR} \sum_{pr \in PR} SV^j(pr, n, d) - SV^{j-1}(pr, n, d)$
  $SV^{j+1}(Days, n, pr) \leftarrow SV^j(0, n, pr)\ ,\ \forall n,\ \forall pr$
end while

Figure 3.3: SDP algorithm

In general terms, the SDP approach is basically to start calculations in the future and then step by step compute your way back towards the present. One of the key aspects of solving the optimisation problem and determining the optimal power schedule for the system is the values of future profit or storage value, SV. The SDP algorithm comes in handy for this storage value computation. To do this the continuous storage level need to be made discrete and defined by a number of potential storage level segments NR. For instance, discrete values which corresponds to storage levels such as 100%, 75%, and down to 0%. For the very last period, or in this case the last day, the future value function is specified. This will be set to zero. Then operational profits for each storage level in the last period is calculated. Furthermore, when standing in the second last period the future storage value profit, SV, is now known. Since prices and wind power output are stochastic, different scenarios are calculated. Each scenario has a specific probability. Therefore, the expected future profit for the given storage is weighted by its probability. With this reasoning, the results from the second last period are then used as the future profit in the third last and so on calculating backwards towards the present.

Figure 3.3 illustrates the algorithm for the strategy phase in detail. In line 1 in this figure, the initial values are defined. Here the iteration number (j) is set to 0 and the deviation (Δ) is set to infinity. The initial storage value is set to 0 here. This is the expected future profit value for day 8 since the model operates with 7 days and the start of day 8 is the same as the end of day 7.

Line 2 describes that the iteration will continue until the deviation is smaller than the user defined convergence limit (ϵ). Then for each iteration, the model will calculate a given number of scenarios. This number is based on the size of the parameters which are user defined. The parameters in question are the price and wind production nodes ($pr \in PR$), storage level segments ($n \in NR$) and days ($d \in Days$). The price and wind production nodes, pr, represent a possible combination of energy price, reserve capacity price and wind production given a specific day. When combining a random day, a storage level segment and a price and wind node it provides you with a storage value scenario. Thus, when going through every day, SLS and price and wind node in question it results in a total of $Days \cdot NR \cdot PR$ storage value calculations.

The calculations of the storage values begin in line 7, as seen in Figure 3.3. Here, the model defines specific parameters for the specific scenario instance in question. The parameters defined are the energy price, the capacity price, and the wind power output. These parameters are stochastic and are given by the specific price and wind node in this scenario. Then, line 8 describes the piecewise linear setup for the storage value, and line 9 sets the starting storage level for the battery. Further, in line 10 the objective function for the given price node, α, is defined. This is then the solution to the optimisation problem described in Section 3.1 for this specific scenario. This process is done for each instance creating each an objective function calculation. The weighted objective function, α_w, is then calculated in line 13. This includes $prob_{pr}$ which is the probability of moving from price and wind node pr to pr'. Then, the weighted objective function, α_w, is stored as the offset in value function, $DVal$, if and only if the current storage level is the first. In this case, the storage unit can be considered empty. $DVal$ can also be referred to as the expected profit for the future. When the storage level is not the first, the storage value is calculated with this found weighted objective function, α_w. This is shown in line 17 of Figure 3.3.

After the storage values are calculated for all the given scenarios in an iteration, the deviation must be calculated. This is shown in line 22 in the SDP algorithm in Figure 3.3. Here the storage values from the current iteration will be checked against the storage values from the previous iteration. This deviation decides if the model should carry out another iteration, and this is done if the value is larger than the user defined convergence criteria, ϵ. Ideally, this deviation should be as close to zero as possible, i.e. the storage values at the end are close or equal to the starting storage values. If the deviation is too large and another iteration is necessary, the storage value from day 1 of the previous iteration will be the new initial storage value for day 8 for the next iteration. This can be seen in line 23 in the SPD algorithm. This adjustment of the initial condition is crucial to reach convergence since the starting values should be close or equal to the ending values.

3.3 Simulation Phase

As described earlier in this chapter and in Figure 3.1, the strategy phase must have been run before beginning the simulation phase. This is because the storage values obtained in the strategy phase are necessary for the simulation phase. There are storage values for each possible scenario in the model, and these are used to find the optimal scheduling for the scheduling period. Since the storage values represent uncertainty there should be computed multiple scenario simulations with different scenarios in the simulation phase. In that case, many potential scenarios will be analysed, and the average behaviour and result will represent the reality in the best way possible. In other words, the result of this simulation phase will represent the behaviour of the storage unit in the scheduling period. For instance, this includes the profits gained and storage levels throughout the period.

1: $B^{Start}(0) \leftarrow B^{Initial}$
2: **while** $i < Iterations$ **do**
3:     **for** $d \in Days$ **do**
4:         $s \leftarrow Rand(pr \in PR)$
5:         $\{E_{price}, C_{price}, Wind_{power,SV}\} \leftarrow StochVar(d, s)$
6:         $OBJ \leftarrow Optimise$
7:         $B^{Start}(d+1) = B^{End}(d)$
8:     **end for**
9:     $B^{Start}(i+1) = B^{Start}(Days+1)$
10: **end while**

Figure 3.4: SIM algorithm

Figure 3.4 illustrates the algorithm for the simulation phase in detail. In line 1 in this figure, the initial storage level for the first iteration is set. The iteration process will go on until a user defined number of iterations (could also be called "scenarios" or "periods") has been completed. This is shown in the while-loop in line 2.

For every iteration, the optimal energy schedule is calculated for every day ($d \in Days$) in sequence. For each day a random scenario consisting of energy price, reserve capacity price, and wind production output will be chosen. This is represented by line 4 and 5 in the algorithm figure. In line 6, we compute the performance of the system for the given day and scenario, in which the results are stored for analysis. The end result of the optimisation in line 6 for the battery state of charge is stored in line 7 to be the start-value in the next scheduling day, to couple the days together. Thus, the algorithm make sure that the days are simulated sequentially.

If the optimal scheduling is calculated for all the wanted iterations, the simulation phase is finished and the performance acquired from this phase is stored. If not finished, the next iteration is simulated. Then, the starting storage value must be set for the next iteration. This time, the storage level at the end of the previous iteration is set to be the starting level for the next, as illustrated in line 9. This means that the simulation is kept sequential. Note that every iteration has a randomised scenario based on the stochastic data of prices and wind production. This ensures that uncertainty is included in the simulation phase and that average performance can be analysed to show how the scenarios play a role.

3.4 This Thesis in Light of the Literature Review

After the methodology of this model and thesis has been outlined in Chapter 2 and 3, this section will try to put the work done here in perspective to other literature within this field of research which is described in Section 2.1.

There are some common aspects between this thesis work and relevant literature. For instance, the objective of this thesis is economical since it is basically to maximise the energy storage system's profit. This is an objective that has been thoroughly researched in previous literature, as described in Figure 2.2 in Section 2.1. Furthermore, a battery storage system will be used in this thesis, even though the model in this thesis does not rule out any energy storage type that fulfils the requirements of the model. This is mainly because it may be simpler to envision a battery in the system and it is reasonable to use a battery in combination with both the grid and wind turbine. Also, the model operates with day-ahead scheduling. These two elements concerning the usage of a battery as a storage unit and the day-ahead time horizon are some common features between this thesis and other relevant publications.

However, some aspects of this thesis make it stand out. One aspect is that the energy storage system consists of a storage unit and a wind turbine connected to the grid. Previous work done with an earlier version of this model has been focused around storage only perspective [3] [2], while this thesis aims to widen the scope to a more producer-oriented scope by including a wind turbine. Even though storage only and producer-oriented scopes are slightly less discovered areas in the literature, wind and battery setups has been investigated previously as mentioned in the literature review. However, producer-oriented scope combined with the uncertainty handling makes this thesis stand more out.

Furthermore, the model is a multi-market model which means that it operates within two markets to gain profit (i.e. the energy market and the reserve capacity market). This means that proposition 4 from Section 2.1 is covered by this thesis. Another significant feature is that the model used SDP to deal with uncertainty. This means that it also covers proposition 7 and it is an uncertainty approach that is less used in previous energy storage system scheduling literature. Consequently, two of the propositions suggested in Section 2.1 are reflected in this thesis. In that way, this master's thesis has some key advantages compared to other literature on the energy storage system scheduling concerning time horizon, addressed markets and uncertainty handling.

Chapter 4

Case Study Description

The objective of the energy system model is to plan an optimal strategy with uncertainty for an energy storage unit and a wind turbine connected to the grid and where the system operates in multiple markets. One of the main motivations behind this thesis is to analyse the behaviour and result of the model in various cases depending on prices and wind production. Also, various sizes of wind power and storage will be tested. Two deterministic tests have been included. One to test the model using a range of wind turbine sizes in combination with various storage sizes and a deterministic test to investigate an extreme scenario. In the stochastic case study, two seasonal cases will be examined. There, the focus is to see what impact seasonal variations have on the model's behaviour, result and multi-market operation. Several storage capacities will be investigated in the stochastic case study, but only one wind power rating since that is examined in the deterministic case study. Seasonal data is chosen because of the natural variations in energy prices, capacity prices and wind production throughout the year. An overview of the case study is given in Figure 4.1

For all the cases, it is assumed that the storage unit and wind turbine are located in Trøndelag, Norway. This means that the energy system is within the bidding area NO3. Both the price data and the wind data will be referenced to this area. There is a transfer limit to and from the grid in the system. In this thesis, the energy system is meant to contribute with a load-shifting service and thus a relatively low power:energy ratio is used. If, for instance, the storage system was participating in frequency control, a larger converter would be needed. Each case will check the performance of the energy system over the duration of a week. To test the multi-market operation, every instance tested in the case study will be tested when only allowed to participate in the energy market and when allowed to participate in both the energy and reserve capacity market. Thus, every instance is tested in single-market versus multi-market operation.

In this chapter, the general input data for all cases will be discussed in Section 4.1. Furthermore, each case study will be discussed more detailed in Section 4.2.

	Deterministic Case Study		Stochastic Case Study	
	Test 1	**Test 2**	**Winter case**	**Summer case**
Main motivation	Test the system with various storage and wind sizes in multi-market setup	Test the system in an extreme scenario in multi-market setup	Test the system with various storage size under winter conditions in multi-market setup	Test the system with various storage size under summer conditions in multi-market setup
Seasonal data	Average autumn	Artificial data set for simulating high wind and reserve prices higher than energy prices	Winter	Summer
Storage capacities tested	1-15 MWh	5 MWh	1-10 MWh	1-10 MWh
Wind power ratings tested	0.5-2.0 MW	0.5-2.0 MW	1.5 MW	1.5 MW

Figure 4.1: A general overview of the case study

4.1 Input Data

All the cases contain various input data which consist of price data, wind data, energy storage system specifications, wind turbine power rating and data about the simulation period. It can be noted that many of the input data will be the same for all cases. The input data used will be acknowledged and described in this section. There will also be a discussion around the motivation behind this setup.

4.1.1 Scheduling Period and Time Step

Each case will have a scheduling period of one week. The scheduled week will not have an affiliation to a specific year since the historical price data is gathered from 2018 and the historical wind speed data is from 2012. However, the weeks scheduled will represent an individual season since it uses seasonal input data. The deterministic case study uses autumn data in test one and in the other test it uses a data set not related to a specific season to test an extreme scenario. The stochastic case study uses winter and summer data to create two cases. Thus, there are two tests in the deterministic case study and two different seasonal stochastic cases in the stochastic case study.

The historical data is gathered for each individual season. The price data used in the model are composed of data from around the middle of the respective season, while the wind data is assembled from the whole respective season. Hopefully, this will give a fairly good interpretation of the seasonal variations. For all cases, the decision stages are set to every day and the stage consist of 24 time steps, i.e. 7 stages with 24 steps. This is a natural setup since it will reflect the hourly price change and the hourly wind production change. It is also convenient that both the price data and wind data are stored with hourly resolution.

4.1.2 Price Data

Historical price data has been used to create stochastic data which is used in the stochastic dynamic programming model. The price data consist of both energy price data and the reserve capacity price data. Python scripts were used to create price nodes from specific historical price data obtained from Nord Pool [29] and Statnett [12]. The price data used for this project is from 2018. The reason for using data from 2018 is that this year includes some unusual price patterns and it is interesting to study the model under these circumcises. Information and discussion on how the different stochastic scenarios are made from the historical price data can be found in Section 4.1.6. The historical source data used to construct these price scenarios is plotted in Appendix B.

The year 2018 had some unusual energy price patterns in Norway. For example, it can be seen from Figure 4.2 and Figure B.1 in the appendix that the prices in the summer weeks are abnormally high. This is irregular since the prices in the winter tend to be higher than the summer prices. This can be explained by the Norwegian weather situation in 2018 and by a higher CO_2 price [30]. From Figure B.2, it can also be seen that the prices for reserve capacity are abnormally high for both the spring, summer, and autumn period. The mean capacity price for the winter period is low and this price level is more commonly found in other years. The reserve capacity prices are heavily dependent on the weather situation, just like the energy prices. This is especially true for Norway since the reserve capacity is mainly made up from hydropower plants with reservoirs. It can also be seen by the peaks that the capacity price can have a significant high variance with some very high price spikes.

Figure 4.2: The historical energy price for NO3 (Trondheim) in 2018. The red squares are approximately in the middle of each respective season. The data within each red square has been used to make price nodes for the stochastic input data. The data is collected from Nord Pool [29].

4.1.3 Reserve Capacity Sale Blocks

In Section 2.3.4 about the capacity market, it is described that the reserve capacity is sold in blocks. To simulate this realistic behaviour of how the reserve capacity is sold, some parts of the day need to sell the equal amount of reserve capacity. These periods are the morning, day, and night. This is implemented in the model by creating reserve capacity sale blocks. These blocks require the same reserve capacity sales for each time step. The time steps that must have the same amount of reserve capacity traded are k1-k8, k9-20 and k21-24. This represents the morning, the day and the evening.

4.1.4 Wind Turbine Specifications

The power rating of the wind turbine should be adjustable in the model. This raises a challenge since each wind turbine model has its own characteristics such as power curve and hub height. However, this is simplified so that the only thing adjustable in the model is the rated power of the wind turbine and the power curve and the height of the turbine are fixed at a general level. Note that this will not provide a physically accurate simulation of the wind power production when altering the power rating, but it is sufficient for the integration of a wind turbine in this model.

The hub height of the wind turbine is of importance because the wind speed increases with the increase in height above ground level. Thus, the wind data must be adjusted to the chosen hub height of the wind turbine. A particular wind turbine could be produced at different hub heights by the manufacturer. For the scope of this thesis, the interesting set of wind turbines are in the range of 500 kW to 2000 kW. Within this power range, many turbines can be delivered with a hub height of 60 meters, as shown by two wind turbines in Table 4.1. Thus, the wind turbine for this study has been given a hub height of 60 meters.

	Enercon E-53	Enercon E-82 E4
Rated power:	800 kW	2 350kW
Hub height:	50 / 60 / 73 m	59 / 69 / 78 / 84 m

Table 4.1: Two examples of wind turbines in the power range that is interesting for this thesis [31].

Each wind turbine model also has a specific power curve. However, for simplicity in this thesis, one power curve has been used in simulation impartial of the power rating chosen. The power curve used is from an Enercon E-53 with a rated power of 800 kW [31]. The curve is illustrated in Figure 4.3.

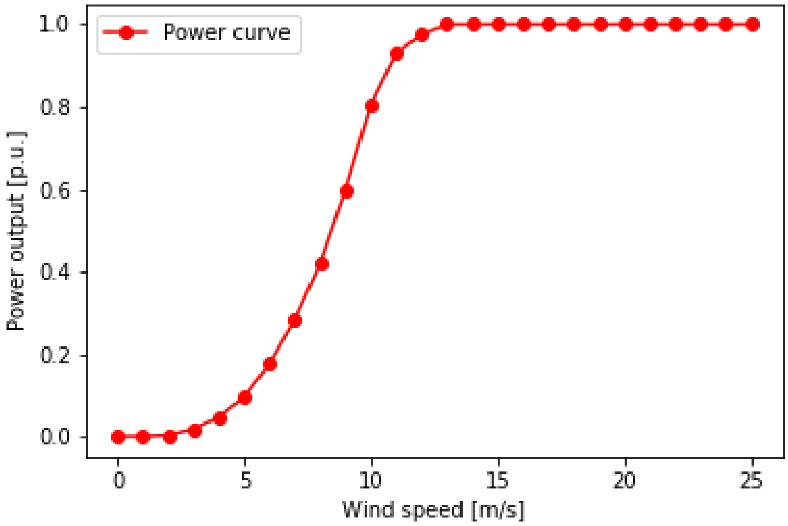


Figure 4.3: The power curve for an Enercon E-53 wind turbine [31]. The curve are presented in per unit based on the original power rating of 800 kW.

As seen from the power curve figure above the cut-in wind speed is around 2-3 m/s which is relatively low. This is where the wind turbine starts producing power. The cut-out wind speed is 25 m/s. If the wind speed exceeds this threshold, the wind turbine will stop producing power. The curve is constructed by linearisation between power output points which have a resolution of 1 m/s.

4.1.5 Wind Speed Data and Wind Power Output Data

The wind speed time series used to simulate the integration of a wind turbine in this thesis is based on measured data from 2012 for an actual wind farm at Hundhammerfjellet in Trøndelag in Norway. The data is gathered from a master's thesis written in 2013 where the measurements were provided by NTE [32]. The wind speed time series has an hourly resolution and are illustrated in Figure B.3. In this figure, the seasonal differences can be seen and are most plainly demonstrated in the mean value. The average wind speed is highest in the winter months and lowest in the summer months. These seasonal differences are also discussed in Section 2.8.1.

The wind data is originally measured at an altitude of 82.6 meters, but in this thesis, a wind turbine with a hub height of 60 meters is studied. In order to simulate the wind turbine with wind speeds at 60 meters height, the wind speed data were extrapolated using the wind power law given in Equation 4.1. Here, the reference wind speed v_r is measured at height h_r and the wanted wind speed v is the wind speed at height h. Note that α is the wind shear coefficient or Hellman exponent. This coefficient is a site specific factor because it depends on the atmosphere, wind speed and terrain. A more precise estimation of the coefficient is usually made by wind speed measurements at two or three heights for at least a period of one year. However, in this case study, the Hellman exponent is set to be $1/7$ (0.143) which characterise a flat terrain. This is a rough estimate, but a commonly used value in the literature [33]. When this value is used in the wind power law it can generally be referred to as the one-seventh power law.

$$v = v_r \cdot \left(\frac{h}{h_r}\right)^{\alpha} = v_r \cdot \left(\frac{60}{82.6}\right)^{1/7} \tag{4.1}$$

It is important to note that it is not the wind speed data that are the input data for the model. The input data is the power output given in p.u. for each time step. After extrapolating the wind speed data, it is used in combination with the power curve described in Section 4.1.4 to give an hourly power output for the wind turbine. It is this power production output that is part of the stochastic data used in the optimisation model. The creation of this stochastic data is discussed further in Section 4.1.6.

4.1.6 Stochastic Scenarios of Prices and Wind Production

The historical price data, consisting of both energy prices and reserve capacity prices, and historical wind data are used to create scenarios for the stochastic dynamic programming model. Each scenario consists of individual prices and wind production output, and this individual data can be called price nodes and wind nodes. By using historical data this gives the scenarios a sense of realistic behaviour. Ideally, the price data and wind data should have been created with the use of time series modelling. This means that historical data for several years would be applied to create the wanted number of nodes. In this way, both extreme scenarios and expected scenarios will be included, and there would exist a valid probability factor between each scenario. However, since the focus of this thesis is to study the performance of the model and not to create realistic price and wind nodes, the price data and wind data used as an input will be created in a bit more simplified way.

