Master's thesis

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Department of Electric Power Engineering

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Techno-economical optimization of energy storage for increased wind farm integration

Master's thesis in Energy and Environmental Engineering
Supervisor: Jayaprakash Rajasekharan
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Kunnskap for en bedre verden

Summary

The problem with an increasing share of renewable energy sources (RES) is that the fluctuating nature of some of the most prominent RES, wind turbines and solar photovoltaic panels, can cause stability issues in the grid [1]. A solution to mitigate this can be to install Energy Storage Systems (ESS). ESS can be used both to provide ancillary services and improve RES integration. However, as Distribution System Operators (DSOs) in the current EU legislation cannot own ESS, ESS investments must be profitable [2]. The main objective of this thesis has, therefore, been to assess the profitability and benefits that can be obtained with an ESS investment.

A review of previous studies and optimization techniques for ESS and wind farms was conducted to shed light on potential research opportunities. The review showed that most articles have focused on the economic aspects of ESS installment, and that participation in reserve markets could provide profitable ESS investments.

A real case study of ESS investment for the wind farm owned by Midtfjellet Vindkraft AS wind farm was conducted. The model for the case study system consisting of a load, wind farm, Li-Ion battery energy storage system (BESS), and energy market structures for the Nordic Day-Ahead, normal frequency containment reserves (FCR-N) and fast frequency reserves (FFR). The model was made in PSS®DE, an optimization software developed by Siemens AG. The FFR market was modeled by raising the SoC level of the battery in PSS®DE to reserve capacity, and the revenue for this calculated using discounted cash flow in Excel. For the case study, 44 scenarios with a ten-year horizon were developed, using projections for the future price of Li-Ion BESS and power markets. Techno-economical optimization was performed for the scenarios with a project lifetime of 20 years.

The results from the case study showed that it was possible to obtain a positive business case for ESS coupled with Midtfjellet wind farm using revenue stacking. Concretely, participation in the FCR-N and Day-Ahead market was sufficient to provide a positive change in net present value (NPV) for the combined wind farm, load, and Li-Ion BESS system already in 2020. For the 2030 scenarios, inclusion of any two markets yielded an increase in NPV compared to the reference case.

Sammendrag

Med en økende andel av fornybare energikilder som har en varierende produksjonsprofil, for eksempel vindturbiner og solcellepaneler, kan det oppstå problemer knyttet til stabiliteten i nettet [1]. En løsning for å forbedre stabiliteten kan være å installere energilagringssystemer. Energilagringsystemer kan brukes både for å anskaffe nettjenester og forbedre tilkoblingen av fornybare energikilder. Nettselskaper kan ikke med dagens regelverk i EU eie energilagringsystemer, og dermed må slike prosjekter være lønnsomme [2]. Derfor har hovedmålet med denne masteroppgaven vært å se på lønnsomheten og fordelene som en investering i ett energilagringsystem kan gi for en vindpark.

Et litteraturstudie med oppsummering av tidligere studier og optimaliseringsteknikker for energilagringssystemer og vindparker har blitt utført for å finne potensielle forskningsfelt. I litteraturstudiet kom det fram av de fleste tidligere studier har fokusert på de økonomiske aspektene ved energilagringssystemer, og at reservemarkeder har gitt positive resultater i forhold til lønnsomhet.

Det ble gjennomført en studie av et energilagringssystem for vindparken som eies av Midtfjellet Vindkraft AS. Modellen besto av en last, vindpark, litium-ion batterilagringssystem, og kraftmarkeder for Elspot, primærreserver (FCR-N) og hurtige primærreserver (FFR). Modellen ble laget i PSS®DE, en optimaliseringsprogramvare for distribuerte energisystemer utviklet av Siemens AG. FFR-markedet ble modellert ved å heve SoC-nivået på batteriet i PSS®DE for å reservere kapasitet, og inntektene for dette beregnet ved å bruke diskontert kontantstrøm i Excel. Scenarioene ble laget med en tiårshorisont og inneholdt forskjellige fremtidige priser for litium-ionbatterier og kraftmarkeder. Tekno- økonomisk optimalisering ble utført for scenarioene med en prosjektlevetid på 20 år. Totalt ble 44 scenarier konstruert og simulert.

Resultatene fra studie viste at det var mulig å få en positiv investering for et litium-ion batterilagringssystem kombinert med Midtfjellet vindpark ved å delta på flere markeder. Konkret var deltagelse i FCR-N- og Elspot markedet tilstrekkelig til å gi en positiv endring i nettonåverdi for systemet, allerede i 2020. For 2030 verdier ga alle scenarioer som inneholdt to eller flere markeder en økning i nettonåverdi i forhold til referansen.

Preface

This thesis is written as a part of the course TET4900 - Electric Power Engineering and Smart Grids, Master thesis at NTNU the spring of 2020. It should be noted that the thesis is a continuation of my specialization project, [3], completed during the fall of 2019.

I would like to thank my supervisor, Associate Professor Jayaprakash Rajasekharan for his guidance and feedback. I would also especially like to thank my co-supervisor, PhD Candidate Kasper Emil Thorvaldsen, for valuable contributions and opinions during the course of the work on this thesis. Finally, I would like to extend my thanks to Sindre Solberg at Siemens AS for providing the necessary data and lending me access to Siemens software, PSS®DE.

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Abbreviations

aFRR	=	automatic Frequency Restoration Reserves
AGC	=	Automatic Generation Control
ANN	=	Artificial Neural Network
BESS	=	Battery Energy Storage System
CAES	=	Compressed Air Energy Storage
DA	=	Day Ahead
DCF	=	Discounted Cash Flow
DCM	=	Direct Calculation Method
DES	=	Distributed Energy Systems
DoD	=	Depth of Discharge
DP	=	Dynamic Programming
DSO	=	Distribution System Operator
EoL	=	End of Life
ESS	=	Energy Storage System
FBESS	=	Flow Battery Energy Storage System
FC	=	Fuel Cell
FCR	=	Frequency Containment Reserves
FCR-D	=	Frequency Containment Reserves - Disturbance
FCR-N	=	Frequency Containment Reserves - Normal
FESS	=	Flywheel Energy Storage Systems
FFR	=	Fast Frequency Response
FIKS	=	Funksjonskrav i Kraftsystemet
FIT	=	Feed In Tariff
GHG	=	Green House Gases
HES	=	Hydrogen Energy Storage
HOMER	=	Hybrid Optimization Model for Multiple Energy Resources
HVAC	=	Heating, Ventilation and Air Condition
IEC	=	International Electrotechnical Commission
IPP	=	Independant Power Producer
KPI	=	Key Performance Indicator
LCA	=	Life Cycle Analysis
LFC	=	Load Frequency Control
LP	=	Linear Programming
LVRT	=	Low Voltage ride through support
mFRR	=	Manual Frequency Restoration Reserves
MGC	=	Micro grid Control
MGMS	=	Micro Grid Management System
MILP	=	Mixed Integer Linear Programming
MIMO	=	Multiple Input Multiple Output