To limit the possible scenarios for each stochastic category (i.e. energy price, capacity price and wind production), it is created a low, average, and high scenario. The average scenario is created by calculating the average value for every hour for a specific day in the data set. In other words, the value for the first hour on Monday in the average scenario is found by calculating the average value over the first hour in all Mondays in the data set. This is then done for all hours in each day of the week. To create low and high scenarios, the same approach has been used in addition to either subtract or add the standard deviation of the values in question. Table 4.2 summarised this method of creating three different scenarios for each category of stochastic data.

Low scenario	=	The average value minus the standard deviation
Average scenario	=	The average value
High scenario	=	The average value plus the standard deviation

Table 4.2: Examples of how the different scenarios for energy price, reserve capacity price and wind production are created.

It is assumed that there is no correlation between the reserve capacity prices, the energy prices and wind production. Considering three different scenarios for each category, the model will have 27 different price and wind nodes or scenarios for each day. It can be noted that the price data and wind data for each day is given on an hourly basis.

When having a low, average, and high scenario for each stochastic category, the probability of going between nodes can be set based on a normal distribution. When doing this it is assumed that the data sets have a normal distribution. The probability of being in a low or high scenario is 15.9 % and the probability of being in an average scenario is 68.2 %. This is summarised in Table 4.3. Thus, for example the probability for a scenario consisting of low energy price, low capacity price and low wind production is $15.9\% \cdot 15.9\% \cdot 15.9\% \approx 0.4\%$. Note that the sum of all the probabilities for one day always must add up to be 100 %.

Scenario	**Probability**
Low	15.9 %
Average	68.2 %
High	15.9 %

Table 4.3: The probability of a scenario within either energy price, reserve capacity price or wind production based on normal distribution.

Keep in mind that this method of creating the price nodes and wind nodes is not very realistic and therefore should not be used in real decision making. This method used is motivated by simplifying the complexity of stochasticity and thus hopefully also the computation time. However, it should give a solid foundation for studying the behaviour of the model.

4.1.7 Energy Storage Unit

There is no specific energy storage unit type that must be used in this model. Many different types could be used depending on the wanted performance of the system, as described in Section 2.5. The only requirements for the model itself are that it could store energy and have sufficient capacity to participate in the energy market and capacity market. However, a common type of energy storage used in connection with wind power and the grid is a battery. This may also be the easiest type of unit to visualise in an energy system. Thus, a battery is chosen to represent the storage unit in the various cases.

When an energy storage unit operates in real life there will be losses, and it will often depend on the usage. However, for the purpose of this thesis, the storage unit will be assumed ideal. This means that the unit has no losses when charging and discharging. In this setup, the only losses in the energy system are within the converter. Furthermore, it is not assumed any changes in the storage unit's rating over the different seasons, even though this may be realistic as discussed in Section 2.5.6. To justify this, it can be assumed that the storage unit is kept at normal and stable temperature and without any direct contact with the elements.

4.1.8 Converter

Since a battery was chosen as the storage unit, there needs to be a converter between the storage unit and the grid side. This is to convert the AC power from the wind turbine and grid to the needed DC power in the battery while charging, and from DC power from the battery to AC power when discharging. Because of this, the convert must be a bi-directional converter. In this thesis, the inverter chosen is the "Satcon PowerGate Plus PV" from Satcon [34]. This is an inverter originally meant for PV systems with a rated power of 1 MW. The efficiency of such converters tends to be non-linear. This means that the efficiency depends on the power level it operates with. However, in this study, a constant efficiency will be used. The chosen efficiency for both charging and discharging will be set to 0.95. This efficiency value represent the lowest efficiency the converter could provide and is based on extrapolation of the lowest value found in the converter datasheet [34].

4.1.9 Grid Transfer Limit

Since the energy system consisting of the storage unit and wind turbine is connected to the main grid, it is interesting to study how this energy system behaves when the grid connection has a transfer limit. A weak grid connection is not unusual for wind power plant as they are often placed in rural areas. This can be a reason for including energy storage and are briefly discussed in Section 2.8.1.

When there is a transfer limit to the grid the model needs to choose carefully what this transfer capacity should be used for, i.e. buying power, selling power, or reserved for up/down-regulating in the reserve capacity market. If there were no limit the wind turbine would not have an incentive to cooperate with the storage unit. In that case, the wind turbine would sell its power to the grid, while the battery would operate more or less independent. In this case study, a transfer limit of 1 MW is used. This limit is chosen to be in line with the already existing bottleneck in the system, which is the converter. Thus, there are two bottlenecks with the capacity of 1 MW in the system, the converter and the grid connection point.

4.1.10 Storage Level Segments (SLS)

The storage unit is divided into storage level segments (SLS). An example of one segment could be 0.5 p.u., which means that the storage unit is at half capacity. These segments are then transformed into state variables to be used in both the strategy and simulation phase. The number of segments is a highly significant factor in the model. A high number of SLS will mean that the accuracy goes up, but this will also include a higher computation time. Thus, there exists a trade-off between accuracy and computation time when deciding the number of SLS. In work done with previous versions of this model, it is proposed that 22 is a satisfactory number of SLS, in which it gives an acceptable accuracy and computation time [2]. Based on this, the number of SLS used for the cases in this thesis will be 22.

Convergence is obtained in the strategy phase when the different SLS have a sufficient low deviation between each iteration. The convergence criterion is set to be 100. This may seem large, but is done as an attempt to ease the computation time, since there may not be a need for doing iterations if the deviation already is relatively small. Furthermore, the maximum iteration limit is set to be 10. This is done mainly to save computation time, but from experience, it could be stated that if the model does not converge within 10 iterations it probably will not converge at all. Therefore, 10 iterations are an acceptable limit.

The initial storage capacity used in the simulation phase is set to $SOC^{start} = 0.5$ $[p.u.]$. This is the storage capacity at the start of the simulation. However, this value will have little impact since there is often a high number of periods or weeks simulated in the cases.

4.1.11 Computer Power and Time Limit

When considering the data input into this model, it could potentially have high computational time. Some of the factors have a greater impact on time usage, such as SLS and the number of probability scenarios. In this thesis, there has been a focus to lower the computational time while not compromising too much on the accuracy and the integrity of the model. If referred to time usage in the report, it could be beneficial to know that the simulations were done with an Intel i5-6200 processor with 2.40 GHz and 8 GB ram installed.

There exists a time limit in the model to prevent an extremely high use of time for each simulation step. This limit is set to 20 seconds. This time limit value is decided with the intention to decrease the total computation time and time needed in the decision stage. Determining this time limit is a trade-off between computation time and time needed to find an optimal value.

4.2 The Cases

In this case study, two different setups will be explored, a deterministic setup and a stochastic setup. The stochastic setup will contain various stochastic data input that will make up two seasonal cases. A deterministic case study has been included to investigate the impact of including wind turbines in different sizes more rapidly. This is because the computation time for the stochastic setup is high and it would be very time consuming to test a high number of instances with this setup. The deterministic case study and its input data is explained in Section 4.2.1 below, while the stochastic case study and the seasonal cases are discussed in Section 4.2.2. The range of sizes tested for wind power and energy storage is specified in these sections.

4.2.1 Deterministic cases

A deterministic setup is used to quickly analyse the behaviour and decision making of the model under specific conditions. This will allow for a more rapid analysis since the computation time for the deterministic setup is considerably lower than for the stochastic setup. This deterministic case study will focus on finding an ideal wind turbine size given the setup and limitations in the system, in addition to studying the model under an extreme scenario.

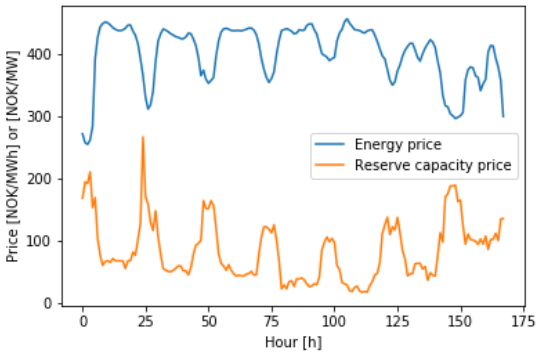
Two tests with different input data will be performed in this deterministic study and each test setup is explained briefly below. Beside the input data described in Section 4.1, other input data used in this deterministic case study is summarised in Table 4.4. These parameters are used in both tests. From this table, it could be noted that many of the input data is the same as for the stochastic setup. However, one key difference is that it is only one scenario because it is a deterministic setup. Furthermore, a low number of periods (10) have been chosen in the simulation phase due to a deterministic nature where the periods are same and thus less periods are needed.

Wind Power and Energy Storage Sizes

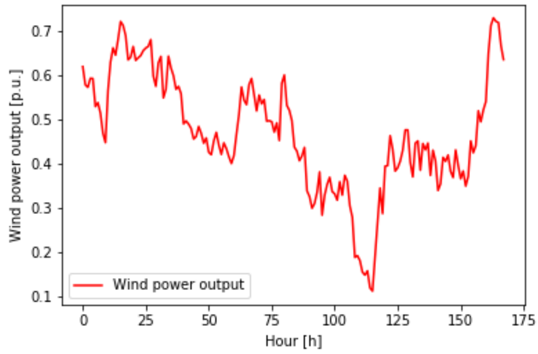
Different wind turbine ratings and with different energy storage capacity will be tested in the deterministic case study, with a focus on analysing the effects of various sizes of wind power in the system. The wind power ratings that are tested are within the range of 500 kW to 2 000 kW, because the wind turbine rating needs to be in line with the other components in the system. A too small wind turbine will not influence the system since it produces an insignificant amount of power most of the time. In the other way, a too large wind turbine would propose problems regarding the disposal of all the produced power since there is a grid transfer limit. When it comes to the storage capacity, four different capacities will be tested in the deterministic test 1, and only one size will be investigated in test 2. Several storage capacities are chosen in test 1 because it is interesting to analyse the cooperation between different storage capacities and different wind power ratings. In test 2, the analysis focuses on the effects from an extreme scenario and thus only one storage capacity is tested since the effects in question are general. The various power ratings and storage capacities used in the deterministic tests are summarised in Table 4.5.

Test 1: Deterministic average autumn data

The deterministic price and wind production input data in this test have been obtained from the average scenario in the autumn season from the stochastic lists and is shown in Figure 4.4. This can thus be considered a seasonal test. The reason for choosing autumn data as input data for this deterministic test is that the reserve capacity price is high compared to the winter season and therefore participation in both markets could be expected. If the reserve capacity price is low, the model may choose to not participate in this market at all. In addition, the wind production is at a midpoint in the autumn which makes this data set good for testing various wind sizes under a ”typical” condition.



(a) The deterministic price data used for test 1.

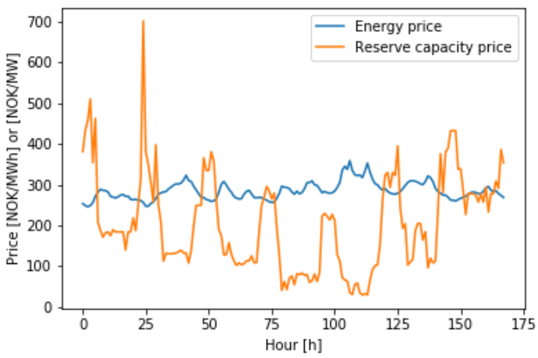


(b) The deterministic wind data used for test 1.

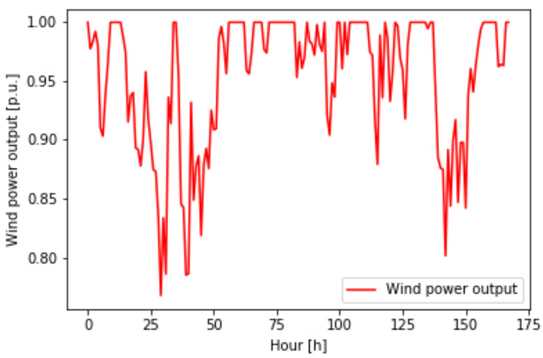
Figure 4.4: The deterministic input data used for test 1.

Test 2: Deterministic data for high wind production

This test is included to study what happens in the system when the conditions for wind power production is very high, in addition to low energy prices and high capacity prices. This is because it could be interesting to see if the model sheds wind power to participate in the capacity market. The data set used in this deterministic test is gathered from various seasons from the stochastic data sets to fit the wanted premises and is shown below in Figure 4.5. The wind data is gathered from the high scenario in the winter case and the energy price is gathered from the low winter scenario. To test the capability of the model when reserve capacity prices are high, the test uses data from the high autumn case with a x1.5 multiplier for reserve capacity prices.



(a) The deterministic price data used for test 2.



(b) The deterministic wind data used for test 2.

Figure 4.5: The deterministic input data used for test 2.

Strategy Phase		**Simulation Phase**	
Parameter	**Value**	**Parameter**	**Value**
Convergence criteria, ΔSV	100	SOC^{Start}	0.5 p.u.
Max iterations	10	Number of periods	10
Number of days	7	Number of days	7
Number of scenarios	1	Number of scenarios	1
Number of storage level segments	22	Number of storage level segments	22
Number of discrete states	154	Time limit	20 s
Time limit	20 s		

Table 4.4: List of the parameters for both tests in the deterministic case study.

	Energy storage capacities tested, B^{max} **[MWh]**	**Wind turbine ratings tested,** $P^{wind,rated}$ **[MW]**
Test 1	1 — 5 — 10 — 15	0.5 — 1.0 — 1.5 — 2.0
Test 2	5	0.5 — 1.0 — 1.5 — 2.0

Table 4.5: List of the different storage capacities and wind turbine ratings that are simulated in the deterministic case study.

4.2.2 Stochastic cases

It is within the stochastic case study where the seasonal cases are analysed more thoroughly with two cases that represent the winter and summer season. These cases have been chosen since the summer and winter season differ quite significantly in both prices and wind production. The cases are solved when only allowed to participate in the energy market, and when participating in both the energy market and the capacity market. In both market cases, the energy system will try to maximise its profit. When participating in only the energy market it does so by taking advantage of the hourly price difference. When participating in both markets the unit must find the preferable strategy in both markets while operating within the system limits. The system could potentially choose to just participate in one market if that gives the highest total profit. The scheduling period is one week in the respective season. Table 4.8 give an overview of some of the parameters used.

Seasonal Stochastic Input Data

The cases reflect their respective season using historical data to create stochastic scenarios. The historical data is from 2018 and 2012. It can be mentioned that this is not a perfect setup since both prices and wind production can vary within the season, which is seen in the figures in Appendix B. When constructing the wind scenarios used in the case study, data from the whole season has been used. While the historical price data used to create price scenarios are more or less from the middle of their respective season. The creation of these scenarios or nodes is described in Section 4.1.6. Table 4.6 summarise which time period of the historical data is used to create the stochastic data.

	Historical price data used	Historical wind data used
Winter case	From 8. January to 4. February, 2018 (4 weeks)	January, February and December of 2012
Summer case	From 9. July to 5. August, 2018 (4 weeks)	June, July and August of 2012

Table 4.6: Overview of the historical data that has been used to create the stochastic data.

The stochastic input data consists of three possible scenarios for energy price, reserve capacity price and wind power production, which make up the possible price and wind nodes. In total, the stochastic input data consists of 27 different stochastic options or nodes for each day. The data which make up these nodes are illustrated in Figure C.1, C.2, and C.3 in Appendix C.

The seasonal differences can clearly be seen from the stochastic input data in Appendix C. For instance, the low scenario for wind production in the summer case is almost constantly on zero production output, while the high scenario for the winter case is most of the time producing at 100 %. Figure C.1 shows the energy price scenarios and it can be noted that the prices are high during the day and low during the night. This is expected since the prices reflect the current power situation and thus the load pattern, as discussed in Section 2.4. To keep this pattern in the stochastic data the approach of taking the average over each individual weekday to create the different scenarios was crucial. Note that from Figure C.2, the capacity prices tend to be higher at the start of the day.

Wind Power and Energy Storage Sizes

Different energy storage capacities will be tested in the stochastic case study while the wind power rating is set to be 1.5 MW. This wind power size is set based on the experiences gathered from the deterministic case study. This power rating may be large when it produces at maximum, but keep in mind that the wind turbine only produces power equal to the rated power output in some time steps when the wind conditions are very good.

The focus for the stochastic seasonal case study is to investigate the interaction between battery and wind turbine under various conditions, and how the energy system participates in the two markets. To accomplish this, different storage capacities have been tested within the range of 1 MWh to 10 MWh. This storage range is suitable for the wanted output of the energy system with a low power:energy ratio. An increase in storage capacity increases the possibility of storing more cheap energy to be sold at a higher price is present. This would also imply that profit increases. However, there are still some limitations in the converter which especially limits the capacity market participation. In theory, the profit increases with additional storage capacity until the capacity reaches an ideal peak capacity for the system. Then, the marginal profit from increasing the storage capacity even further will become zero because of the converter's charge/discharge restriction. The various wind power ratings and storage capacities used in the stochastic case study are summarised in Table 4.7.

Note that it is slightly different from the storage sizes tested in the deterministic study. A 15 MWh battery may be considered too large for this system, but it suited the purpose of analysing the various wind power ratings in cooperation with a very large storage capacity as tested in deterministic test 1. Therefore, the largest storage size tested in this stochastic case study is 10 MWh. Also, a few more capacities are tested in this stochastic study in an attempt to highlight the effects of small changes in the storage capacity. However, the deterministic and stochastic studies are not directly compared and the differences do not pose a problem to the analysis. studies are not directly compared.

	Energy storage capacities tested, B^{max} [MWh]	**Wind turbine ratings tested, $P^{wind,rated}$ [MW]**
Winter	1 — 3 — 5 — 7 — 10	1.5
Summer	1 — 3 — 5 — 7 — 10	1.5

Table 4.7: List of the different storage capacities and wind turbine ratings that are simulated in the stochastic case study.

Strategy Phase		**Simulation Phase**	
Parameter	**Value**	**Parameter**	**Value**
Convergence criteria, ΔSV	100	SOC^{Start}	0.5 p.u.
Max iterations	10	Number of periods	100
Number of days	7	Number of days	7
Number of scenarios	27	Number of scenarios	27
Number of storage level segments	22	Number of storage level segments	22
Number of discrete states	4158	Time limit	20 s
Time limit	20 s		

Table 4.8: List of the parameters that for the stochastic cases.

Chapter 5

Results

5.1 Deterministic Cases

The results from the deterministic case study will be presented separately for each test in Section 5.1.2 and 5.1.3. Information regarding the presentation and setup of these results will be shortly discussed below in Section 5.1.1. Note that the results presented are selected based on the analysis focus in the given case. All strategy phase simulations in the deterministic study converged, usually even within 2-3 iterations and with a low computation time.

5.1.1 Result Setup

Number of figure or table	Information presented	Storage capacities presented [MWh]	Wind power ratings presented [MW]	Single-market and/or multi-market presented
Test 1				
Figure 5.1	Storage values depending on SoC	1 and 5	0.5, 1.0, 1.5 and 2.0	Both E and EC
Figure 5.2	Weekly profit in different markets depending on wind power ratings	1, 5, 10 and 15	0.5, 1.0, 1.5 and 2.0	Both E and EC
Figure 5.3	Wind power utilisation and SoC	5	1.5	Both E and EC
Figure 5.4	Wind power utilisation and SoC	5	2.0	Both E and EC
Test 2				
Figure 5.5	Wind power utilisation and SoC	5	1.0	Both E and EC
Figure 5.6	Wind power utilisation and SoC	5	1.5	Both E and EC

Figure 5.1: An overview of the figures and tables presenting the deterministic results.