MPC	=	Model Predictive Control
NaS	=	Sodium Sulphur
NPC	=	Net Present Cost
NPV	=	Net Present Value
O&M	=	Operation and Maintenance
OF	=	Objective Function
OPF	=	Optimal Power Flow
OSIP	=	Optimal Storage Investment Problem
PCPD IP	=	Predictor Corrector Primal-Dual Interior Point Method
PHS	=	Pumped Hydro Storage
PID	=	Proportional-integral-derivative
PSS®DE	=	Power System Simulator for Distributed Energy
PV	=	Photovoltaic
QP	=	Quadratic Programming
RES	=	Renewable Energy Sources
RKM	=	Regulerkraftmarkeded
RKOM	=	Regulerkraftopsjonsmarkedet
RMSE	=	Root Mean Square Error
SC	=	Super Capacitor
SCIP	=	Solving Constraint Integer Programs
SFI	=	Storage Fulfillment Index
SISO	=	Single Input Single Output
SMES	=	Superconducting Magnetic Energy Storage
SoC	=	State of Charge
SSI	=	Storage Surplus Index
SVS	=	Static Voltage Stability
TOD	=	Time Of Use
TSO	=	Transmission System Operator
VPP	=	Virtual power plant
VRB	=	Vanodium Redox Battery
WACC	=	Weighted Average Cost of Capital
WEC	=	Wind Energy Converter
WPPT	=	Wind Power Prediction Tool

Chapter 1

Introduction

As seen in recent investments and future projections, an increase of renewable energy sources (RES) compared to conventional generation is imminent. This is mainly due to two factors; a growing energy demand worldwide and environmental concerns. There is also the fact that RES in recent years has become cost-competitive, even without incentives. For instance, in [24], RES proved a cheaper investment than coal plants for many locations in the US.

With growing RES installment, investments into RES with a volatile production are also increasing rapidly. In 2019, the largest investments into RES, excluding large-scale hydropower, were investments into wind turbines and solar photovoltaic (PV) panels [25], which have a fluctuating power production [26]. Hence, balancing demand and production is increasingly difficult in areas where RES is prominent. This may lead to stability issues in the grid. In particular, wind turbines are often decoupled from the grid by power electronics, and hence do not contribute to ancillary services like inertia provision (page 632, [27]). Ancillary services, are services the grid needs to tackle imbalances and remain stable.

A solution to improve RES integration, explored in [24, 28], is to use Energy Storage Systems (ESS) in combination with RES. As Distribution System Operators (DSOs) are prohibited from owning ESS in the current EU legislation [2], the ESS investments must be profitable. However, as found through both the literature review and proof of concept study conducted in my specialization project [3], it is not easy to obtain a positive investment for ESS. Hence, it becomes apparent that ways to increase the revenue obtained by the ESS must be explored further so that ESS can increase RES integration.

In this master thesis, the aim has therefore been to asses the techno-economical benefits of an ESS investment for a wind farm to help RES integration, with particular focus on profitability. This is explored through a case study concerning the investment of ESS for a real wind farm of 149.6 MW, owned by Midtfjellet Vindkraft AS. This wind farm is situated on the island of Fitjar in Norway. In the case study, different scenarios are explored within a 10-year horizon, and revenue stacking through participation in multiple power markets is explored as an option for profitability. It was also crucial that the chosen ESS should be tailored to the Midtfjellet wind farm.

For the master thesis, the main research question is:

- Is there a positive business case for ESS coupled with Midtfjellet wind farm within 2030?

To achieve this, this master thesis aims to:

- Present an assessment of the relevant ESS technologies for application on transmission level and coupled with a wind farm
- Asses previous literature in the field of study to find research gaps.
- Propose reasonable future scenarios with a 10-year horizon for relevant parameters with special focus on Norwegian markets and systems
- Present relevant optimization theory and the chosen method and program, PSS®DE, for the case study
- Present a case study of Midtfjellet with and without ESS and include revenue stacking
- Perform a techno-economical optimization of ESS for Midtfjellet wind farm using PSS®DE

The master thesis is a continuation of the work conducted in my specialization project [3]. The relevant parts of the specialization project will, therefore, be included in the thesis. A comprehensive theory chapter is found in Chapter 2, with special emphasis on the Norwegian power system and power markets, to give the theoretical insight needed for assessing ESS suited for wind farm integration. An overview of previous literature on ESS and optimization is found in Chapter 3, including a subsequent discussion and summary of the chosen direction for the master thesis based on the findings. The method chapter in Chapter 4 gives the theoretical background for the optimal operation of an ESS, load, and wind farm connected to an external grid, along with the main aspects of the chosen optimization program, PSS®DE. The case study for the Midtfjellet wind farm is presented in Chapter 5. The results from the conduction of this case study are shown in Chapter 6. A brief conclusion on the project is found in Chapter 7, while Chapter 8 outlines areas for future development.

Chapter 2

Theory

As wind turbines depend on weather conditions, their production is volatile and constantly changing, which causes a fluctuating power output. Energy storage systems (ESS) can help mitigate this by smoothing the power output from wind farms and also provide ancillary services [12]. A brief introduction to ESS suited for wind farm integration is provided in this chapter. The chapter starts with an explanation of large scale ESS, presented in Section 2.1. The ESS are then compared in Section 2.2, based on the method in Appendix A.1. Possible applications for large scale ESS tailored for wind power integration is presented in Section 2.3. A description of the chosen power grid and associated power markets is needed to assess the types of services different types of ESS is allowed to deliver. Therefore, a review of the Norwegian Power markets is presented in Section 2.4. The chapter is concluded with a section describing theory relevant to the scenarios conducted in the case study in Section 2.5. The theory chapters Section 2.1 to Section 2.4 are based on chapter 3 of my specialisation project [3], with minor modifications pertaining spelling and small additions. In particular, Section 2.4, concerning the Norwegian Energy markets, has been expanded with the inclusion of the fast frequency reserve (FFR) market. It has also been updated with the new regulations for 2020. Section 2.5 is written for the master thesis exclusively.

2.1 Energy Storage Systems for large scale application

In this section, relevant ESS for large scale applications is presented. As demand and production of electricity must be balanced, it is of high importance that the power system is composed such that the load can be reliably met. With fluctuating renewable sources, this can prove a real challenge. In general, there are four different solution patterns to this challenge: Invest in ESS, acquire back-up generation, have geographical diversity, or invest in different kinds of renewable resources [29]. It is often necessary to combine several of these solutions to create a reliable and stable grid with renewable energy sources (RES). Currently, procuring ESS is quite expensive compared to the other solutions, but the nature of the ESS might make it an economical and technical desirable option. For instance, batteries are among the fastest at discharging / charging, making them ideal for rapid compensation of volatile production. The suitable uses for different types of ESS are presented in Figure 2.1.