The deterministic cases are tested when the model is allowed to participating in both the energy market and the reserve capacity market, and when only allowed to participate in the energy market. In the further chapters, when multi-market operation is possible the results will be labelled with *EC*, and the results from when the model is tested in only the energy market will be labelled with *E*. Thus, this is a way to compare single-market operation (E) to multi-market operation (EC).

To analyse the simulation phase, Figure 5.2 displays the storage values for the various wind power ratings tested in deterministic test 1. These plots represent the storage values for each of the 22 state of charge segments used in the model. Since this is a deterministic setup, the data containing the storage values only have one probability for each SoC segment in each day. To present these results, day one of the scheduling week has been chosen. The storage unit capacity in these plots is 1 MWh and 5 MWh to illustrate a small and medium/large battery. Note that the storage value behaviour is similar for battery sizes of 5-15 MWh.

In test 1, the profits for various wind power ratings are shown for each storage capacity in Figure 5.3. The various profits are obtained from one of the periods tested in the simulation phase when the battery level change is converged and does not change between the periods. Due to the deterministic setup, the output result will be the same for each period after this convergence. In the profit graphs, both the energy market profit and the reserve capacity market profit is included separately, as well as the total energy profit. The total energy profit is the combined profit from both markets. The storage value at the end of the period is not included in the total profit. The presented result is thus the *real* value of the profit throughout the week.

For the deterministic test 1, the wind power usage is shown in Figure 5.4 and 5.5. Both these graphs illustrate the wind production throughout the scheduling week and how much of that available power that is actually used by the energy system. The difference between the maximum wind power output and the wind power used is the wind power shed. Figure 5.4 showcase a system with a 5 MWh storage capacity and 1.5 MW wind power installed, while Figure 5.5 also show a 5 MWh battery but with 2.0 MW wind power. Note that since the purpose of these plots is to highlight the difference in behaviour from installing a high and very high wind power rating, only one storage capacity is shown. In both figures the state of charge for the battery throughout the week is plotted together with the wind production, showcasing the possible connection between battery and storage unit. The two different market participation is plotted separately. In the same way as the profit plots, the various results are obtained from one of the converged periods in the simulation phase.

In test 2, only the wind power plots are displayed. Figure 5.6 showcase a system with a 5 MWh storage capacity and 1.0 MW wind power installed and Figure 5.7 represent a system with 5 MWh storage and 1.5 MW wind power. In the same fashion as for the figures for wind power in test 1, these graphs include the wind power potential, the wind power used and the state of charge. However, the two different market participations (i.e. E and EC) are plotted together.

5.1.2 Test 1: Deterministic average autumn data

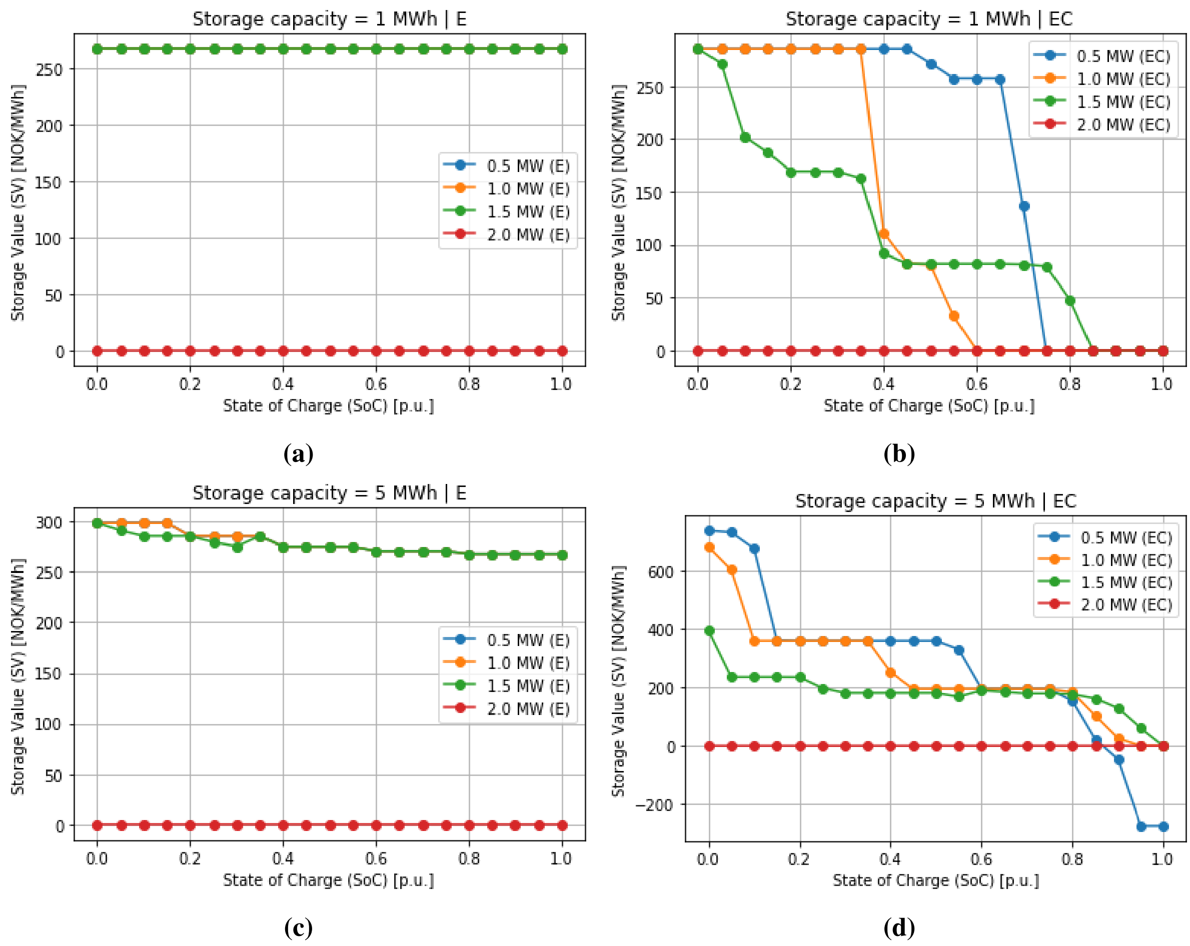


Figure 5.2: Plot of the storage values with respect to the SoC for all wind power ratings when participating in different markets in deterministic test 1. The storage capacity is 1 MWh and 5 MWh. The results are from day one of the scheduling week.

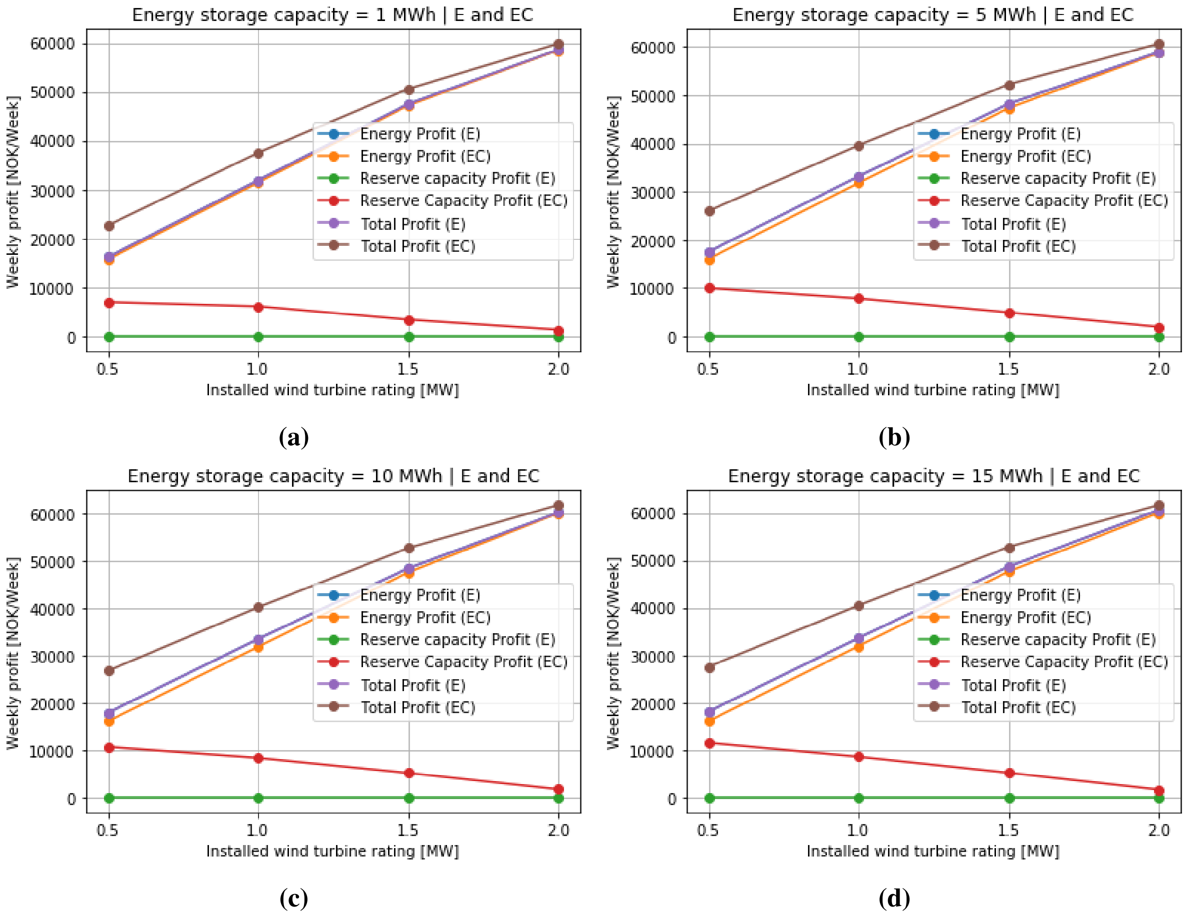
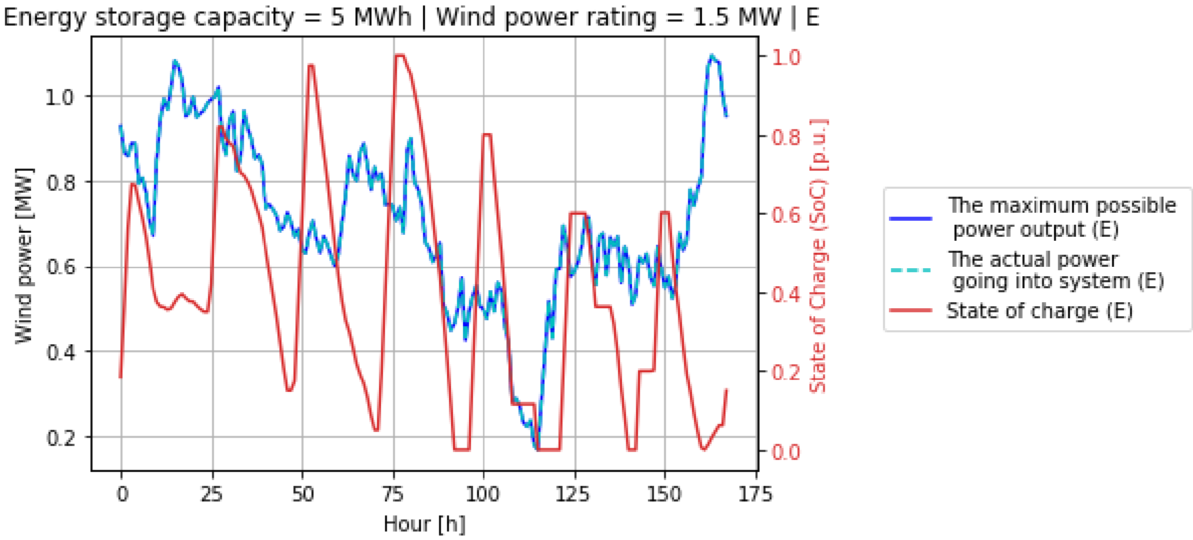
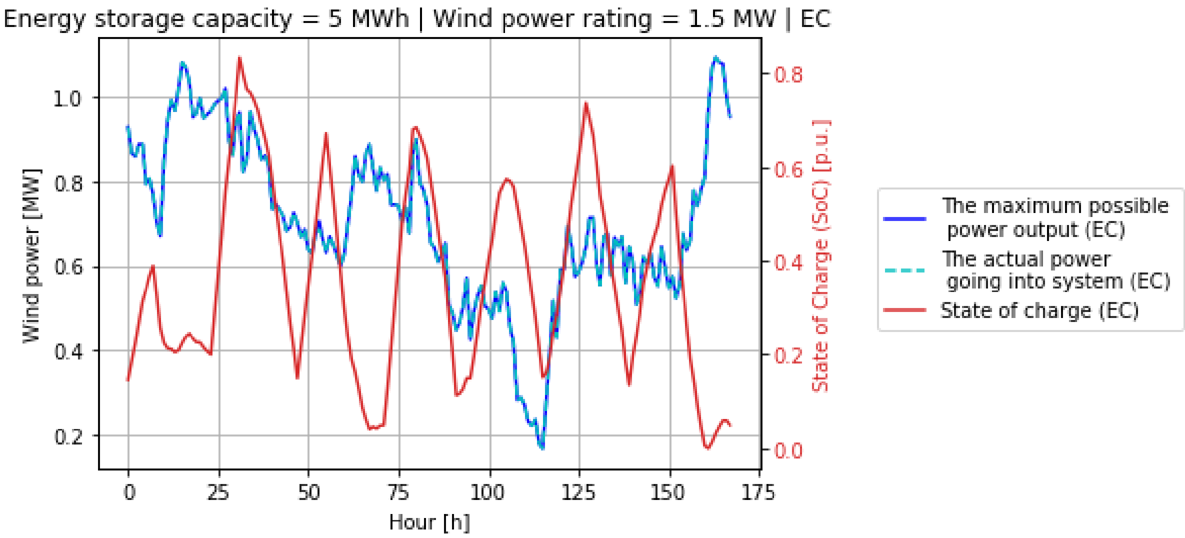


Figure 5.3: Plots of the weekly profit for the different wind power ratings tested for all storage capacities. Includes the energy profit, the reserve capacity profit and the total profit when participating in both markets and only the energy market.

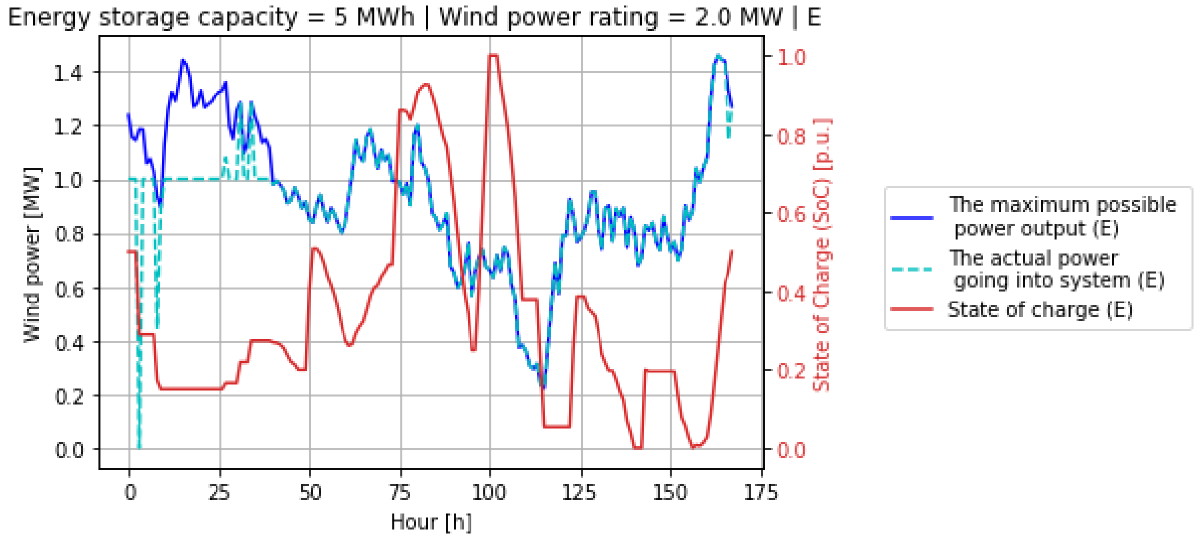


(a) Operating in only the energy market.

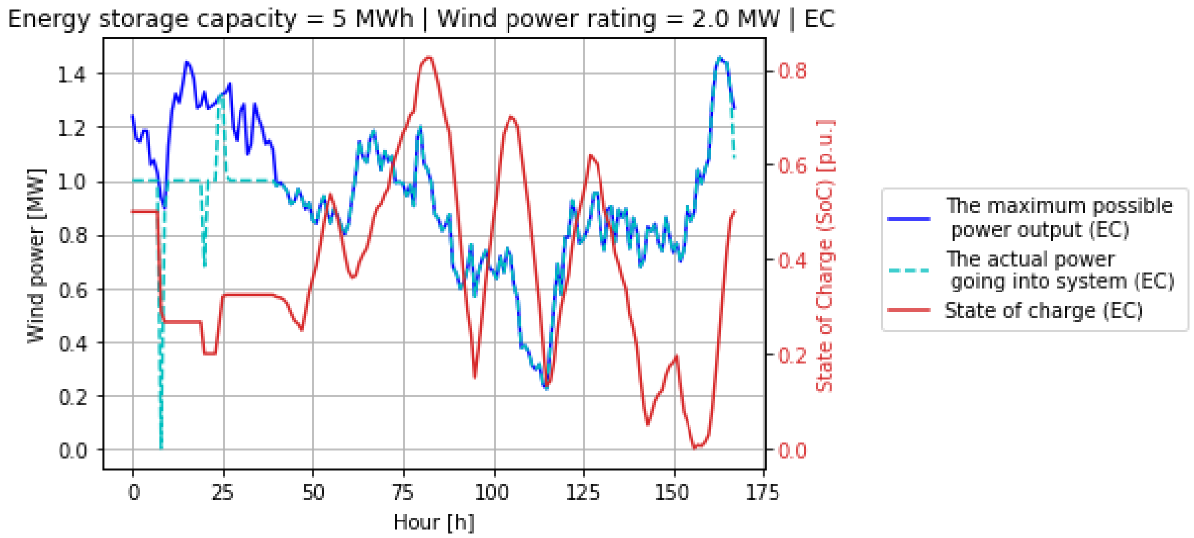


(b) Operating in both markets.

Figure 5.4: Plots of the maximum wind power production and how much of that power that are utilised in the energy system, together with the battery state of charge, throughout the scheduling week. The plots show results for both market participation instances and with 1.5 MW of wind power installed.



(a) Operating in only the energy market.



(b) Operating in both markets.

Figure 5.5: Plots of the maximum wind power production and how much of that power that are utilised in the energy system, together with the battery state of charge, throughout the scheduling week. The plots show results for both market participation instances and with 2.0 MW of wind power installed.

5.1.3 Test 2: Deterministic data for high wind production

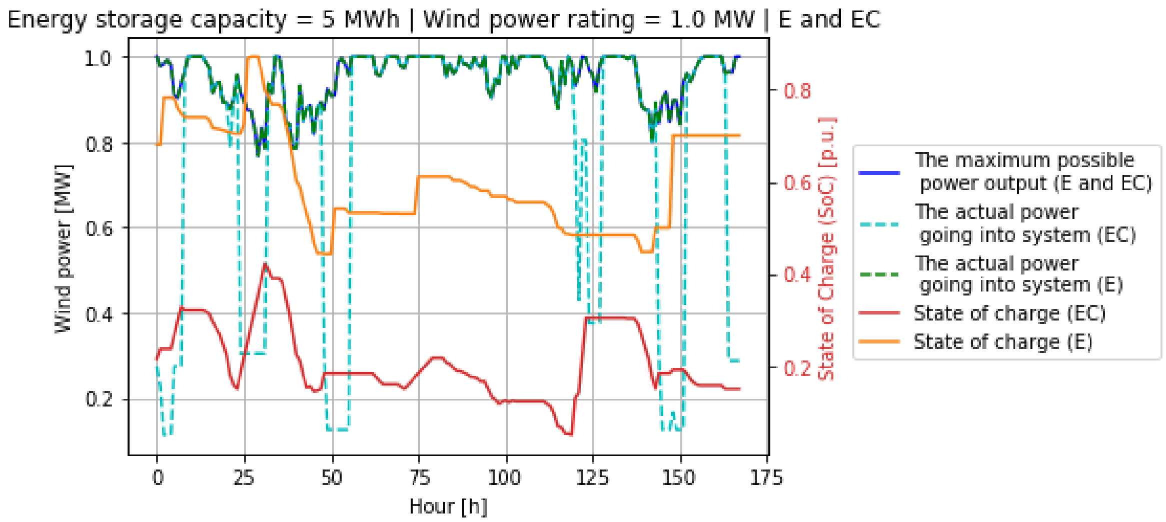


Figure 5.6: Plot of the maximum wind power production and how much of that power that are utilised in the energy system, together with the battery state of charge, throughout the scheduling week. The plots show results for both market participation instances and with 1.0 MW of wind power installed.

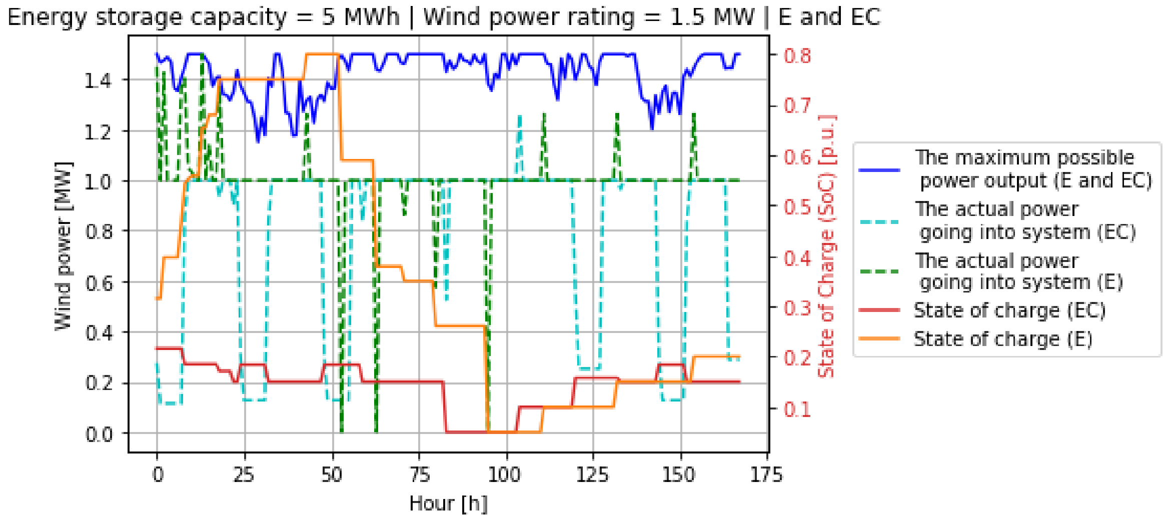


Figure 5.7: Plot of the maximum wind power production and how much of that power that are utilised in the energy system, together with the battery state of charge, throughout the scheduling week. The plots show results for both market participation instances and with 1.5 MW of wind power installed.

5.2 Stochastic Cases

The main profit results from the case study will be presented in Section 5.2.2. Thereafter, the individual results for the winter and summer case will be presented separately in Section 5.2.3 and 5.2.4. Information regarding the presentation and setup of the results will be discussed below in Section 5.2.1. Note that the results presented are selected based on the analysis focus in the given case.

5.2.1 Result Setup

Number of figure or table	Information presented	Storage capacities presented [MWh]	Single-market and/or multi-market presented
Both winter and summer			
Table 5.1	Weekly profit in different markets for both summer and winter case	1, 3, 5, 7 and 10	Both E and EC
Figure 5.7	Weekly profit in different markets for both summer and winter case per MWh of storage	1, 3, 5, 7 and 10	Both E and EC
Winter			
Table 5.2	Strategy phase performance	1, 3, 5, 7 and 10	Both E and EC
Figure 5.8	Storage values depending on SoC	1, 5 and 10	Both E and EC
Figure 5.9	State of charge	1	Both E and EC
Figure 5.10	State of charge	5	Both E and EC
Figure 5.11	Wind power utilisation	1	Only EC
Figure 5.12	Wind power utilisation	5	Only EC
Figure 5.13	Net power exchange	1	Both E and EC
Figure 5.14	Net power exchange	5	Both E and EC
Summer			
Table 5.3	Strategy phase performance	1, 3, 5, 7 and 10	Both E and EC
Figure 5.15	Storage values depending on SoC	1, 5 and 10	Both E and EC
Figure 5.16	State of charge	1	Both E and EC
Figure 5.17	State of charge	5	Both E and EC
Figure 5.18	Wind power utilisation	1	Only EC
Figure 5.19	Net power exchange	1	Both E and EC
Figure 5.20	Net power exchange	5	Both E and EC

Figure 5.8: An overview of the figures and tables presenting the stochastic results.

As for the deterministic cases, the stochastic cases are presented with the label *EC* when multi-market participation is allowed and tested in both the energy market and the reserve capacity market, and when the model is tested in only the energy market it is labelled with *E*. In other words, label *E* means single-market operation and *EC* means multi-market operation.

Table 5.1 in Section 5.2.2 contains the profit results for both season cases. The various profits are obtained through the average result value of the 100 periods tested in the simulation phase. In the table, both the energy market profit and the reserve capacity market profit is included separately, as well as the total energy profit. The total energy profit is the combined profit from both markets. The storage value at the end of the period is not included in the total profit. In addition, the profits per MWh capacity installed have been plotted in Figure 5.9.

In each section containing the individual results, there is a table with technical data about the performance in the strategy phase. This includes Table 5.2 and 5.3. The information in these tables specifies if there was convergence in the simulation, the deviation result between the last iteration, the total number of iterations and the total computation time for that phase.

To analyse the simulation phase, Figure 5.10 and 5.17 present the storage values for some of the storage capacities tested in the winter and summer case. Note that the results for 3 and 7 MWh are excluded from this plot to present it more orderly. However, the storage values for these capacities are similar to the storage values for capacity 5 and 10 MWh. The plots represent the storage values for each of the 22 state of charge segments used in the model. Note that the data output from the simulation phase contains storage values for the 27 probabilities for each storage segment in each day. Therefore, these results are presented using the average storage value from all probabilities for day one of the scheduling week.

Percentile plots are used to present the individual results from the winter and summer case. This is because the stochastic cases are simulated with 100 periods and the results consist thus of 100 individual results for each of these periods. Percentile plots is thus an orderly way to present all these results. The different percentile curves represent the relative standing of a distinct value within the data set containing the value for all 100 periods in every hour. To limit the number of plots, the results presented in percentile plots and described below are obtained with 1 and 5 MWh of storage capacity to represent a small and medium/large battery. Note that the behaviour from a battery size of 3, 7 or 10 MWh strongly resembles the behaviour of a 5 MWh battery.

The battery use is illustrated with percentiles plots for the state of charge for the storage unit throughout the whole operation week. Figure 5.11 and 5.16 present this for the winter case, while Figure 5.18 and 5.19 present the SoC for the summer case. In each figure it is two graphs; one when participating in both markets (EC) and one when only participating in the energy market (E).

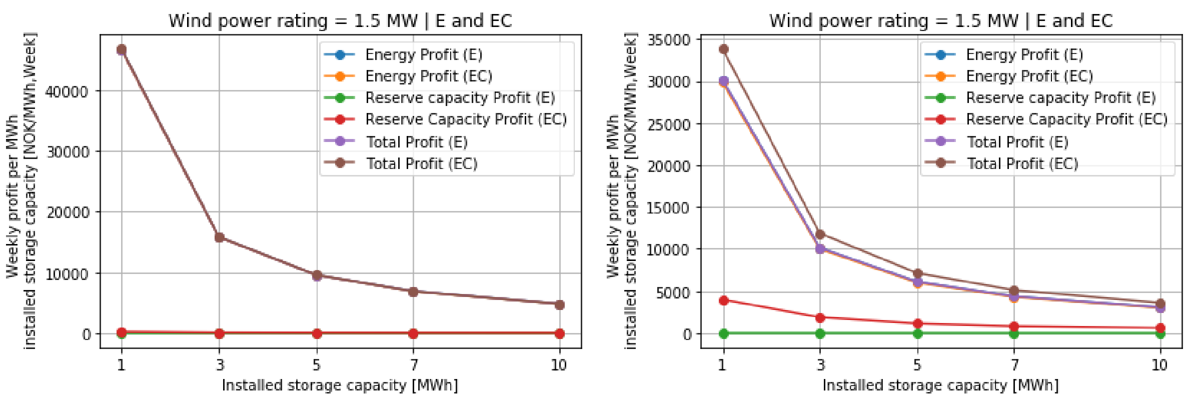
The wind power usage for the winter and summer case is shown in Figure 5.13, 5.14 and 5.20. In all these figures there is one graph illustrating the relative utilisation of the available wind power and one graph showcasing the wind power that is going into the energy system. Both are percentile plots. Note that the wind power shed is the difference between the available wind power and the utilised wind power. For the winter case, storage capacities of 1 MWh and 5 MWh have been presented in 5.13 and 5.14. In the summer case, only 1 MWh have been included in 5.20 since the result does not change significantly with other storage capacities. Note also that only the multi-market operation is presented in these wind power figures since the results from only participating in the energy market is very similar.

The power exchange with the grid, and thus with the energy market, is showcased in Figure 5.15, 5.16, 5.21 and 5.22. This is percentile plots over the power exchange trough the scheduling week for both market participation instances. The results presented in these plots are also gained with 1 and 5 MWh of storage capacity.

5.2.2 Profit Results for Winter and Summer Case

Season Case	Storage Capacity [MWh]	Energy Profit [NOK/Week]	Reserve Capacity Profit [NOK/Week]	Total Profit [NOK/Week]
Winter	1 (E)	46 716	0	46 716
	3 (E)	47 443	0	47 443
	5 (E)	47 737	0	47 737
	7 (E)	48 142	0	48 142
	10 (E)	48 148	0	48 148
	1 (EC)	46 614	195	46 809
	3 (EC)	47 343	191	47 534
	5 (EC)	47 693	162	47 855
	7 (EC)	47 907	131	48 038
	10 (EC)	47 992	120	48 112
Summer	1 (E)	30 120	0	30 120
	3 (E)	30 392	0	30 392
	5 (E)	30 473	0	30 473
	7 (E)	30 501	0	30 501
	10 (E)	30 531	0	30 531
	1 (EC)	29 840	3 979	33 819
	3 (EC)	29 986	5 618	35 604
	5 (EC)	30 000	5 682	35 682
	7 (EC)	30 005	5 704	35 709
	10 (EC)	29 987	5 938	35 925

Table 5.1: The different profits in the winter and summer case.



(a) Winter case **(b)** Summer case

Figure 5.9: Plot of the weekly profit per MWh of storage capacity installed for the winter and summer case. Includes the energy profit, the reserve capacity profit and the total profit when participating in both markets and only the energy market.

5.2.3 Winter Case

Storage capacity [MWh], Market participation	Convergence, Last Deviation	Number of iterations	Total time usage [s]
1 (E)	True, ΔSV = 0.1	2	765
3 (E)	True, ΔSV = 1.9	5	1 919
5 (E)	True, ΔSV = 0.3	3	1 149
7 (E)	True, ΔSV = 7.1	4	1 546
10 (E)	False, ΔSV = 13 314.6	10	3 832
1 (EC)	True, ΔSV = 54.5	2	771
3 (EC)	True, ΔSV = 1.7	3	1 178
5 (EC)	True, ΔSV = 2.6	4	1 558
7 (EC)	True, ΔSV = 1.2	4	1 588
10 (EC)	True, ΔSV = 6.3	4	1 562

Table 5.2: The strategy phase performance for the winter case.

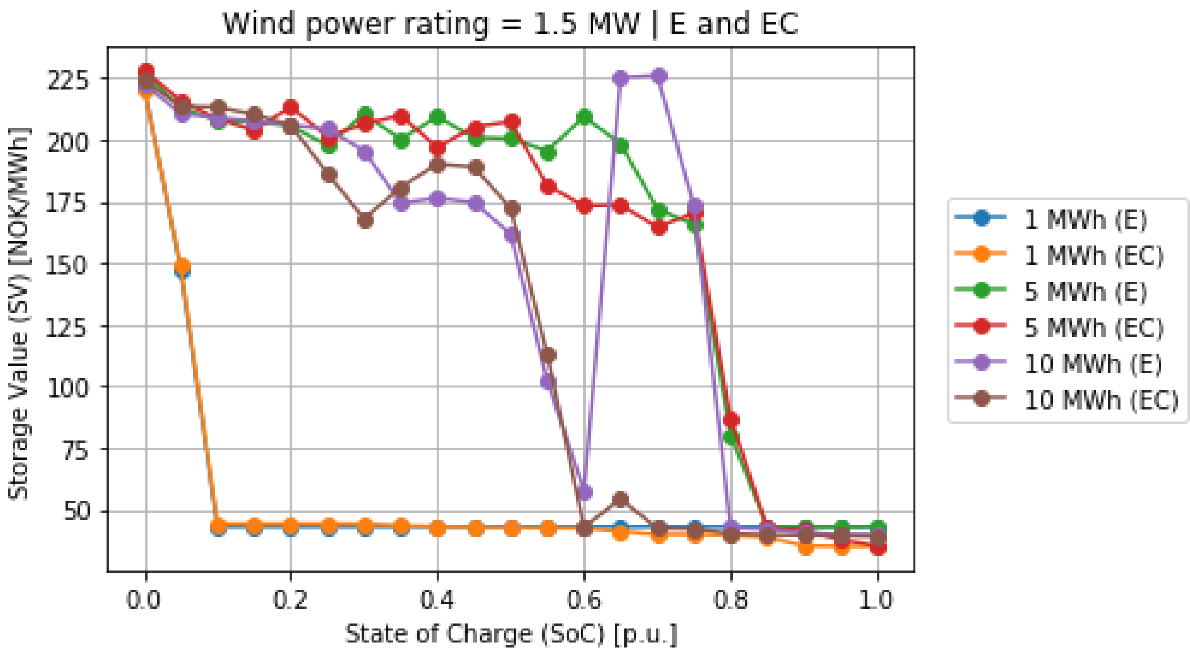
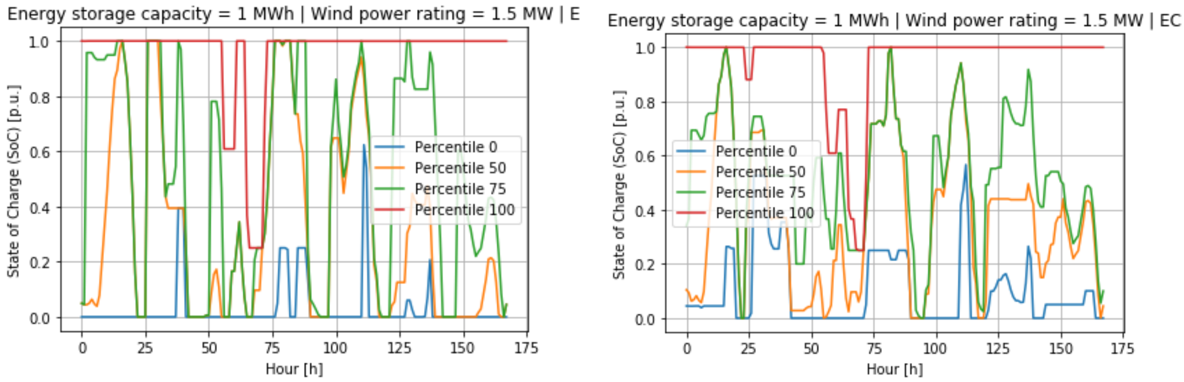
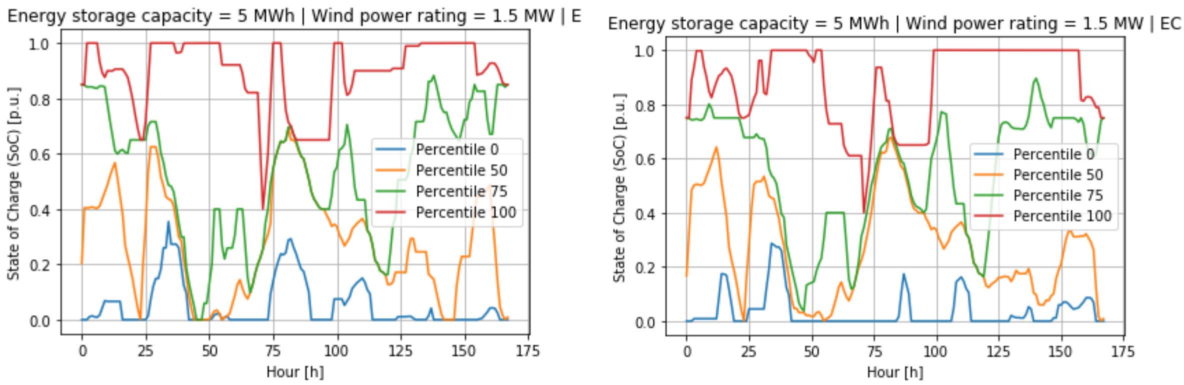


Figure 5.10: Plot of the storage values with respect to the SoC for storage units with all the capacities when participating in different markets in winter case. The results are from day one of the scheduling week.



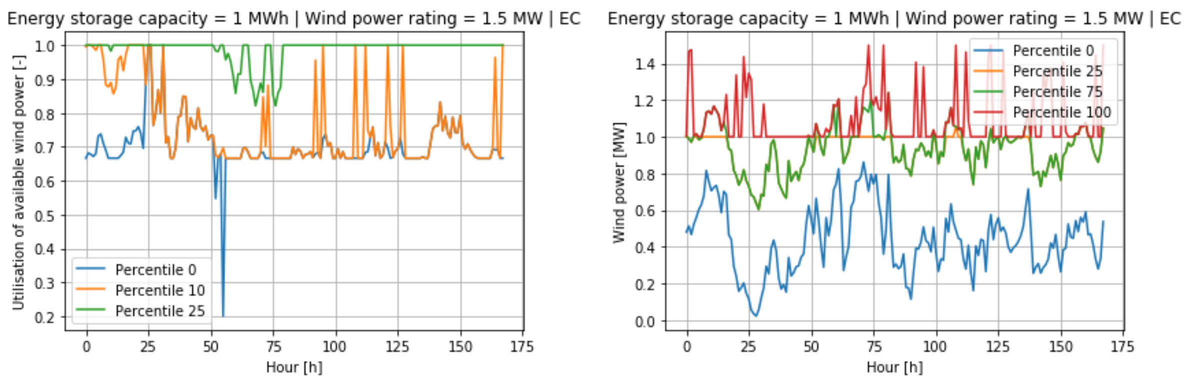
(a) Only the energy market. **(b)** Both markets.