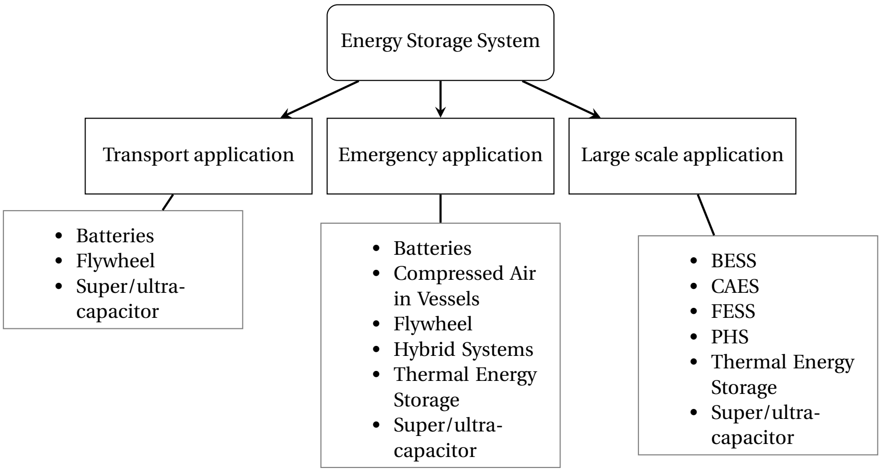


Figure 2.1: Classification of ESS applications adapted from [12]

As Figure 2.1 shows, the suitable ESS for large scale applications today are BESS, CAES, FESS, PHS, SMES, and ultracapacitors. In the transmission grid, the suitable ESS often need high power to energy ratio. Figure 2.2 shows the power to energy ratio of the most prominent types of ESS.

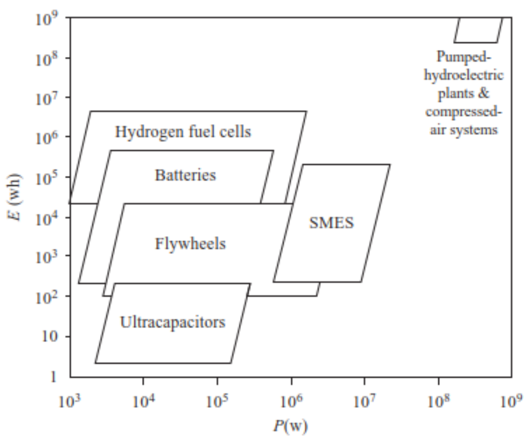


Figure 2.2: Power to Energy ratio of different storage solutions (figure 7.2 [12])

For this thesis, BESS, and in particular Li-Ion batteries, is the main focus. Therefore, the reader is referred to the specialization project [3] for further details concerning other ESS for large scale applications.

2.1.1 Battery Energy Storage Systems

Battery Energy Storage System (BESS) technology stores energy in the form of chemical energy. There are two main types of BESS, secondary batteries and flow batteries. BESS for large scale applications are divided into Lead Acid, NaS, Li-Ion, and flow batteries [30]. A common denominator for BESS is their fast charge and discharge capabilities [31]. The basic principle of how secondary batteries function is described in the following paragraph and include Lead Acid (LA), Sodium Sulphur (NaS), and Li-Ion batteries. A battery cell consists of a cathode and anode with either a solid, paste or liquid electrolyte. Energy is stored in the battery by applying a potential to the electrodes, which sparks an internal chemical reaction. This chemical reaction is reversible, allowing the battery to release the stored energy as electricity during discharge. To achieve the desired electrical characteristics, conventional secondary batteries often consist of low voltage/power battery cells connected in series and parallel. Among the secondary batteries, Li-Ion is unmatched in the current battery technology precisely because of its excellent power and energy density capabilities [32]. Still, flow batteries show much promise for large scale application [33]. An issue for all batteries is degradation, which occurs naturally due to all battery actions (charging, storing, and discharging, for instance). Degradation in batteries is defined as an irreversible chemical process that causes a lowered capacity of the battery. In particular, processes that contribute to the degradation of Li-Ion batteries are overcharging, high temperatures, a high DoD, and a high cycling rate, according to [34]. A general problem for the battery types presented is the high toxicity of their metal materials, which poses an ecological concern at the end of life. Li-Ion batteries are given a further explanation below. Further details concerning Lead-Acid, Sodium Sulphur or flow battery energy storage systems (FBESS), can be found in [3], which is a summary of information collected from [31, 35, 36].

2.1.1.1 Lithium ion batteries

Li-Ion batteries operate by an electrochemical reaction between positive lithium ions with different materials used for the anode and cathode. The cathode is usually made up of lithium oxide, for instance, lithium cobalt, and the anode is made of graphite. Sony produced the first commercial Li-Ion batteries in the 1990 [35], so compared to the other storage technologies, it is relativity new. The main advantages of Li-Ion batteries are high energy density and specific energy, as well as fast response time ($\approx$ 200 ms [37]). These features make Li-Ion an excellent ESS candidate when weight and response time are essential [31]. Disadvantages of the Li-Ion batteries include a high cost, fragility since it needs to operate within certain limits of voltage and temperature and lifetime dependant on cycle DoD.

2.2 Comparison of Energy Storage Systems

The ESS relevant for large scale application, as presented in Figure 2.1 is in this section compared based on selected features. The features are chosen based on important characteristics for large scale ESS application and are presented for each storage type in Table 2.1 and Table 2.2.

Table 2.1: Technical features for the ESS in Section 2.1

Type	Discharge time	Response time	Efficiency [%]	Power rating [MW]	Energy rating [MWh]	Specific power [W / kg]	Specific energy [Wh / kg]	Num. of Cycles	Lifetime [years]
PHS	1-24h+	min	70-80	100 - 5000	500-8000	-	-	>15000	>50
FC	s - 24 h +	s - min	34-44	0-50	120	-	100-150, 400-1000	103-104	10.0-30
FESS	s -h	<s	80-90	0-0.25	0.025-5	11900	5-100	104-107	15-20
LA	s - h	<s	75-90	0-20	0.01-40	180-200	30-50	250-1500	3.0-15
Li-Ion	min - h	<s	65-75	0.1-100 [38]	0.0016-126[38]	245-2000	80-200	600-1200	5-100
VRB	s - 10 h	s	60-75	0.03-3	1.2-120.0	166	20-35	>10000	5.0-20
SC	ms - 1h	<s	85-98	0-0.3	0.01	800-23600	2 - 30	104-105	4.0-12
SMES	ms - 8s	<s	75-80	0.1-100	0.015	-	10.0-75	-	-
CAES	1-24h+	min	41-75	5 - 300	580-2860	-	3.2-5.5	>10000	>25
NaS	s-h	<s	70-85	0.05-8	0.4-244.8	90-230	100-175	2500-4500	10.0-15.0

Table 2.2: Additional features for the ESS in Section 2.1

Type	Capital cost [USD / kWh]	Self discharge [%/day]	Geographical location	Maturity of technology
PHS	5.0-100	Very small	Limited	Mature
FC	300-2000	0	Requires space and/or gas infrastructure	Developing
FESS	1000-5000	100	Flexible	Mature
LA	200-400	0.1-0.3	Temperature sensitive	Mature
Li-Ion	600-2500	0.1-5	Temperature sensitive	Developed
VRB	500	Small	Requires space	Developed
SC	300-2000	20-40	Flexible	Developed
SMES	1000-10000	10.0-15	Flexible	Developed
CAES	2.0-50	Small	Limited	Developed
NaS	300-500	-20	Flexible	Developed

Table 2.1 and Table 2.2 are based on the most resent numbers from table 1 and 2 in [31], table 1 in [35] and table 1 and 2 in [33]. In addition, the definition of the maturity of technology is based on figure 1 in [35]. It should be mentioned that technologies close to being mature, like the flywheel, have been moved from developed to mature, since the article is from 2009.

A method for comparing the different types of ESS based on the ESS features displayed in Table 2.2 and Table 2.1 was developed. The description of the method along with Table A.1 that was used to create Figure 2.3 can be found in Appendix A.1.