Figure 5.11: Percentile plot of the state of charge throughout the scheduling week in winter case. The presented result are obtained with a 1 MWh storage capacity.



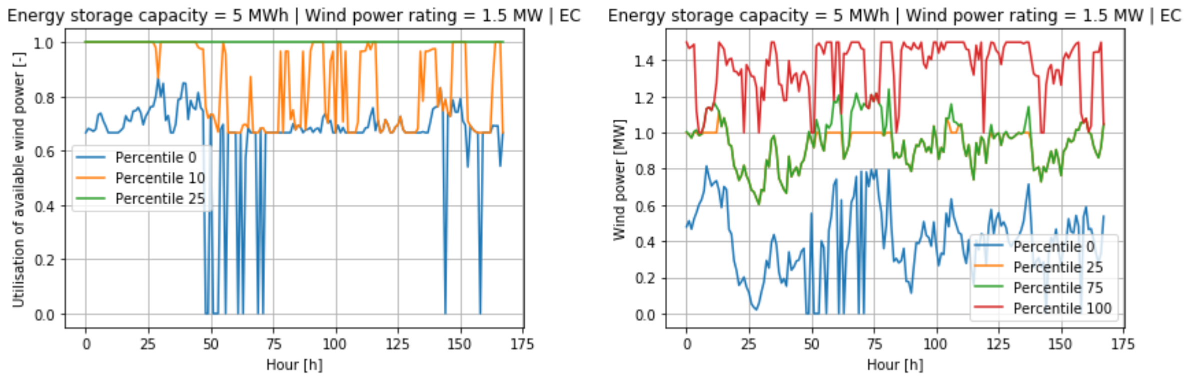
(a) Only the energy market. **(b)** Both markets.

Figure 5.12: Percentile plot of the state of charge throughout the scheduling week in winter case. The presented result are obtained with a 5 MWh storage capacity.



(a) Percentile plot of how much of the available wind power that is utilised. **(b)** Percentile plot of the wind power going into the energy system.

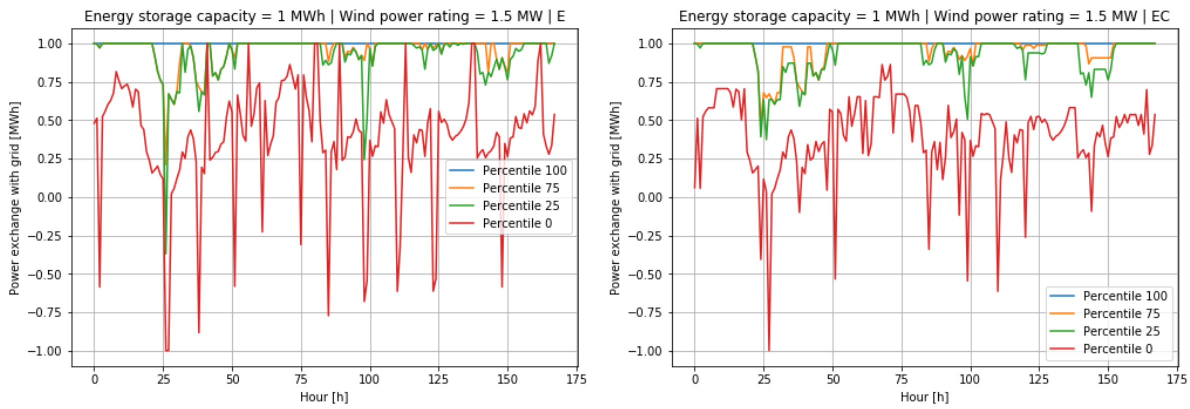
Figure 5.13: Two plots illustrating the wind power use throughout the scheduling week in winter case. The presented result are obtained with participation in both markets and with a 1 MWh storage capacity.



(a) Percentile plot of how much of the available wind power that is utilised.

(b) Percentile plot of the wind power going into the energy system.

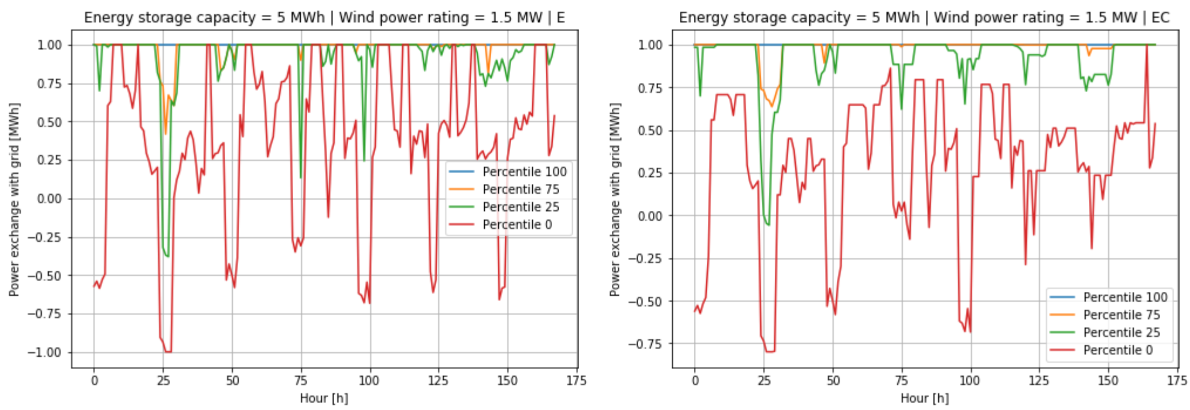
Figure 5.14: Two plots illustrating the wind power use throughout the scheduling week in winter case. The presented result are obtained with participation in both markets and with a 5 MWh storage capacity.



(a) Only energy market.

(b) Both markets.

Figure 5.15: Percentile plot of the power exchange with the grid the scheduling week in winter case. The presented result are obtained with a 1 MWh storage capacity.



(a) Only energy market.

(b) Both markets.

Figure 5.16: Percentile plot of the power exchange with the grid the scheduling week in winter case. The presented result are obtained with a 5 MWh storage capacity.

5.2.4 Summer Case

Storage capacity [MWh], Market participation	Convergence, Last Deviation	Number of iterations	Total time usage [s]
1 (E)	True, ΔSV = 50.1	3	1 142
3 (E)	True, ΔSV = 70.3	3	1 156
5 (E)	True, ΔSV = 4.2	3	1 125
7 (E)	True, ΔSV = 2.6	3	1 150
10 (E)	True, ΔSV = 90.7	3	1 132
1 (EC)	True, ΔSV = 11.4	4	1 522
3 (EC)	True, ΔSV = 6.5	3	1 162
5 (EC)	True, ΔSV = 4.0	3	1 170
7 (EC)	True, ΔSV = 2.9	3	1 202
10 (EC)	True, ΔSV = 4.7	3	1 168

Table 5.3: The strategy phase performance for the summer case.

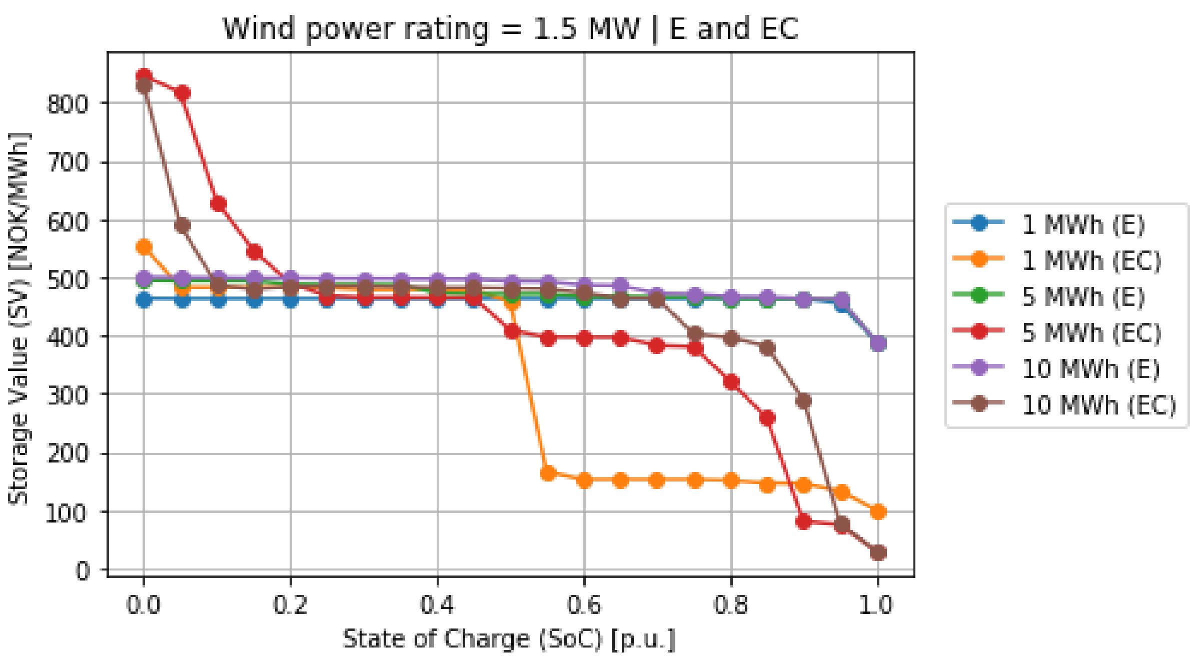
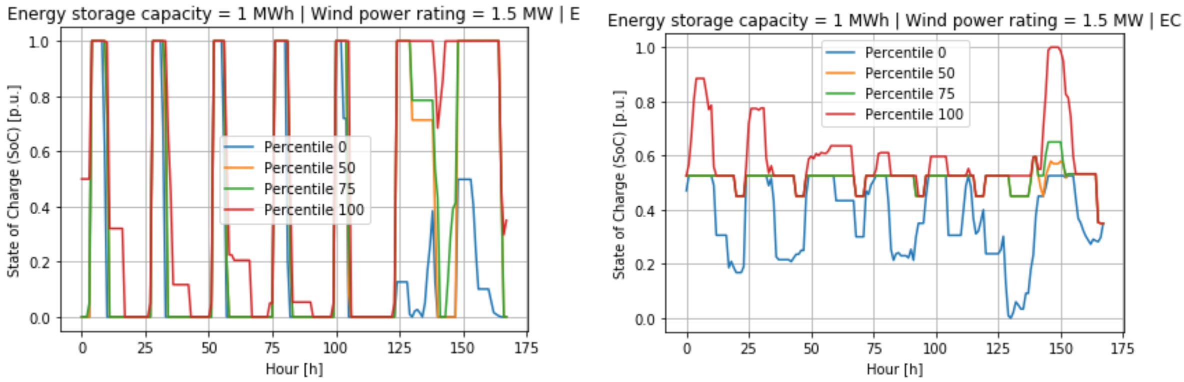


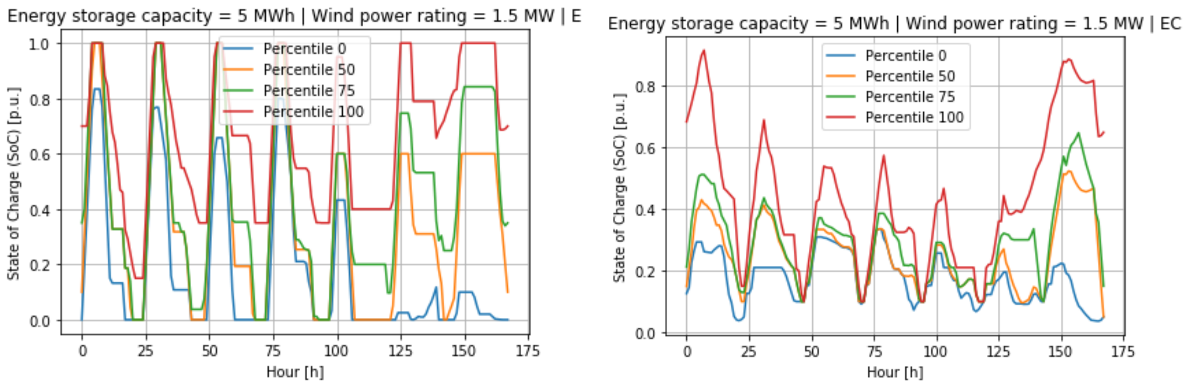
Figure 5.17: Plot of the storage values with respect to the SoC for storage units with all the capacities when participating in different markets in summer case. The results are from day one of the scheduling week.



(a) Only the energy market.

(b) Both markets.

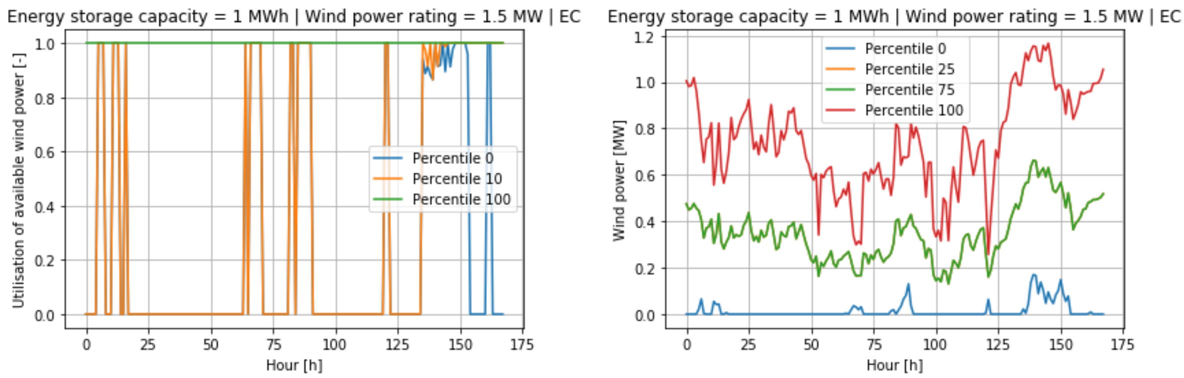
Figure 5.18: Percentile plot of the state of charge throughout the scheduling week in summer case. The presented result are obtained with a 1 MWh storage capacity.



(a) Only the energy market.

(b) Both markets.

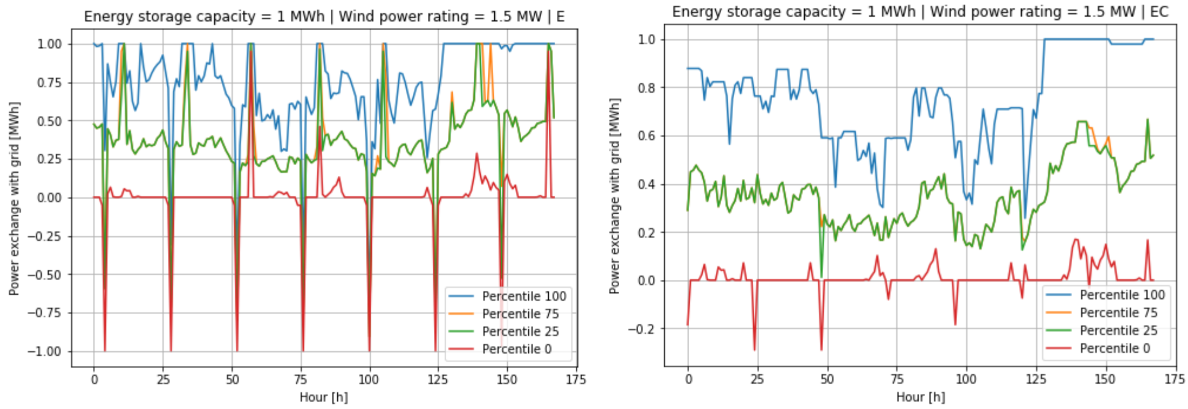
Figure 5.19: Percentile plot of the state of charge throughout the scheduling week in summer case. The presented result are obtained with a 5 MWh storage capacity.



(a) Percentile plot of how much of the available wind power that is utilised.

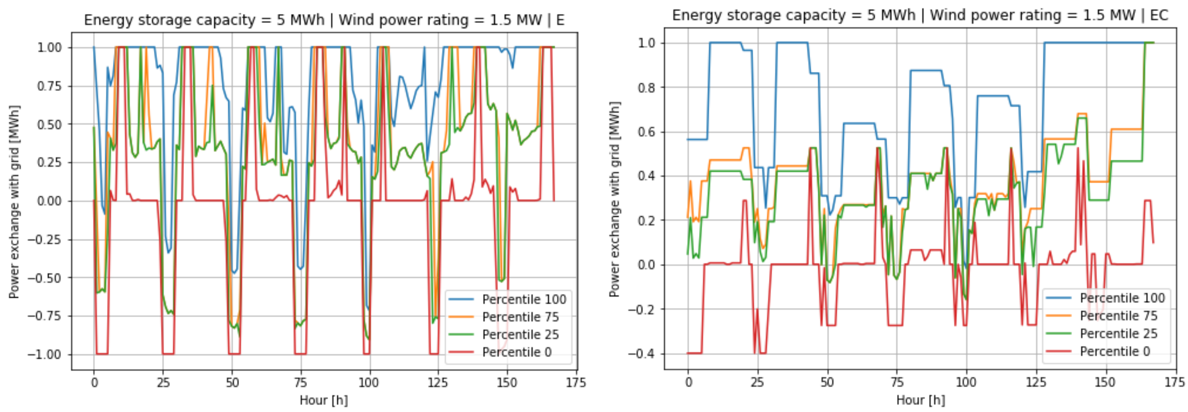
(b) Percentile plot of the wind power going into the energy system.

Figure 5.20: Two plots illustrating the wind power use throughout the scheduling week in summer case. The presented result are obtained with participation in both markets and with a 1 MWh storage capacity.



(a) Only energy market. **(b)** Both markets.

Figure 5.21: Percentile plot of the power exchange with the grid the scheduling week in summer case. The presented result are obtained with a 1 MWh storage capacity.



(a) Only energy market. **(b)** Both markets.

Figure 5.22: Percentile plot of the power exchange with the grid the scheduling week in summer case. The presented result are obtained with a 5 MWh storage capacity.

Chapter 6

Analysis of the Results

In this chapter, the results from both the strategy phase and simulation phase presented in Chapter 5 will be discussed. The deterministic case study will firstly be discussed individually for test 1 and test 2 in Section 6.1 and 6.2. Thereafter, an overall discussion about the deterministic results will take place in Section 6.3. The individual results from each stochastic seasonal case will be examined in Section 6.4 and 6.5, followed by an overall discussion in Section 6.6.

6.1 Deterministic Case Study: Test 1

The focus in this deterministic test is the behaviour and profit impact the different wind turbine sizes and storage capacity sizes have under in a relatively normal autumn conditions.