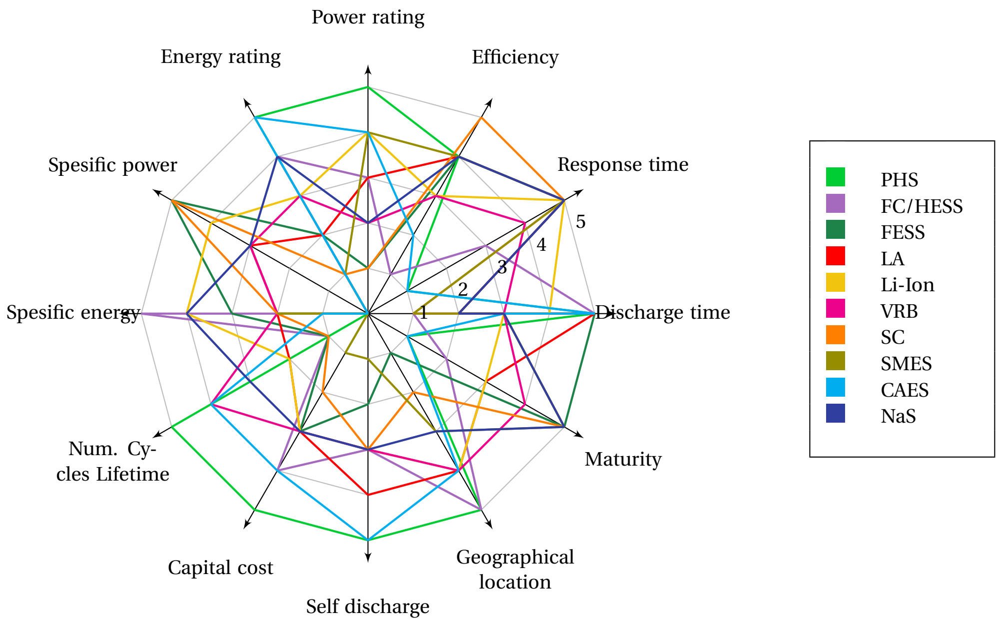


Figure 2.3: Graphical comparison between different types of ESS

As can be seen from Figure 2.3, the PHS and CAES storage has the highest score for a range of features, like self-discharge and energy rating. The only potential drawback of pumped storage is that it requires ample space and a sufficient height difference between the lower and upper reservoirs. For the CAES, a large cavern or facility in which to compress the air is needed. In other words, the geographical location is vital for the viability of PHS and CAES storage, and they are, therefore, unsuitable for many case studies. Li-Ion BESS has a relatively high specific power and energy and a rapid response time, making it suitable for fast acting reserves.

2.3 Applications for Energy Storage Systems

The use of ESS to provide ancillary services for the integration of wind turbines presented here. In Section 2.3.1, the definition of ancillary services is given, while section Section 2.3.2 discusses the different ancillary services needed for integration of wind power and which ESS is best suited for each of them.

2.3.1 Ancillary services

Definition of ancillary services as defined by International Electrotechnical Commission (IEC) section 617-03-09:

Ancillary services: *services necessary for the operation of an electric power system provided by the system operator and/or by power system users* [1]

As defined in the description above from IEC, ancillary services include a large number of features and are necessary for the quality of the electricity supply. Ancillary services can, for instance, be reactive power and voltage support, loss compensation, system protection, fault ride-through capabilities, and frequency-active power control (Ch. 28 [40]). The quality of the electricity supply is tied to voltage, frequency, and security of supply. As the quality of the electricity supply is a collective good, it cannot be left to the market alone. It is, therefore, responsibility of the transmission system operator (TSO) to provide it through ancillary services. The provision of ancillary services in Norway through the balancing market is discussed further in Section 2.4.3.

2.3.2 Energy storage systems for wind power integration support

Ancillary services and other services that ESS can provide for wind power integration support is presented in Table 2.3, based on table 3 in [33].

Table 2.3: Ancillary services and other implementations of ESS for wind power integration support

Application	Time scale	Suitable ESS
Energi arbitrage	h-days	PHS, NaS, CAES, VRB
Frequency regulation	s-min	Li Ion, NaS, FESS, VRB
Inertia emulation, oscillation damping, LVRT	<1s	LA, NaS, FESS, VRB
Primary reserves	10 min	PHS, FESS,BESS
Secondary Reserves	min-h	PHS
Efficiency use of transmission network	min -h	Li Ion
Emergency power supply, black start	min-h	LA

The following parts of this section are based on section 3.2 in [33] and section 3 in [31].

2.3.2.1 Energy arbitrage / load leveling

ESS can be used to store energy during hours with excess production and release this energy to the grid during peak periods. This can either be used to obtain maximal profit for a wind farm owner or by the grid operator to reduce the market risk exposure to volatile on-peak prices.

[1] IEC definition [39]

2.3.2.2 Inertia emulation

A system with high inertia is slower to change than a system with low inertia. The grid function in much the same way, thus higher grid inertia equals a grid that is less sensitive to sudden changes in production or consumption. The inclusion of ESS can artificially raise the apparent inertia to the grid, making it more robust to changes.

2.3.2.3 Frequency regulation

Wind farms are required to offer frequency regulation to the grid. By additional droop control, the wind farm can achieve this, but not without risk of causing fatigue to the turbines and instability problems. Therefore, ESS can be used instead, with local droop control for primary reserves and active power command from the Automatic Generation Control (AGC) for secondary reserves.

2.3.2.4 Reserve application

Reserves are necessary for the power system to cope with imbalances in production and load. The reserves are divided based on response time into primary, secondary, and tertiary reserves. A broader description of the different types of reserves and the Norwegian balancing market for procuring these reserves is given in Section 2.4.3.

2.3.2.5 Oscillation damping

Changes in power for interconnected systems might lead to unwanted oscillations that, in the worst case, can result in loss of synchronism for connected units. For large wind farms, the volatile production can be mitigated and additional system stability obtained by the inclusion of ESS with a damping controller.

2.3.2.6 Voltage control support

ESS can provide reactive power to compensate for the local voltage. This is achieved through the grid-connected converter and might be especially useful for compensating fluctuating wind power production.

2.3.2.7 Low voltage ride through support

For severe grid faults, wind farms need Low Voltage Ride Through support (LVRT) capabilities to remain connected to the grid. If the grid demands reactive compensation during a fault, the converter needs to draw real power to compensate for the switching losses gained by the supply of reactive power. If the fault is severe enough, no power may be drained from the grid; thus, the converter switches are blocked. In these instances, the ESS can supply the required DC voltage so that the converter is compensated for the real power loss and can supply the grid with the needed reactive power and prevent further instabilities.

2.4 Norwegian Power Markets

The wholesale market for electricity in Norway consists of the following markets: day ahead, intraday, and balancing. The balancing market is used to ensure that there are sufficient reserves in the power system. Since ensuring the necessary reserves is a TSO responsibility, Statnett manages the balancing market. Nordpool Exchange operates the day ahead market and intraday market. The time frame for the different markets is shown in Figure 2.4.

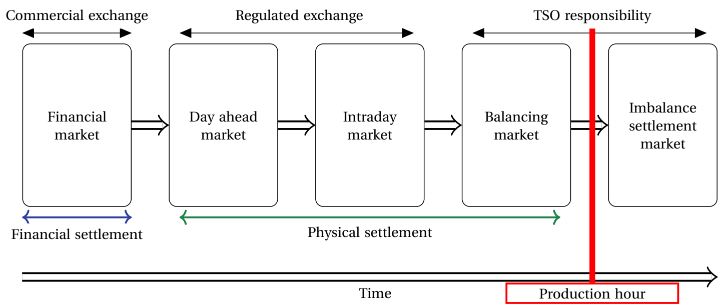


Figure 2.4: Time frame of Nordic Electricity Market (adapted from Norges vassdrags og -energidirektorat (NVE) [13])

The financial market is placed under financial legislation and is regulated by the Financial Supervisory Authority of Norway, and typically is used to secure positions for market participants several months or even years ahead of delivery time. The financial market will, therefore, not be discussed further here. The Nordic region is divided into different price areas for intraday and day ahead markets. Statnett does this area division according to provisions for system responsibility in the power system (FoS). The division is done to be able to manage major and long-term congestion in the central and regional grid or due to a possible lack of energy in defined geographical areas [41]. In Norway, there are currently 5 price areas: NO1, NO2, NO3, NO4 and NO5 [42].

2.4.1 Day ahead market

The day ahead market, named Elspot in Norway, is managed by Nordpool. A day ahead market is a financial market where bids are placed for selling and buying of electricity for the following day. In Elspot, the available capacities are given at 10:00, and the bids must be placed by 12:00 for delivery the following day. The market is cleared to obtain maximum social welfare with network constraints taken into consideration. The hourly clearing prices are posted to the participants at 12:42 or later [43]. Constraints concerning bids in the day ahead market are given in Table 2.4.

Note that trade lot here means both the minimum size of bid and the bid resolution.

Table 2.4: Criteria for Elspot market [4]

Trade lot [MW]	Price [Euro / MWh]	Order types	Block order volume limit [MW]
0.1	0.1-3000	Hourly, Flexible, Block, Exclusive groups	500

2.4.2 Intraday market

Nordpool also manages the intraday market. An intraday market is a continuous market for electricity, where trading takes place around the clock every day. The TSOs supply the available capacity for the Nordpools intraday market based on a flow study done on the result of the Elspot auction. The intraday market is open 24/7, 365 days a year, with 15-min, 30-min, hourly, and block products. The intraday market opens at 14:00 (normally) each day after the Elspot prices are set. The trading is continuous throughout the day, and trading closes 1 hour before delivery [44].

2.4.3 Balancing market

In Norway, Statnett is the responsible TSO, and acquires the primary, secondary and tertiary reserves necessary through market solutions. In the following subsections, the power systems response to a frequency change and the different balancing markets are explained.

2.4.3.1 Frequency response and activation of reserves in the Norwegian Power System

The power grid is subject to constant changes in both production and consumption. The immediate response to an imbalance (i.e., change of production/consumption) in the grid is to convert the inertia of the system's components into electrical energy. This causes a drop/rise in the system frequency. This frequency change activates the primary reserves, called Frequency Containment Reserves (FCR). The main task of the FCRs is to stabilize the frequency (i.e., prevent further drop/raise in the frequency) [5]. After FCR has stabilized the frequency, the secondary reserves are activated to liberate the FCR and bring the frequency back to 50.00 Hz, i.e., balance the system. Secondary reserves are called automatic Frequency Restoration Reserves (aFRR) or sometimes Load Frequency Control (LFC). aFFR are, as FCR, activated automatically by the TSO [45]. If there is a need for permanent or additional frequency regulation, the tertiary reserves are used. Tertiary reserves are often called regulating reserved and are manually activated with an activation time of up to 15 minutes [46].

The grids' response to an imbalance and the time frame of the activation of the different reserve types is displayed in Figure 2.5.

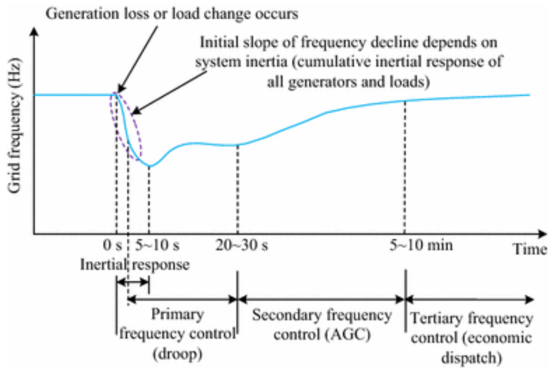


Figure 2.5: Frequency response of a system (Figure 1 [14])

In Figure 2.5 primary frequency control (droop) corresponds to activation of FCR, secondary frequency control to activation of aFRR and tertiary frequency control is equal to activation of tertiary reserves. The different reserve types and how their markets are built is given a brief explanation in the following subsections.

2.4.3.2 Primary reserves

Primary reserves are used as the main frequency regulator to compensate for the imbalances that might occur. The FCR regulation is fully automated and is divided into normal operating reserves, FCR-N, and disturbance reserves, FCR-D. To secure that the system has sufficient FCR, a market has been defined for trading both weekly reserves and D-1 reserves. The weekly market is run before the Elspot (day ahead market of Nordpool), while the D-1 market is run after the Elspot to cover residual needs. The bidding areas for FCR are the same as the current Elspot areas [42].

Table 2.5: Primary reserves as defined by Statnett [5]

Primary Reserve	Type of reserve	Activation	markets
FCR-N	Symmetric (both up and down)	Automatic at ± 0.1 Hz	Weekly and D-1
FCR-D	Up	Automatic at 49.9 Hz, fully activated at 49.5 Hz	D-1

Submission of bids in the weekly market opens 6 days before the delivery periods. The bids consist of period and bid area. There are six available bid periods for each Elspot area, day (08-20), evening (20-00) and night (00-20) for weekdays (Mon-Fri) and day (08-20), evening (20-00) and night (00-20) for weekends (Sat-Sun) [6]. Statnett gives feedback on accepted bids in the market on the day of trade by 15:00. Producers must submit errors in bids by 15.30 the day of trade [6]. Bidding in D-1 market is run in hourly resolution and opens at midnight the day before delivery. The bids consist of: type of reserve (FCR-N or FCR-D), per hour and per bid area. Statnett gives feedback on accepted bids in the market on the day of trade by 18.00. Producers must submit errors in bids by 20.00 on the day of trade [6].

Table 2.6: Criteria for bidding in D-1 primary market [6]

Bid for	**Submit bid by**	**Period**	**Min. size of bid**
Next day	Day before at 18.00	Hourly	1 MW

2.4.3.3 Fast frequency reserves

Fast frequency reserves, FFR, are a type of frequency reserves that are activated when the system frequency dips below a predefined level and should be fully activated within approximately a second. Statnett wishes to implement a market for the procurement of FFR. A demo version for the FFR market is, therefore, to be tested in 2020. In this demo version, it is proposed that the reserves can be activated for different values in the interval between 49.5, 49.6, and 49.7 Hz, with a maximum activation time of 0.7, 1.0, and 1.3 s, respectively. In addition to these requirements presented, the reserves must be available either as short support or long support FFR reserves. Short support implies that the reserves are available for a minimum of 5 s, while long support entails that the reserves are available for at least 30 s. Statnett does not foresee that these reserves are to be activated often, and predicts activation with a frequency of less than once a year [47].