Figure 5.2 shows a clear difference in storage value when having a 1 MWh storage unit compared to a large one at 5 MWh. When the storage capacity is only 1 MWh and the system is only operating in the energy market, the storage value for all wind power ratings except 2.0 MW is around 270 NOK/MWh. This is slightly over the minimum value for the energy price the first day in the data set used in this deterministic value. It seems like the model sets the storage value to around the minimum profit it could obtain in the energy market that day regardless of the state of charge. In the Plot 5.2c, where the storage capacity is 5 MWh, it could also be seen a linear storage value curve going from around 300 NOK/MWh and decreasing to around the same value as for the 1 MWh capacity. A steeper decrease in the storage value when the storage level fills up was expected since the known pattern from hydropower optimisation is that the storage value is high when the storage unit is nearly empty and when the storage unit is close to full it is low. However, in this deterministic setup, the state of charge has a low impact on the storage level when only operating in the energy market.

When introducing both markets, plotted in Figure 5.2b and 5.2d, another pattern emerges. Here, the storage value starts off high before decreasing around a state of charge of 20 %. It finds a more stable value between a state of charge of 20 % and 80 %, before dropping towards zero around 80 % SoC. This is due to there being less capacity to participate in the reserve capacity market with when the battery is nearly full and thus causes a low storage value. One could expect the storage unit to not operate much within this state of charge range because of the low storage value.

Another very interesting aspect is the negative storage value obtained in Figure 5.2d. Here, the storage value becomes negative when the battery is nearly full. This only happens when the wind power rating is 0.5 MW, meaning a small wind turbine is installed. In this case, the model deems it very unprofitable to store energy when the state of charge is above 80 % - 90 %. This is because filling the battery up completely ruin the possibility to participate in the reserve capacity market since the battery must contribute with both up- and down-regulating. Hence, it undermines the possibility to earn a profit in that market without making up for the lost profit in the energy market.

Note that the wind power rating has little or no impact on the storage value when operating in just the energy market. When operating in both markets, a high wind power rating seems to give a lower storage value. This is because when the wind power rating increases the wind production also increases, causing the energy system to make less use of the storage unit. Since energy is abundant in high wind situations the system focuses on getting rid of all the energy by selling it. Furthermore, note that the storage value is zero when the installed wind power is 2.0 MW. The reason for this is that the wind production is very high in this situation and causes the system to sell all possible energy and shed the rest. When much power is shedded, the storage value is of no use to the model causing the value to be zero.

When analysing Figure 5.3, it can clearly be seen that the installed wind power size has a huge effect on the profit. The profit seems to increase with around 12 000 - 13 000 NOK per every 0.5 MW of wind power installed. One could see that the profit increase becomes a bit lower when the wind power rating reaches 2.0 MW. This is because the wind turbine becomes so large that it produces excess power in some time steps and thus must shed power or potentially store it in the battery if there is enough capacity. Since there is a limit on the power transfer to the grid, there exists a trade-off between installing a large wind turbine which utilise the wind potential better in gaining more power output and thus increase the need of power shed when the wind production becomes too high, or installing a smaller wind turbine that never produces so much power that it needs to shed. An ideal wind turbine size would utilise the wind potential to an optimum while reducing the wind power shed throughout the year to a minimum. Seen from the results in Figure 5.3, a 2.0 MW wind turbine may be a bit large considering the limits the energy system face. Especially, when wind production is high, such as in the winter, the power shed would become very high.

It could also be seen from Figure 5.3 that the profit does not change notably with higher storage capacity, at least not relative to the profit increase by installing a larger wind turbine. A small profit increase in the reserve capacity market can be seen when increasing the storage from 1 MWh to 3 MWh. Note also that with a larger wind turbine the energy system participates less in the reserve capacity market. The reason for this is that the transfer capacity is used to sell more wind power as the wind turbine size increases and thus the capacity available for the reserve capacity market decreases.

In Figure 5.4 the available wind power and the utilised wind power are plotted with a wind power rating of 1.5 MW. Here, it could be seen that the wind power going into the system always match the available wind power. This means that in this case, the energy system utilises all the wind power production, i.e. there is no wind power shed. This is true for both the instance when participating in only the energy market and when participating in both markets, seen in

Figure 5.4a and 5.4b. Considering the state of charge in these figures, it is clear that they follow a cyclic pattern. The battery charges in the nighttime and discharges in the day. This is because of the price variation. Since the energy prices are higher at the daytime, the model will try to save as much power for that time as possible and sell less in cheaper periods. In both figures, and especially Figure 5.4a, it can be seen that slightly less power is going into the battery in time periods when there is less wind power available. The battery is also charged to a higher state of charge when the system only participates in the energy market. This is due to the low storage value when reaching a high state of charge when participating in both markets as explained in the paragraph about storage values above.

When investigating a system with a large wind turbine on 2.0 MW, shown in Figure 5.5, it becomes clear that the battery operates less cyclic. There is a less obvious cyclic pattern of when the battery charges and discharges, as seen in the state of charge. When the wind production decreases a bit between hour 75 and hour 125, the cyclic pattern becomes more visible. This gives the idea of the model being less interested in using the battery when energy is abundant. Note also, that at the beginning of the scheduling week the model sheds wind power. The maximum wind power that can go into the system is around 1 MW, but this could be higher than 1 MW in small sequences because the energy could be used to charge the battery. However, the model will not use the storage possibility if it does not see it as profitable.

6.2 Deterministic Case Study: Test 2

In this deterministic test, a data set with high wind production and high peak values for reserve capacity has been used. This is done because it is interesting to study the model under certain extreme scenarios.

From Figure 5.6 it could be seen that the utilised wind power closely match the total available wind power when the installed wind power is 1 MW even though the wind production is very high. The energy system uses all available wind power when only participating in the energy market. The state of charge for this instance does also resemble some of the patterns seen in Figure 5.4 when the wind input is high and around 1 MW. The battery is not used very actively, with a low degree of charging and discharging. It is more or less on standby with a more stable energy level. When participating in both markets in Figure 5.6, it could be seen that in some periods the model choose to shed power. The reason for this is the high reserve capacity prices. In Figure 4.5, which illustrate the wind and price data used in deterministic test 2, one could see that the periods with higher capacity price than energy price match the time steps which the model chooses to shed power in Figure 5.6. This causes the assumption that the model sheds power to participate in the capacity market when this price exceeds the energy price. Since the energy system has access to ”free” energy from the wind turbine, the profit is not made from the surplus when buying in cheap periods and selling in more expensive periods. The profit equals the given energy price in the time step which the wind power is produced and sold, unless it is stored for later purposes. Therefore, to outperform the energy profit and actively using the available transfer capacity in the reserve capacity market instead, the prices must exceed those in the energy market. One could also see that the state of charge is at a generally lower level when participating in both markets and around 30-40 % in the time steps where the capacity market is prioritised. When the storage is used for up- and down-regulating, the state of charge should ideally not be too high or too low.

Many of the same aspects discussed in the paragraph above could also be seen in Figure 5.7. One key difference is that even though the available wind power is constantly higher than 1 MW, the utilised wind power is generally at 1 MW. In some very short moments when operating in only the energy market, the utilised wind power exceeds 1 MW. In those time steps the storage unit is charged, as could be seen by the state of charge increase around those time steps. However, when operating in both markets this rarely occurs.

6.3 Overall Deterministic Case Study Analysis

Key findings in the deterministic case study:

- An increase in wind turbine size leads to a significant increase in profit.
- To minimise power shed and maximise profit a 1.5 MW turbine is considered ideal for this system.
- An increase in wind power size and thus wind power production decreases the multi-market operation. In other words, the model prioritises the transfer capacity for the energy market when there is much wind power available.
- The model will only prioritise the reserve capacity market over the energy market when the reserve capacity price is higher than the energy price.

After analysing the deterministic case results it could be stated that the wind power rating has a huge effect on the total profit. This makes sense since a wind turbine is a source for ”free” power, which can be sold at market price for a profit. A larger wind turbine would give better utilisation of the wind potential and thus more wind power to sell. However, since the system defined in this thesis have transfer limitation, the increase in wind power installed reaches a point where wind power is shedded and thus reduces the marginal revenue by increasing the size further. The maximum wind power input to the system is 1 MW, apart from a few time steps it can be higher due to energy being stored in the battery. If installing a wind turbine at 2.0 MW, one produces 1 MW power when the wind production output is 0.5 p.u. From Figure C.3, which illustrates a few wind scenarios for the different seasons, it could be stated that there would be power shedding in at least the winter, spring and autumn season when having a wind power rating of 2.0 MW. If the installed wind turbine is 1.5 MW, the turbine would produce 1 MW at 0.67 p.u. power output. This would cause some power shed in the winter season, but likely avoid it most of the time in the other seasons. Keep in mind that it is very few moments throughout the year where the wind turbine produces at 1 p.u.

Based on this discussion the wind power rating tested in the stochastic case study is 1.5 MW. Then, some wind power shedding is expected, but a high utilisation of the potential is also fulfilled. When sizing a wind turbine in real life, investment and maintenance cost must be taken into consideration. However, for the scope of this thesis, the focus is on potential profits and not the costs.

When considering the multi-market performance, the operation in the markets depends heavily on the installed wind power size. It can be seen from Figure 5.3 that when a small wind turbine is installed the energy system participate more equal in the two markets. Although, an increase in wind power rating decreases the participation in the reserve capacity market. A small wind turbine of 0.5 MW will not produce enough power to cover all of the transfer capacity and thus some could be used in the reserve capacity market. If a large wind turbine of 2.0 MW is installed, the energy system prioritises almost solely the energy market. A larger turbine leads to more wind power being sold to the energy market and thus less transfer capacity is available to be used in the reserve capacity market. This verifies the fact that it is more profitable to sell wind power in the energy market instead of using the transfer capacity in the capacity market as long as the energy prices are higher than the reserve capacity prices. If the reserve capacity prices are higher than the energy prices, it can be seen from test 2 that the system sheds wind power because the transfer capacity is rather used in the regulating market.

6.4 Stochastic Case Study: Winter Case

In Section 5.2.2, it is clearly shown that the winter case chooses to operate in the energy market even though it has the opportunity to also participate in the reserve capacity market. This result was expected due to the high wind production and relatively low reserve capacity prices, but the difference in profit is so large that the reserve capacity profit basically is insignificant in this case. Another interesting aspect is that the profit does not increase significantly when increasing storage capacity. When increasing the storage capacity from 1 MWh to 10 MWh the profit increases with only 3 %. This means that it is not very beneficial to install a large battery in this energy system when it mainly operates in the energy market. The converter capacity has probably limited the benefit of installing a large battery.

One instance failed to converge in the winter case, as illustrated in Table 5.2. This was the instance with a 10 MWh storage capacity and only operating in the energy market. The last deviation was considerably high and with a detailed look at the results, it can be seen that the iteration deviation loops with this deviation value for almost all iterations. Such an incident could sometimes occur because the model cannot find a better solution and each iteration will thus have the same deviation, creating a loop. All other instances converged in a fairly low number of iterations for all the various capacities. The computation time was therefore kept fairly low. It should be mentioned that when convergence is not obtained, the results for this instance become more invalid, especially when the deviation is so large as in the 10 MWh (E) instance. The effects a non-convergence have on the results can be seen in Figure 5.10, as this instance has a peculiar peak at a high state of charge that does not make much sense.

Analysing Figure 5.10 it could be seen that the storage value for operating in only the energy market and for operating in both markets are very similar for each storage capacity. However, this is to be expected since the model almost only operate in the energy market, as seen in Section 5.2.2. The general pattern is that the storage value start of high and slowly decreases before it suddenly drops to a much lower value when reaching a high state of charge. It could be seen that the storage value drops earlier when a large storage capacity is installed. With a 10 MWh battery, the storage value drops around 50 % SoC, while with a 5 MWh battery the storage value does not drop until 80 %. This means that the model deems it less valuable to use all of the capacity of a large battery. It could also be seen that the storage value for the 1 MWh capacity behaves differently. It drops very quickly, making the value of storing energy low for almost all state of charge.

In Figure 5.11, the state of charge of a 1 MWh storage unit is plotted in a percentile plot. Figure 5.11a illustrates the instance when the energy system only operates in the energy market. Here, it can be seen that the 50th and 75th percentile curve behave cyclically going from around an empty battery to a full battery. This means that many of the scenarios cyclically charge and discharge the battery. An interesting aspect is that the battery seems to charge and discharge based on wind production, and not strongly depend on the price variations. For instance, in all plots in Figure 5.11 and 5.12 a drop in state of charge can be seen from hour 50 to 75. In these hours, there is also a significant wind production and some power shedding, as seen in Figure 5.13 and 5.14. This means that when the wind production gets high the battery is used less. A possible reason for this is that the model prepares itself for high wind production by having sufficient storage capacity available. It should also be mentioned that the charge-peaks tend to appear in the hours that make up the start of the day, which contribute to the fact that the energy price influences the charge/discharge cycle.

When introducing a large battery, such as a 5 MWh unit in Figure 5.12, it becomes clear that the full battery capacity is rarely used. In 50 percent of the periods, seen by the 50th percentile curve, the state of charge seldom reaches 50 %. This point in the direction of not having an increased profit in the system when having additional storage capacity. It can also be noted that the is a high similarity in state of charge between operating in only the energy market and in both markets when large storage capacity is installed. This is due to the model operating almost exclusively in the energy market even though it could trade in the reserve capacity market. In both Figure 5.12a and 5.12b, a more stable charge/discharge pattern can be seen. There are less charge/discharge peaks, meaning the battery is used less actively in market competition, but more for long term storage in case of lower wind production.

The wind production and wind power utilisation is illustrated in Figure 5.13 and 5.14. The plots include only the instances with multi-market participation since the model heavily priorities the energy market and thus the plots for only energy market participation is almost the same. In Figure 5.13a and 5.14a, the wind power used in the system are almost always all of the available wind power from the turbine. When the 25th percentile curve lies at a utilisation rate of 1, this means that at least 75 of 100 periods used the maximum available wind power. Note that in approximately 10 % of the periods there is power shed. This may be in scenarios where wind production is extra high. Note also that in Figure 5.13a, there is power shed between hour 50 and 75 which do not occur in Figure 5.14a. In this period it is very high wind production in many scenarios, but when only a 1 MWh storage unit is installed as in Figure 5.13a, some of the power cannot be sold or stored due to limited capacity. With a larger storage capacity, as in Figure 5.14, more wind power is used in the system due to the possibility to store more energy. Note that some scenarios shed all available wind power in Figure 5.14a between hour 50 and 75, because the model empty out the battery also seen in this period in Figure 5.12b. The reason is that the battery wants to have available storage capacity for a potentially long period of high wind production.

Many of the already discussed aspects are also showcased in Figure 5.15 and 5.16. These plots show the net exchange with the grid and thus the energy market. From both these figures, a general trend can be seen; when the energy price is low there is less power sold to the market. These time periods tend to be at the start of the day. In the periods simulated, it can be seen that drops in exported energy means that the battery is charged. The energy system even buys power from the grid to fill up the storage capacity in some time steps. Note that the drops in exported power are longer in Figure 5.16 since a large battery is installed. The drops in exported power is slightly less frequent and significant when operating in both markets, seen in Figure 5.15b and 5.16b. This may suggest a less use of the battery in the energy market. Despite the exception of a few drops in exported power, the model prefers to maximise its power export by selling 1 MWh in most of the time steps in a very high percentage of the periods.

6.5 Stochastic Case Study: Summer Case

Table 5.1 in Section 5.2.2 gives a overview of the profits gained in the summer case. It can be seen that the energy system clearly increases profit in participating in both markets. The profit increase by operating in both markets is 12-18 % depending on the storage capacity. The profit benefit by installing a large storage unit versus a small is very insignificant when only participating in the energy market. This was also pointed out in the discussion about the winter results in Section 6.4. However, when participating in both markets the profit rises with 5 % by increasing the storage capacity from 1 MWh to 3 MWh. Thereafter, the profit benefit by increasing the capacity further is very small. Note that the gain in profit solely comes from the reserve capacity market.

All the instances tested in the summer case converged, as shown in Table 5.2. Furthermore, all instances converged within four iterations or less. This made sure that the computation time was relatively low. Since all instances converged at such few iterations and the deviation in these instances is low, a stricter converge criterion could be beneficial without increasing the computing time or making convergence more unlikely.

Some of the results from the strategy phase are showcased in the storage value plot in Figure 5.17 and from this a distinct pattern can be seen for both market operations cases. When participating in both markets the storage value starts at a high value before dropping to a lower value when the state of charge reaches around 10 %. However, this is less evident for the 1 MWh capacity. The value then drops even further when the state of charge is in the area of 50 to 90 % depending on the storage capacity. A large storage capacity will have the steady middle storage value for a longer state of charge range. The reason for the step-wise drops in storage value when engaging in both markets is because the storage system deems it valuable to store some energy in the battery which it can use in the capacity market. When the battery is empty, it is very valuable to store some energy so it can contribute with both up- and down-regulating and also contribute with regulation at the start of the next day. When the battery gets to full, the opportunity to participate in the capacity market decreases and thus also the storage value. When only participating in the energy market the storage value is stable and decrease very slowly before it has a small drop at the last state of charge. The storage value for these instances is approximately 500 NOK/Week most of the states. This is also the average energy price for the data set used.

Figure 5.18 and 5.19 shows the state of charge plotted in a percentile plot for 1 MWh and 5 MWh storage units. When trading in the energy market alone the state of charge have a predictable charge/discharge cycle, which can be seen in both Figure 5.18a and 5.19a. It charges in the nighttime and discharges in the day, which makes it charge when the price is low and discharge when the price is high. This makes the state of charge heavily dependant on the energy price variations. Note that close to all the periods simulated take more or less the same decisions. When having a battery of 1 MWh, which is expressed with the 0th and 100th percentile curves. With a battery of 5 MWh, it can be seen that the full storage capacity is less frequently used. Note also the disarray at the end of the scheduling week. This could be due to a sudden increase in wind production seen in Figure 5.20.

Trading in both markets, as showcased in Figure 5.18b and 5.19b, the state of charge is more even and behave less cyclic for nearly all scenarios. This is because the battery capacity is used in the reserve capacity market. Having a 1 MWh capacity installed, the state of charge tend to centre around 50 % for most of the scenarios. This is the optimal value for up- and down-regulating when having such capacity size. The state of charge tends to fluctuate around 20-30 % when having a 5 MWh battery. This means it can contribute with 1 MW up- and down-regulating which is the maximum capacity it could sell due to other limitations.

To showcase the wind production and utilisation, only the instance with 1 MWh storage capacity and multi-market participation is shown in Figure 5.20. This is because wind power utilised is basically independent of the storage capacity and market participation in this case. As seen in Figure 5.20a, the utilisation degree is almost always at 1 (i.e. full utilisation). However, some drops to zero utilisation can be seen. This is due to the low wind production scenario in the summer case where close to no wind power is produced. This could be seen in the data set used for this case in Figure C.3. One could see from Figure 5.20b that the wind power going into the system very seldom venture over 1 MW. The model wants to use all of the available wind power since there is not an abundance of this resource in this season.

In Figure 5.21a and 5.22a the usage of the energy price variation is showcased through the net exchange with the grid. When the energy price is low there is less power sold to the market and in many scenarios power is even bought from the market in these periods. Then the energy system could export more power in the expensive periods. When participating in both markets, the exchange with the grid is different. In Figure 5.21b where 1 MWh capacity is installed, the net power exchange tend to follow the wind production very closely. The reason for this is that the available wind power is just sold immediately and the rest of transmission capacity is used in the reserve capacity market. Since the battery is relatively small, nearly all of the battery capacity is used in the capacity market. When larger storage capacity is installed, such as in Figure 5.22b, the energy price utilisation appears slightly. This means that the battery is large enough to participate in the reserve capacity market and at the same time used to exploit the energy price variations. Note that this makes the net exchange less fluctuating since the curves are more smooth.

6.6 Overall Stochastic Case Study Analysis

Key findings in the stochastic case study:

- Most or all of the profit in both seasonal cases are earned by selling wind power in the energy market.
- High wind production leads to high or solely participation in the energy market and thus strengthening the fact that an increase in wind power production decreases the multi-market operation.
- Low wind production leads to participation in both markets.
- A storage capacity above 1 MWh does not lead to a significant profit increase in the energy market.
- A storage capacity of 3 MWh is considered ideal when participating in the reserve capacity market.

A clear difference between the winter and summer case can be seen in both profit and behaviour. In the winter case, the wind production is high and the reserve capacity price is low. This lead to a close to zero participation in the reserve capacity market, while the high profits are solely obtained in the energy market. In the summer case, wind production is low, and the capacity price is relatively high. This leads to participation in both markets, even though the highest profit is gained in the energy market. The multi-market operation is thus heavily dependant on the wind production. An increase in wind power production, either by installing a larger turbine or experiencing high wind periods, decreases the multi-market operation.

When mainly participating in the energy market, it could be noted that the storage capacity does not have a significant effect on the profits. However, this is not due to the fact that the battery is not used. The battery is still used to balance the wind power based on the price variations, but the profit benefit comes from the difference between low price and high price and this difference may not be that large. This leads to a small profit increase, but the battery contributes to a more steady power exchange.

While participating in the reserve capacity market one could see that a storage capacity around 3 MWh appears to be most beneficial. With this capacity, the battery could provide maximum up- and down-regulating at 1 MW, or it could be used in combination in the two markets more easily.

The combination of a storage unit and wind power indicates better yearly performance in total since they complement each other. The wind power potential is high during wintertime, but struggles to make much impact during summer in which the battery provides an alternative market operation in the reserve capacity market. Note that this multi-market operation is more often used when the wind production is low. With this multi-market setup, the battery can provide support for the whole year and in different seasonal situations. For instance, from balancing the energy export in high wind periods, to participate in the regulating market in low wind period.

Chapter 7

Conclusion

This thesis seeks to include an unregulated power source such as wind power in an already existing optimisation model and test this in deterministic and stochastic cases based on data from different seasons. The optimising model provides energy system scheduling and the model seeks to maximise the profit from the energy market and reserve capacity market based on methods from long-term scheduling for hydropower. Stochastic dynamic programming is thus used to find the storage values, which is the marginal value of stored energy, in the strategy phase. These values are then used in the simulation phase to obtain the optimal production schedule for the energy system. In this section, the main conclusion from the case study is derived. Note that the key findings are summarised at the end of this section.

When sizing the wind turbine for this energy system, both the wind energy utilisation and potential power shed must be considered. In this thesis, costs are not considered and thus it was found that a 1.5 MW wind turbine suited this system. This power rating would utilise the wind potential so that it produced 1 MW in many time steps, but at the same time, the power shed would become small and just occur in certain seasons.

With the introduction of an unregulated power source in wind power, a clear increase in profit could be seen. The wind turbine offers ”free” energy that could be sold to the market and potentially making a high profit. The model will favour the market in which it can gain the highest profit and this strongly affects the multi-market operation. When the wind power production is high, the reserve capacity market participation decreases. Therefore, it could be concluded that an increase in wind power production, either by installing a larger turbine or experiencing high wind periods, decreases the multi-market operation. To make the model shed wind power to participate in the capacity market the capacity price must be higher than the energy price. If not, the model will mainly operate in the energy market and supply with selling reserve capacity in time step where the wind production is low. An installed storage capacity above 3 MWh did not give a significant additional profit in either market.

The motivation of including a storage unit in an energy system with wind power, must not be based solely on the profit benefit. This is because the profit gain of including a battery is small compared to the profits gained from selling the wind power directly and this is also true for an increase in storage capacity. For instance, the rise in profit from increasing the storage capacity from 1 MWh to 10 MWh in the winter case is only 3 %. The reason for this is that the turnover which the storage unit gain from utilising price variations is relatively small compared to the full price the wind power gets. Nonetheless, the storage contributes to a more steady and balanced power exchange which is beneficial in itself.

From the results in the seasonal analysis, it becomes clear that the seasonal variations have a great impact on the energy system. A strong variation of prices and wind production between the seasons causes different behaviour and resulting profit. Considering the stochastic case study, the difference between weekly profit from the highest profitable season which was the winter and the lowest profitable season which was the summer is large because of the high wind production in the winter season. When participating in both markets with 1 MWh installed capacity the lowest total profit is 30 120 NOK/week and come from the summer case, while the highest total profit comes from the winter case and is 46 809 NOK/Week. With 10 MWh installed capacity the total profit range from 35 925 NOK/Week in the summer case to 48 148 NOK/week in the winter case. The combination of a storage unit and wind power indicates better yearly performance in total since they complement each other. For instance, in low wind periods, the storage unit offers capacity market participation, while in high wind periods it could balance the power output. With this multi-market setup, the battery can provide support for the whole year and in different seasonal situations.

Key findings from the case study:

- Most or all of the total profit is earned by selling wind power in the energy market.
- An increase in wind power production, either by installing a larger turbine or experiencing high wind periods, decreases the multi-market operation.
- High wind production leads to high or solely participation in the energy market and low wind production leads to participation in both markets which is characterised as a contribution from the storage unit.
- The model will only prioritise the reserve capacity market over the energy market when the reserve capacity price is higher than the energy price.
- To minimise power shed and maximise profit a 1.5 MW wind turbine is considered ideal for this system.
- A storage capacity above 1 MWh does not lead to a significant profit increase in the energy market.
- A storage capacity above 3 MWh does not lead to a significant profit increase in the reserve capacity market.

Chapter 8

Future Work

This thesis focused on implementing and analysing an unregulated power source in a stochastic optimisation model for energy storage scheduling. However, the possibilities for further development or extension of the model are immense and some of the possibilities for future work will be discussed in this section.

A suggestion for future work which extends the work done in this thesis is to include a varying efficiency in the converter. This was tried in this thesis, but a problem of overlapping charging and discharging of the storage unit arose. This could possibly be solved by introducing binary variables. Also, losses in the storage unit and/or transmission lines could be investigated. Other aspects of the model could also be expanded. For instance, in this thesis, it was three scenarios for each stochastic category (i.e. prices and wind production). More scenarios could be studied to give a more nuanced picture. Furthermore, this short-term scheduling model could be extended to schedule for several weeks or several months. Note that these suggestions could make the model more complicated and thus also increase the computation time. The complexity could derive a problem for future work with the model.

An interesting aspect to investigate is some of the costs of such a system and the possible profits in light of that. For instance, the cost of using the battery, which is known as degradation cost, could be investigated. This includes usage-related cost factors for the elements in the energy system and thus covering proposition 5 in Section 2.1. With this approach, the battery utilisation and multi-market operation could be different since the cost of how the battery is used must be considered. Also, this could potentially shed a better light of the ideal size of the storage unit within this system.

One possible extension to the model could be to include loads or other energy dependent object in the system. In this way, the model has an obligation to cover the load with either energy from the wind turbine, storage unit or purchased from the grid. The model must thus deal with both covering the load while maximising its profits from the energy market and reserve capacity market. By including a load, the model evolves to consider a single bus microgrid. Even though many studies have investigated this setup, as seen in Figure 2.1 in the literature review, it could be interesting to analyse such a microgrid with the SDP approach used in this thesis. Within this proposal, it could be possible to include industrial consumers with controllable loads, and thus involve proposition 3 in Section 2.1.

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Appendices

Appendix A

Mathematical Model Description

A.1 Model functions

Sets

TS	Time steps in decision stage for both energy sale and sale of reserve capacity
NR	Steps for storage values (a piecewise linear approximation)
K	Steps for power production (a piecewise linear approximation)
C	All the reserve blocks (The given time steps in TS will split the blocks)

Indices

t	Time steps in decision stage for both energy sale and sale of reserve capacity
n	Step for storage values (a piecewise linear approximation)
k	Step for power production (a piecewise linear approximation)
c	Reserve block

Parameters

$E_{price,t}$	Energy price in time step t	[NOK/MWh]
$C_{price,t}$	Price for reserve capacity in time step t	[NOK/MW]
A_{price}	Price for artificial energy	[NOK/MWh]
$Shed_{value}$	An artificial price or value for shedding wind power	[NOK/MW]
$DVal$	Offset or shift in value function	[NOK]
T_t	Duration of time step t	[h]
B^{MAX}	The energy storage unit capacity	[MWh]
$MDOD$	Maximum depth of discharge for the storage unit	[p.u.]
B^{Start}	Capacity for the storage unit at the start of the decision stage	[p.u.]
C^{max}	Maximum sale of reserve capacity	[MW]
P_{ch}^{max}	Maximum power output from the converter while charging	[MW]
P_{dch}^{max}	Maximum power output from the converter while discharging	[p.u.]
$P_{ch,in}^{max}$	Maximum power input into the converter while charging	[MW]
$P_{dch,in}^{max}$	Maximum power input into the converter while discharging	[p.u.]
η_{ch}^{max}	Maximum efficiency for the converter while charging	[p.u.]
η_{dch}^{min}	Minimum efficiency for the converter while charging	[p.u.]
$P_{ch,t}^{max}$	Maximum power output from the converter while charging at time step t	[MW]
$P_{dch,t}^{max}$	Maximum power output from the converter while discharging at time step t	[MW]
$P_{ch,in,t}^{max}$	Maximum power output into the converter while charging at time step t	[MW]

$P^{wind,rated}$	The maximum rated power output for the wind turbine	[MW]
$P^{transf,MAX}$	Maximum power transfer to and from the grid	[MW]
$P_t^{wind,output}$	The maximum power output for the wind turbine in time step t	[p.u.]
SOC_{pts}	List of points for SOC (piecewise linear points) (1-Dimensional list)	[p.u.]
SV_{pts}	List of Storage Values based on SOC (piecewise linear points) (1-Dimensional list)	[NOK]
P_k^{pts}	Output power from converter for each power production point k, for both charging and discharging	[MW]
P_k^{cha}	List of the input power to the converter while charging for each power production point k (a piecewise-linear list)	[MW]
P_k^{dis}	List of the input power to the converter while discharging for each power production point k (a piecewise-linear list)	[MW]
P_c^{list}	List of the reserve sales blocks for each time step c	[-]

Variables

Continuous variables

soc_t	State of charge for the storage unit at the end of time step t	[p.u.]
$p_t^{in,batt}$	Power charged into the storage unit in time step t (energy stored in unit)	[MW]
$p_t^{out,batt}$	Power discharged from the storage unit in time step t (energy discarded from unit)	[MW]
$p_t^{in,conv}$	Power flow into the converter on the grid side in time step t (energy intended to be stored)	[MW]
$p_t^{out,conv}$	Power flow out of the converter on the grid side in time step t (energy to be sold from the storage)	[MW]
p_t^b	Power bought from the grid in time step t	[MW]
p_t^s	Power sold to the grid in time step t (Power going into the grid from the converter)	[MW]
p_t^f	Net power exchange with the grid in time step t	[MW]
cap_t	Reserve capacity sold in time step t	[MW]
p_t^{art}	Artificial power bought in time step t	[MW]
p_t^{wind}	The total power flow from the wind turbine going into the system in time step t	[MW]
$p_t^{wind,store}$	The power from the wind turbine which is stored in time step t	[MW]
$p_t^{wind,transf}$	The power from the wind turbine which is transferred to the grid in time step t	[MW]
$p_t^{wind,shed}$	The power shed from the wind turbine in time step t	[MW]
SV	Energy storage value in the storage unit at the end of the decision stage	[NOK]

Other variables

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

A.2 Objective function

The objective function that are maximised in the optimisation problem.

$$OBJ = \sum_{t \in TS} E_{price,t} \cdot p^f_t \cdot T_t \tag{A.1}$$

$$+ \sum_{t \in TS} C_{price,t} \cdot cap_t \cdot T_t \tag{A.2}$$

$$- \sum_{t \in TS} A_{price,t} \cdot p^{art}_t \cdot T_t \tag{A.3}$$

$$+ \sum_{t \in TS} Shed_{value,t} \cdot p^{wind,shed}_t \cdot T_t \tag{A.4}$$

$$+ SV + DVal \tag{A.5}$$

A.3 Constraints

The initial storage balance
The balance of storage level at the end of first time step, which is the initial storage level plus energy stored or discharged during the first time step.

$$soc_0 \cdot B^{MAX} - p_0^{in,batt} \cdot T_0 + p_0^{out,batt} \cdot T_0 - p_0^{art} \cdot T_0 = SOC^{Start} \cdot B^{MAX} \tag{A.6}$$

The general storage balance
The energy stored or discharged during a time step must equal the change in storage level from the beginning to the end of the time step. Ensures the energy balance throughout the time steps.

$$soc_{t-1} \cdot B^{MAX} + p_t^{in,batt} \cdot T_t - p_t^{out,batt} \cdot T_t + p_t^{art} \cdot T_t = soc_t \cdot B^{MAX}, \quad t \in TS \setminus [ord(t) > 0] \tag{A.7}$$

The boundaries for the state of charge
Limits the state of charge to be between the value of the maximum depth of discharge (MDOD) and the value one. This is a parameter connected to the specific storage unit and is set by the user.

$$(1 - MDOD) \leq soc_t \leq 1 \quad t \in TS \tag{A.8}$$

The net power flow
A constraint that define the net power flow variable, p_t^f, by the variables of sold and bought power, p_t^s and p_t^b.

$$p_t^f \cdot T_t = p_t^s \cdot T_t - p_t^b \cdot T_t \ , \quad t \in TS \tag{A.9}$$

The sold power flow
A constraint that define the variable for net power sold, p_t^s, by the variables for power from the wind turbine and battery, $p_t^{wind,transf}$ and $p_t^{out,conv}$.

$$p_t^s \cdot T_t = p_t^{out,conv} \cdot T_t + p_t^{wind,transf} \cdot T_t \ , \quad t \in TS \tag{A.10}$$

The stored power flow
A constraint that define the variable for net power stored, $p_t^{in,conv}$, by the variables for power from the wind turbine and the bought power, $p_t^{wind,stored}$ and p_t^b.

$$p_t^{in,conv} \cdot T_t = p_t^b \cdot T_t + p_t^{wind,store} \cdot T_t \ , \quad t \in TS \tag{A.11}$$

The limit for power transfer to/from the grid
Sets the limit for power transferred to/from the grid to the maximum transfer limit. The transferred power in a time step are defined by the power sold and power bought in that time step. Also, two constraints that sets the boundaries for bought and sold power.

$$-p^{transf,MAX} \leq p_t^f \leq p^{transf,MAX} \tag{A.12}$$

$$0 \leq p_t^s \leq P^{transf,MAX} \tag{A.13}$$

$$0 \leq p_t^b \leq P^{transf,MAX} \tag{A.14}$$

The limit for input power to the converter
Sets the limit for the amount of power that can go into the converter on the grid side. This is not limited by the converter.

$$0 \leq p_t^{in,conv} \leq \infty \tag{A.15}$$

The limit for output power from converter
Sets the limit for the amount of power that can go out of the converter on the grid side. This quantity is limited by the converter capacity.

$$0 \leq p_t^{out,conv} \leq P_{dch}^{max} \tag{A.16}$$

The limit for output power from storage unit
Sets the limit for the amount of power that can go out of the storage unit. This is not limited by the converter.

$$0 \leq p_t^{out,batt} \leq \infty \tag{A.17}$$

The limit for input power to storage unit
Sets the limit for the amount of power that can go into the storage unit. This quantity is limited by the converter.

$$0 \leq p_t^{in,batt} \leq P_{ch}^{max} \tag{A.18}$$

The power flow when charging
These constraints include the efficiency of the converter, i.e. create the relation between the energy stored in the storage unit and the energy going into the converter from the grid side. Constraint A.19 include the power flow when charging with fixed efficiency for the converter which is used in the thesis.

$$p_t^{in,batt} \cdot T_t = \eta_{ch} \cdot p_t^{in,conv} \cdot T_t \ , \quad t \in TS \tag{A.19}$$

Constraint A.20 and A.21 showcase the possibility for a piecewise linear efficiency curve for the converter that is based on the given power level.

$$\sum_{k=1}^{K} \delta_{k,t}^{1} = 1 \ , \quad \delta_{k,t} \in [0,1] \ , \quad t \in TS, SOS2 \tag{A.20}$$

$$p_t^{in,batt} = \sum_{k=1}^{K} \delta_{k,t}^{1} \cdot P_k^{cha}(p_t^{in,conv}) \ , \quad t \in TS \tag{A.21}$$

The power flow when discharging
These constraints include the efficiency of the converter, i.e. create the relation between the power going out of the converter on the grid side and the energy discharge from the storage unit. Constraint A.22 include the power flow when discharging with fixed efficiency for the converter which is used in the thesis.

$$p_t^{out,conv} \cdot T_t = \eta_{dch} \cdot p_t^{out,batt} \cdot T_t \ , \quad t \in TS \tag{A.22}$$

Constraint A.23 and A.24 showcase the possibility for a piecewise linear efficiency curve for the converter that is based on the given power level.

$$\sum_{k=1}^{K} \delta_{k,t}^{2} = 1 \ , \quad \delta_{k,t} \in [0,1] \ , \quad t \in TS, SOS2 \tag{A.23}$$

$$p_t^{out,batt} = \sum_{k=1}^{K} \delta_{k,t}^{2} \cdot P_k^{dis}(p_t^{out,conv}) \ , \quad t \in TS \tag{A.24}$$

The upper capacity limit from power flow through converter
This constraint limits the the possible up-regulation of the reserve capacity by the maximum power transfer through the converter and the current power flow. The reserve capacity is restricted to the available capacity resource of the converter.

$$-\left(p_t^{out,conv} - p_t^{in,conv}\right) \geq cap_t - P_{dch}^{max} \tag{A.25}$$

The lower capacity limit from power flow through converter
This constraint limits the the possible down-regulation of the reserve capacity by the maximum power transfer and the efficiency through the converter and the current power flow in the converter. The reserve capacity is restricted to the available capacity resource of the converter.

$$-\left(p_t^{out,conv} - p_t^{in,conv}\right) \leq -cap_t + \frac{P_{ch}^{max}}{\eta_{ch}^{max}} \tag{A.26}$$

The upper capacity limit from power transfer with the grid
This constraint limits the the possible down-regulation of the reserve capacity by the maximum power transfer with the grid and the current power flow to/from the grid. The reserve capacity is restricted to the available capacity resource of the grid transfer connection.

$$-p_t^f \geq cap_t - P^{transf,MAX} \tag{A.27}$$

The lower capacity limit from power transfer with the grid
This constraint limits the the possible down-regulation of the reserve capacity by the maximum power transfer with the grid and the current power flow to/from the grid. The reserve capacity is restricted to the available capacity resource of the grid transfer connection.

$$-p_t^f \leq -cap_t + P^{transf,MAX} \tag{A.28}$$

The higher capacity limit from the storage unit
This constraint limits the the possible down-regulation of the reserve capacity by the current energy that is stored in the storage unit. The maximum power efficiency is included since the power go through the converter.

$$cap_t \cdot T_t \leq (1 - soc_t) \cdot \frac{B^{MAX}}{\eta_{ch}^{max}} \ , \quad t \in TS \tag{A.29}$$

The lower capacity limit from the storage unit
This constraint limits the the possible up-regulation of the reserve capacity by the current energy that is stored in the storage unit. The minimum power efficiency is taken into account to avoid the possibility of selling more capacity than the storage unit can deliver to the output side.

$$cap_t \cdot T_t \leq (soc_t - (1 - MDOD)) \cdot B^{MAX} \cdot \eta_{dch}^{min} \ , \quad t \in TS \tag{A.30}$$

Equality in the reserve blocks
A constraint that ensures that the reserve capacity sold within the same reserve block have the same values.

$$cap_t = cap_{t-1}, \quad t \in TS \setminus [ord(t) > 1, t \neq R_c^{list} \ for \ c \in C] \tag{A.31}$$

End value of stored energy
These constraints sets the value for the remaining energy in the storage unit at the end of the given decision stage. This is done with piecewise linear approximation.

$$\sum_{n=1}^{NR} \delta_n = 1 \ , \quad \delta_n \in [0, 1] \tag{A.32}$$

$$SV = \sum_{n=1}^{NR} \delta_n \cdot SV_{pts}[n, soc_{TS}] \tag{A.33}$$

The wind power flow
A constraint that connects the variable for total produced power from the wind turbine, p_t^{wind}, with the variables for stored power from the wind turbine and transferred power from the wind turbine, $p_t^{wind,stored}$ and $p_t^{wind,transf}$.