There are several different technologies that could participate with FFR reserves. Statnett tested FFR response from different sources (industry, hydropower, and datacenters) in a test project in 2018. The main results from this project were that hydropower had a too-slow response, with activation times of 3 seconds or longer, while the data center, switching from grid import to batteries, had a response time within the 2-second response window, but did not deliver for the full 30 s period [48]. The fact that the uninterruptible power supply (UPS) unit controlling the battery used a function for FCR for activation, instead of one tailored for FFR, can have caused this.

In the demo version in 2020, Statnett wished to procure two types of reserves; FFR Profil and FFR Flex. FFR Profil is seasonal and is used to cover a limited volume of FFR reserves during nights (22-07) and weekends from May 1 to September 31. The flexible FFR is to be delivered based on short-term forecasts of demand. The price for FFR will, for the demo version, be decided by the highest accepted bid. If the frequency in the period that FFR is provided drops below the set-point, FFR reserves are activated. In this instance, Statnett pays the producers for the power they deliver. The criteria for bidding in the FFR profile market is given in Table 2.7.

Table 2.7: Criteria for bidding in FFR profile market [6]

Bid for	Submit bid by	Period	Min. size of bid
Season	16. March	1.May-30.Sept. 22-07 weekdays, 24 h weekends	Not specified

The procured FFR for 2020 demo version was released on March 20. There, it was said that Statnett would procure 27.2 MW FFR Profil at the price of 4.6 million NOK. This yields a price of 169 117 NOK per MW, 17 623.33 EUR / MW, (conversion rate of 2018 [49]) that is available for FFR Profil reserves for the period (2037 h in total). Statnett did not procure any FFR Flex in the 2020 demo version.

2.4.3.4 Secondary reserves

Secondary reserves, aFRR in Norway, are used to keep the frequency within the pre-defined frequency band of operation, 49.9-50.10 Hz, and liberate the FCR. The aFRR market includes both reserved capacity and activated energy. Statnett buys reserved capacity for aFRR at weekly auctions. The activation of aFRR reserves is decided by Statnetts LFC function. The LFC function makes decisions based on the measured frequency, and the activation of aFRR is done pro-rata. This means that the activation of aFRR is divided equally among all suppliers in the Nordic region [45].

Statnett sends the market definition to the pre-approved suppliers Monday at approx. 11:00. This signals the start of the bidding period. In the bidding period, all bids can be altered/removed, but on Thursday at 10.00, all bids are binding. The bids are placed for delivery from Saturday (the same week as the bid is placed) to, and including, Friday the next week [50]. During holidays, other bid deadlines might be set by Statnett.
The bid must be made with criteria as shown in Table 2.8.

Table 2.8: Criteria for bidding in secondary reserve market [7]

Bid for	Submit bid by	Period	Type of reserve	Price	Quantity
Saturday-Friday	Thursday 10:00	1 Week	Down or Up	[NOK/MW/h] in the contract period	5-35 MW, bid must be dividable by 5

Also, the bid of secondary reserve capacity, cannot be a part of other obligations. In addition, a bid is bought in its entirety, i.e., parts of a bid volume cannot be traded [7]. As a part of increasing the aFRR reserves, the Nordic TSOs have decided to increase the hourly use of aFRR following the introduction of a Nordic aFRR market. Statnett has decided to increase the aFRR from 84 to 94 hours/week in Q2/2020. In addition, the total volume in the morning hours is raised to approximately 400 MW. The total volume in other hours is set to approx. 300 MW [50].

2.4.3.5 Tertiary reserves

Tertiary reserves, called manual Frequency Restoration Reserves (mFRR), are defined as reserves that have an activation time of up to 15 minutes. The size of the tertiary reserve is decided to be equal to the dimension fault in the given system by the *Nordisk Systemdriftavtale*. In Norway, this dimension fault is 1200 MW. Statnett has decided to add 500 MW to this limit to control regional bottlenecks and imbalances. There are two markets for tertiary reserves in Norway: Regulerkraftmarketed (RKM) and Regulerkraftopsjonsmarketet (RKOM). RKM is a market for the Nordic power system for manual reserves with activation time up to 15 min. RKOM is a capacity market to ensure sufficient reserves in the Norwegian part of RKM and is available both as a seasonal and weekly market. [46]

2.4.4 Norwegian power markets suited for energy storage systems

In this section, the Norwegian power markets have been presented and discussed. Here, an attempt is made as to which are best suited for different ESS types. Of the balancing markets, the tertiary markets require long time storage (days) and a large energy volume (MW) and hence are suitable for few types of ESS except the PHS. For ESS participation in the secondary reserves, the large MW requirement demands a large ESS size, which again rules out most ESS except PHS if economic viability is also considered. Another way to solve this could be that the ESS is a part of a virtual power plant (VPP). In a VPP, the bids of several ESS or production units are aggregated and can be used for secondary reserve participation. The primary energy markets are tailored to several different ESS, as it requires a fast response time and ramp rate. In particular, the FRR market seems especially tailored to fast-acting ESS, of which BESS, of course, is an excellent example. The day ahead and intraday power markets are less suited for ESS participation, but coupled with volatile production, like a wind farm, ESS can help mitigate differences between bids and actual production. This difference could occur due to an error between the forecasted values and actual production. Failing to meet a set bid in either of these markets could lead to penalization or suspension [51]. Hence ESS could here benefit the volatile production unit by keeping it on the market.

2.5 Prerequisites for forecasts and battery operation

This section presents the theory relevant to the 10-year projection scenarios for the case study of Midtjfellet wind farm with ESS. This includes the prerequisites for the Li-Ion BESS selected to participate in the different markets, definitions of revenue stacking and data for producing forecasts of the price of electricity and Li-Ion BESS in the future.

2.5.1 Revenue stacking

A way to increase the revenue from installing ESS, and thus making a potentially positive business case, is to use stacked services or revenue stacking. As these terms imply, the ESS can, in this scenario, contribute with several services, either simultaneously or in different periods. The services depend on the market structure, but could for a battery include balancing reserves, frequency regulation, and time-shifting of volatile renewable production [52].

2.5.2 Price of electricity

To create valid scenarios for the electricity price in 2030, it is vital to include both historical price development, and tie this with recent trends that might influence the future price of electricity. Hence, this section tries to predict, to a certain extent, the reasonable price prognosis for the electricity price in 2030. It should, however, be noted that prediction of the price of electricity is inherently difficult and that if accurate forecasts existed, the owner of these could earn a fortune. It is hence vital to understand that this is merely a suggestion of how the price could develop, based on historical rates and new technologies.

It is plausible that with the increased building of power lines to other countries, the prices in Norway to an increasing degree match the price in the rest of Europe. Hence, it could be argued that the electricity prices could rise some in the coming years, as Norway has one of the lowest prices of electricity in Europe per now, as shown by the average price of electricity for households in 2017 in Figure 2.6, where Norway is found under NO and marked with a red square.