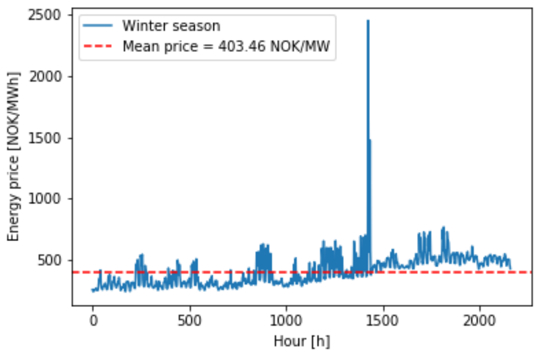
$$p_t^{wind} \cdot T_t = p_t^{wind,store} \cdot T_t + p_t^{wind,transf} \cdot T_t \ , \quad t \in TS \tag{A.34}$$

Limit for wind power production
A constraint that limit the variable for total produced power from the wind turbine, p_t^{wind}, to the maximum power output from the turbine based on the turbine's power rating, $P^{wind,rated}$, and the power output based on the natural energy resources (wind) at that time, $P_t^{wind,output}$. Constraint A.35 gives the wind turbine freedom to adjust the production below the maximum power output by introducing the variable $p_t^{wind,shed}$. This variable define the wind power shed in each time step.

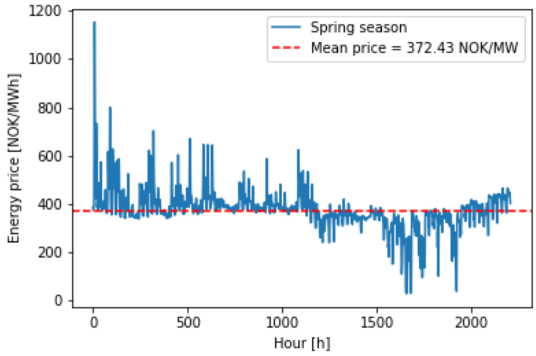
$$p_t^{wind} \cdot T_t + p_t^{wind,shed} \cdot T_t = P^{wind,rated} \cdot P_t^{wind,output} \ , \quad t \in TS \tag{A.35}$$

Appendix B

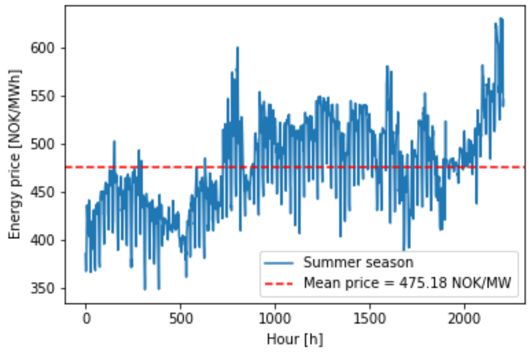
Input data for case study: Source Price and Wind Data



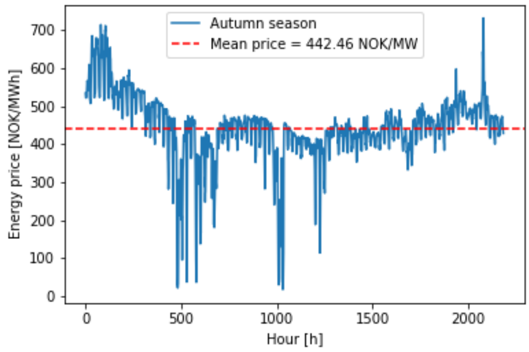
(a) Prices in the winter months



(b) Prices in the spring months

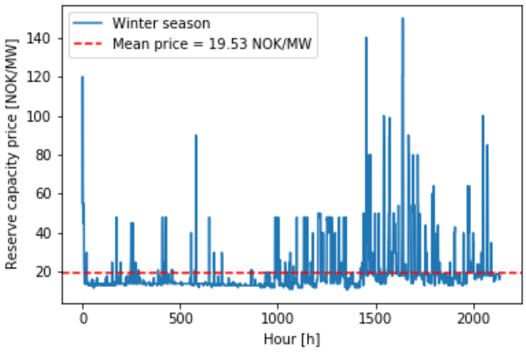


(c) Prices in the summer months

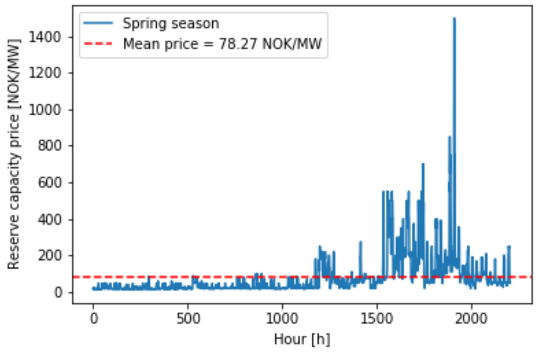


(d) Prices in the autumn months

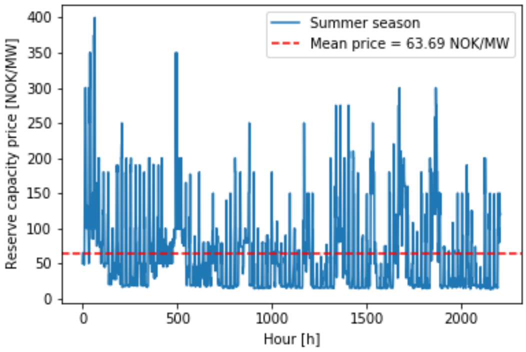
Figure B.1: The historical energy price for the NO3 price area in 2018. Data obtained from [29]



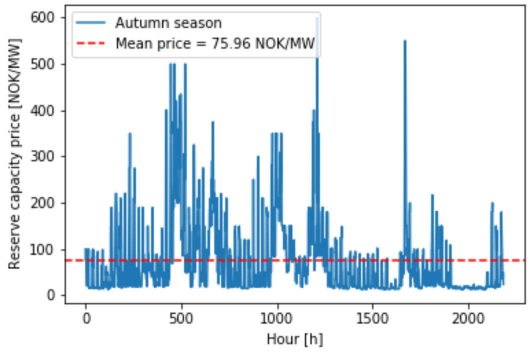
(a) Prices in the winter months



(b) Prices in the spring months

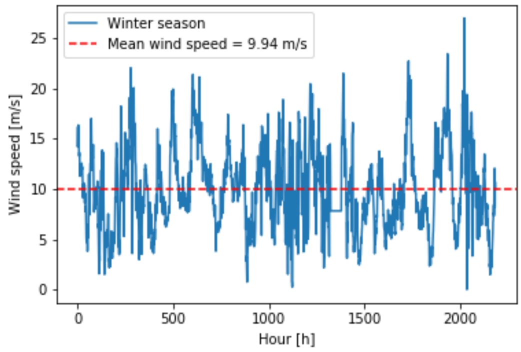


(c) Prices in the summer months

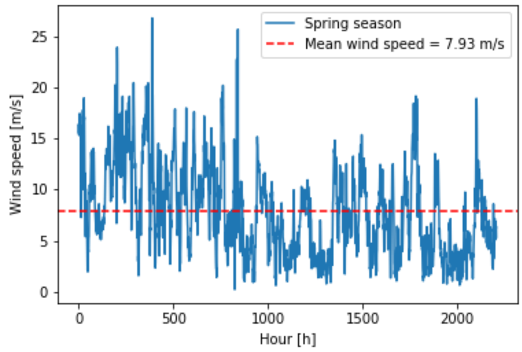


(d) Prices in the autumn months

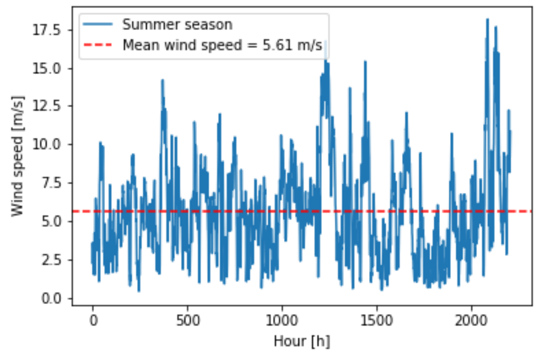
Figure B.2: The historical reserve capacity price for the NO3 price area in 2018. Data obtained from [12].



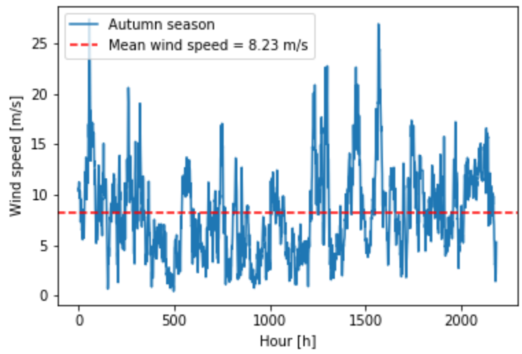
(a) Wind speed in the winter months



(b) Wind speed in the spring months



(c) Wind speed in the summer months

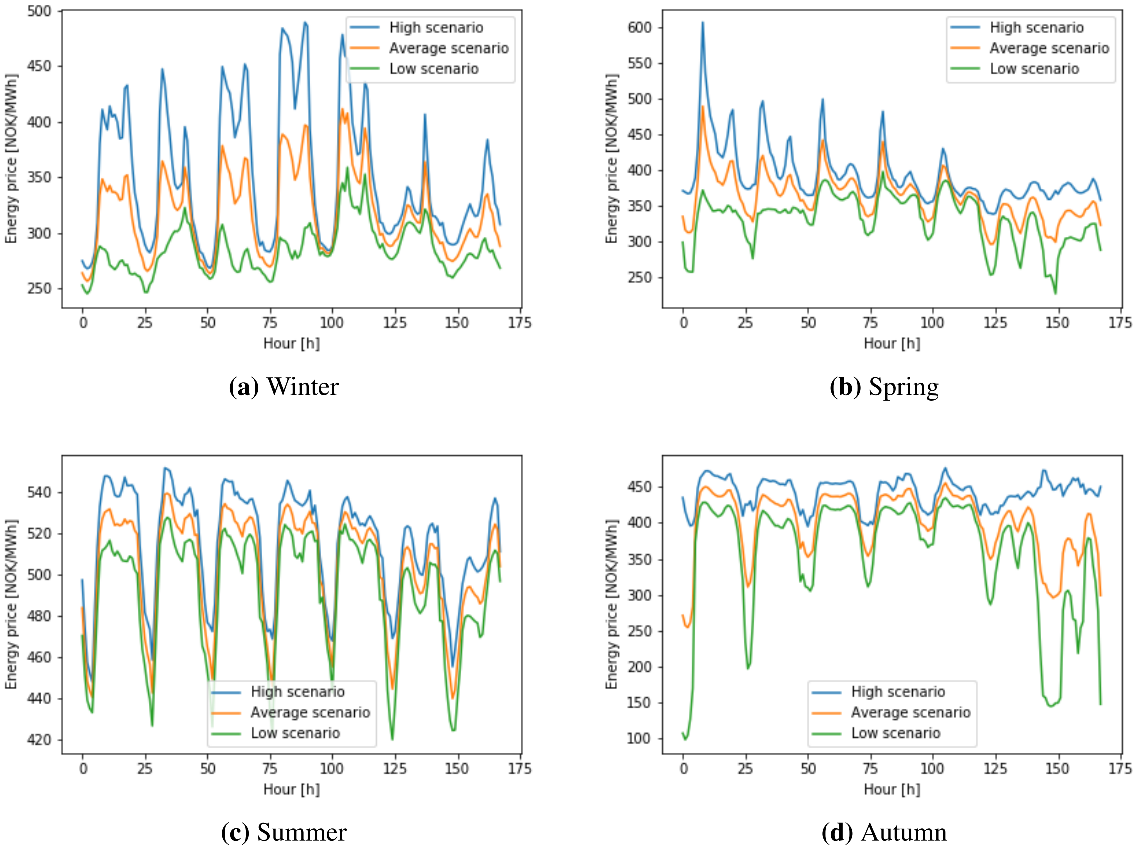


(d) Wind speed in the autumn months

Figure B.3: The historical wind speed at 60 meters at Hundhammerfjellet in Trøndelag in 2012. Original source data obtained from [32].

Appendix C

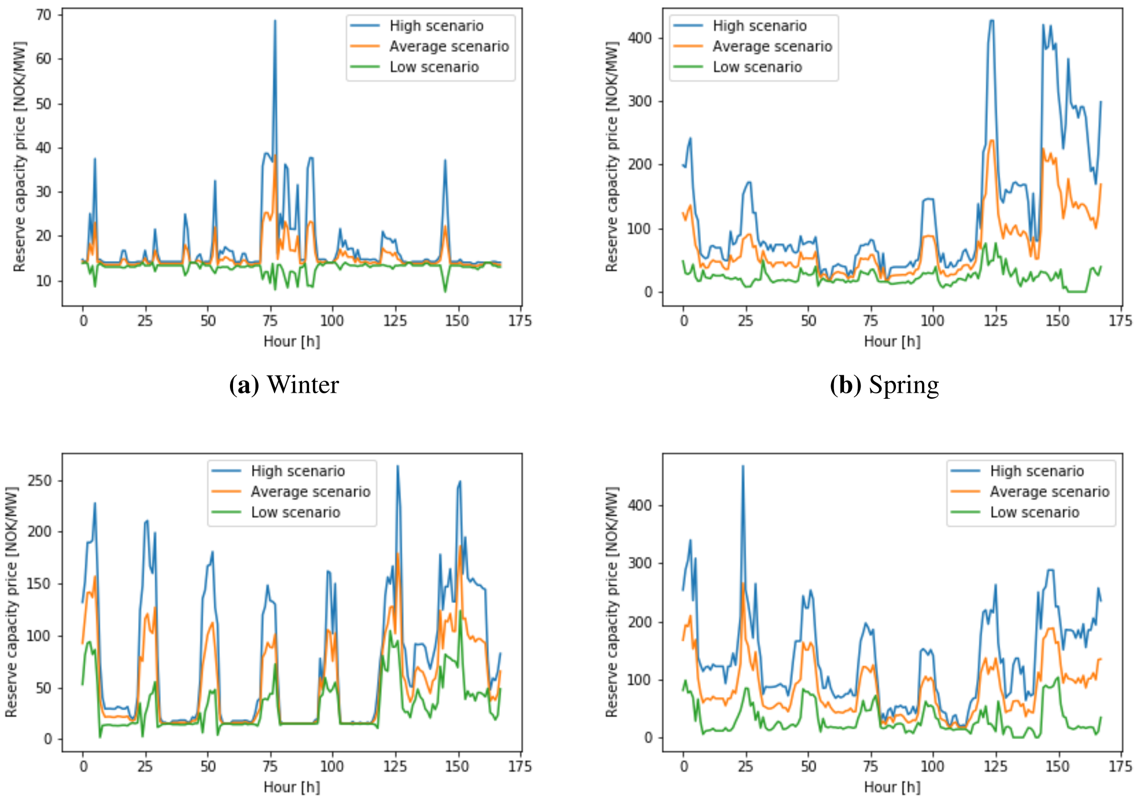
Input data for case study: Stochastic Price and Wind Data



(a) Winter **(b)** Spring

(c) Summer **(d)** Autumn

Figure C.1: The different energy price scenarios used to create different price and wind nodes for the stochastic simulation.



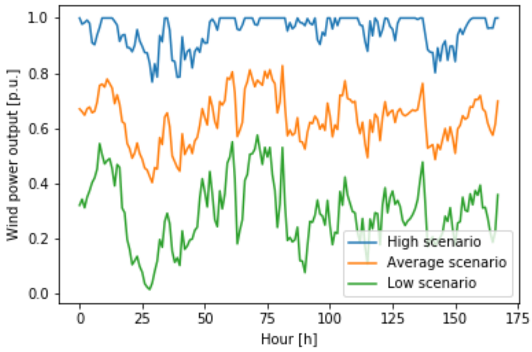
(a) Winter

(b) Spring

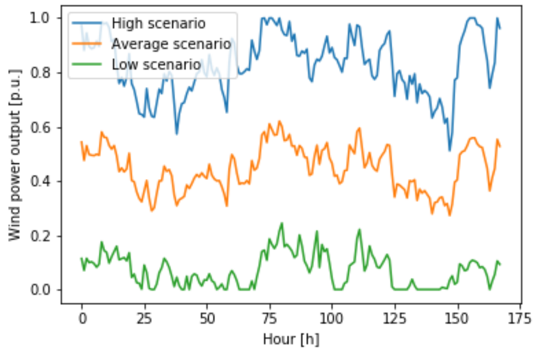
(c) Summer

(d) Autumn

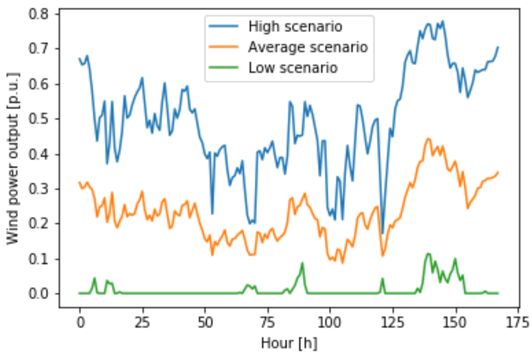
Figure C.2: The different reserve capacity price scenarios used to create different price and wind nodes for the stochastic simulation.



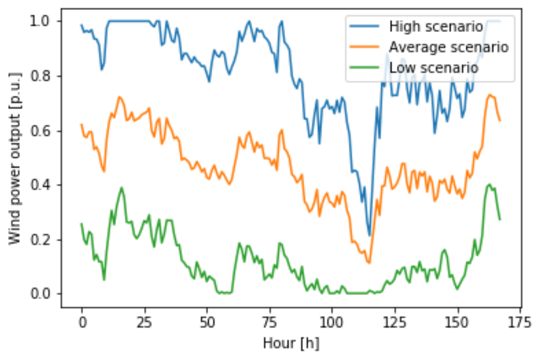
(a) Winter



(b) Spring



(c) Summer



(d) Autumn

Figure C.3: The different wind power output scenarios used to create different price and wind nodes for the stochastic simulation.

Jon Hvideberg Holte

An analysis of energy storage system with wind power for multi-market operation under uncertainty

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