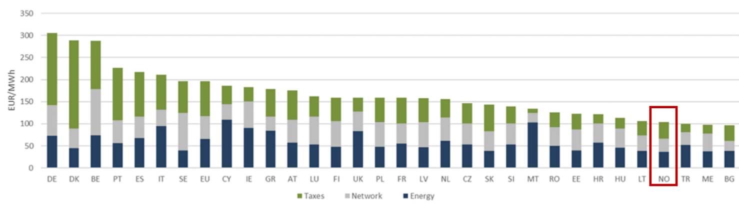


Figure 2.6: Household electricity prices in 2017 (most representative consumption band) (Figure 2 in [15])

Different EU countries have also imposed a tax on CO_2 emissions as a tool to reduce the impact of global warming [53]. If a broader part of the EU countries sets CO_2 taxes on production units for electricity, this could increase the price of electricity.

2.5.2.1 Historic prices

Following the statistics from SSB, the electricity price for Elspot and regulating power (in øre NOk/kWh) from 1998-2019 are presented with quarterly values in Figure 2.7.

The graph presented in Figure 2.7 is based on two statistics from SSB, one for the period from 1998K1-2011K4 [16], and one for the period from 2012K1-2019K2 [17].

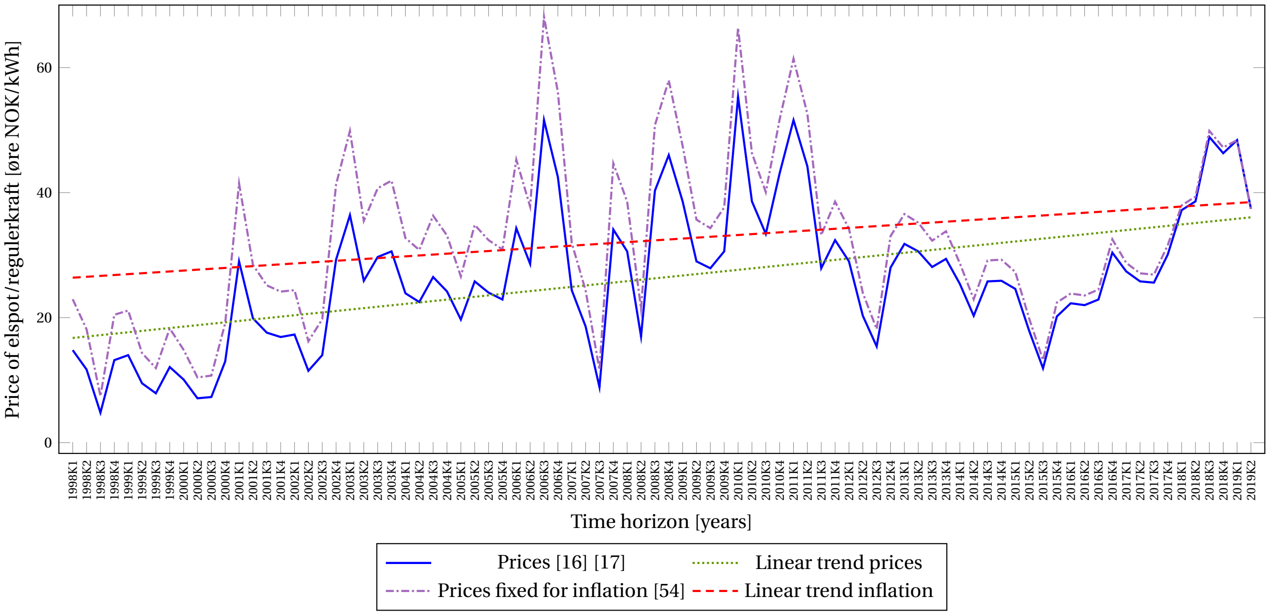


Figure 2.7: Historic elspot/regulerkraft prices øre NOK / kWh 1998-2019 [16] [17]

As can be seen from Figure 2.7, the dotted green line represents the linear trend and which was calculated using the graphical tools in Excel. The green trend line shows an increase in the electricity price from 1998 to 2019. Considering natural inflation, 1 (one) NOK in 1998 would, according to Norges bank, be worth 1.55 NOK in 2019 [54]. Following this argument, the prices were adjusted for inflation, as shown by the purple dash dotted line in Figure 2.7, with a corresponding linear red dashed trend line calculated by diagram tools in Excel. Even when adjusting for inflation, there is still a significant increase in electricity prices between 1998 and 2019, as shown by the red trend line. In numbered values, the linear trend lines show an increase in the 20.5 years of 115.18 %, with a 45.8 % increase when adjusting for inflation. The raw data for the calculation of the linear trend lines based on the acquired data can be found attached to the thesis in the excel file labeled "Appendix_B1_LE_Master_thesis_2020.xlxs"

2.5.3 Requirements for market participation

For producers or energy storage units to participate in electricity markets, they must fulfill different requirements connected to grid codes, market regulations and ownership. The relevant requirements for this thesis is briefly discussed in this section.

2.5.3.1 Grid Codes

Grid codes are rules and regulations for how different power grid components can connect to the grid. This could, for instance, be rules concerning reactive power, black start capabilities, the harmonic content, as well as area-specific requirements. If, for instance, a load is to be connected, the net in the area must be able to support it, or improvements must be made. In Norway, the relevant grid codes for a wind farm of Midtjfellets size (149.6 MW) can be found from Funksjonskrav i Kraftsystemet (FIKS). FIKS is a reference framework developed by Statnett for units connected to the Norwegian power system. FIKS was created to secure the development of a robust and secure power system and is meant to be used as a reference framework for the functionality that grid-connected units are required to have by the TSO. [55]

2.5.3.2 Compliance with market rules

As has been outlined in Section 2.4, there are several rules that bids must fulfill to participate in the different Norwegian power markets. The most limiting for energy storage units like Li-Ion batteries is the minimum bid size and the markets with longer time horizons, like the tertiary reserves market in Norway.

2.5.3.3 Ownership of energy storage units in Norway

The electricity grid in Norway is run as a monopoly, and with the current legislation in Norway, no grid company may own energy storage systems (ESS). A study performed by DNV GL for NVE in 2017 concluded that DSOs should not be allowed ownership of batteries in the future [56]. This means that a grid company cannot invest in ESS to improve grid stability or to provide other grid-related ancillary services.

2.5.4 Price of Li-Ion battery energy storage systems

The current and future development of the price of energy storage is of interest when matters of profitability are discussed. In the case study presented in Chapter 5, Li-Ion BESS is the chosen ESS. It is therefore interesting to look at how the prices for Li-Ion BESS is predicted to change in the future, and what this might entail in terms of profitability. Different price schemes for the future price of Li-Ion BESS is therefore depicted in Figure 2.8.

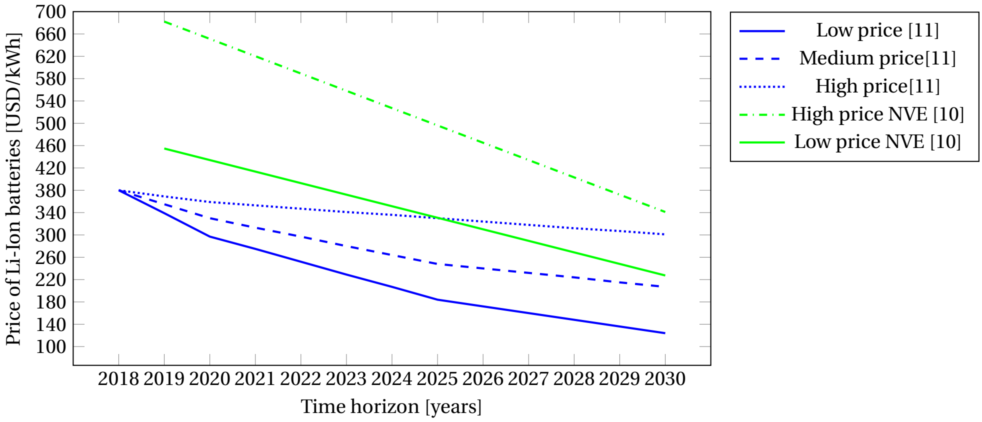


Figure 2.8: Price forecast for Li-Ion BESS, adopted from figure 1 [11] with added values from [10]

Reference [11] made a cost projection of utility-scale 4-hours battery systems, to both 2030 and 2050 values. In this report, the 2030 values are used, as the projection is for a 10-year horizon. The scenarios described in [11] indicate three different prices, low, medium, and high estimates, at 124, 207, and 338 USD/kWh respectively [11].

Reference [11] based their prediction on 25 different sources, where one example is found in [57]. In [57], the authors made their prediction of future Li-Ion prices based on an assumed electricity price of 50 USD/MWh. With the mean conversion rate of 2019 at 1.12 (from EURO to USD), this roughly translates to 44.64 EUR/MWh [58]. The mean spot price in NO5 in 2019 was 39.27 EUR/MWh [59]. Hence, it is clear that the business value of Li-Ion batteries could have been overestimated in [57] compared to the Norwegian market. Therefore, it could be argued that the medium and high estimates might be more suitable and probable for the price of Li-Ion in Norway. This is because the price of electricity is lower than in other countries, and hence the potential business value of Li-Ion batteries is reduced. In the report, the OM costs remain the same, but the investment cost, replacement cost, and EoL costs are scaled linearly according to the findings in [11].

NVE has also published a report regarding the prices of Li-Ion batteries, yielding an estimate of the price for 2019 between 4000-6000 NOK/kWh [10]. Translated with the mean conversion rate of 0.1137 from NOK to USD in 2018, this translates to 454.8-682.2 USD/kWh [60]. As can be seen, this is much higher than the number used in the [11] predictions. This could be because NVE looks at all Li-Ion battery systems, while [11] has focused primarily on Li-Ion batteries with a four-hour duration. It could also be because the prices in Norway differ from the sources used in [11]. However, the authors in [10] predict that the battery price of Li-Ion batteries is halved by 2030. Hence, a halving of this amount would mean prices in 2030 at 227.4-341.1 USD/kWh. Following this, the medium and high scenarios described in [11] are reasonable compared to the estimates by NVE [10].

Chapter 3

Literature Review

This master thesis aims to perform a case study of energy storage systems (ESS) coupled with a wind farm to asses the potential for a positive business case within 2030. A vital aspect related to answering this question is to evaluate relevant previous work within this area. A literature review is necessary for identifying an appropriate course of action and assessing potential research areas that this study can help expand. Besides, a literature review can contribute to a thorough understanding of the chosen area. In this thesis, it is important to asses the benefits of installing ESS with renewable generation. To assess such benefits, it is often vital to perform optimization based on minimizing or maximizing a selected objective. A comprehensive table of 20 articles related to optimization of ESS for technical or economic benefit, often coupled with a wind farm or other volatile production, as well as case studies within this field published in the period 2003-2020, is therefore presented in Table 3.1. The following parts of this chapter are based on chapter 2 in my specialization project [3], which has lain the preliminary groundwork for the master thesis. However, the literature review has been extended with seven articles. The additions have been made due to alterations in the problem formulation and to include new articles published. An overview of the articles studied in the literature review is presented in Table 3.1.

Table 3.1: Overview over articles studied in the literature review

Ref.	Summary	Model	Objective	Main findings
[61]	Operation planning and scheduling of Energy storage	Scheduling problem	Max profit	Shown that ESS with wind farm can take advantage of volatile spot price

[62]	Hourly-discretized optimization model for water storage and wind farm system	LP solved using a predictor-corrector primal-dual interior-point method	Maximisation of 24-h operational profit	Hydro storage increase the economic profit of the wind park. It also contributes to the controllability of the generation output. It can be used to install larger wind farms as the water storage can mitigate network operation restrictions.
[63]	Modelling and operating of CAES coupled with a wind farm as a baseload plant	Spreadsheet of desired output	Meet demand	Combined CAES and wind farm gave a significant reduction in GHG emissions and a substantial increase in efficiency compared to fossil baseload plants
[64]	Operation planning of hydrogen production through electrolysis from excess power from a wind power plant.	MPC model	Max profit	Fuel cells too inefficient for profitable electricity production. The better the forecasts and scheduling, the higher the profit.
[65]	Developed dynamic model of a hybrid system of a wind farm, PHS and HES	Constrained optimization solved by Lingo 9.0	Satisfy electric, hydrogen and water demand	Hybrid system has increased the flexibility compared to wind farm
[66]	Feasibility study for storage control of large scale ESS (Flow battery) to improve wind farm output predictability.	Four control types: Simple, fuzzy, simple- and advanced ANN	Min cost of system	Power flow control strategies have a significant impact on the system's energy and power ratings. ANN control strategies, in particular, gives lower costs than simplified controllers.
[67]	How different factors affect the size of the optimal storage. Optimal storage investment problem for a renewable generator.	Discrete-time average-cost infinite horizon stochastic dynamic programming.	Min cost of ESS	For the energy storage to be economically viable under the given balancing policy, the ratio of amortized storage cost to the peak price should be below $\frac{1}{4}$
[68]	Method for ESS (CAES) design for the regulation of wind power output and to increase grid voltage stability.	OPF, direct-calculation method and V-Q modal analysis	Max profit and SVS improvement	Case studies show that CAES can be used to improve both wind energy revenue and grid voltage stability
[69]	Market-based or technical planning and operation of a wind farm with Na-S batteries. Performed an economic feasibility analysis.	Technical/market-based decision algorithm and NPV calculation	Follow planned schedule and max NPV	ESS permits better integration of wind power through improved market performance and delivery schedule following.

[70]	CAES used to manage the power output of a wind farm by de-coupling its WEC	Sizing of CAES from 1-8 MWh (1 MWh steps) with additional revenue minus costs of additional storage as OF	Max profit	The combined system (CAES + WEC) followed a TOD FIT for feeding electricity to the grid. 30 % gross revenue obtained by peak-system given the economic assumptions taken in the report.
[71]	Control scheme for BESS with wind farm using MPC to sell more energy at peak and store at off-peak	QP solved by MPC	Max profit	The proposed control scheme for BESS improve wind farm dispatch
[72]	MPC to maximize profits from PV and ESS system in realtime tested on PV plant with the el-market structure of Spain.	LP solved by MPC	Max profit	MPC introduce benefit for a PV and ESS system by reduction of imbalance penalties due to better prediction of PV prod. Comp. effort of solving LP with MPC low enough to be can be implemented for a plant with a sampling time of 4 min
[51]	Creation of an EMS to maximize profit but also prolong BESS lifetime	MPC	Max profit and a max lifetime of BESS	Maximum revenue from energy arbitrage with minimal cost during the lifetime of BSS ensured by the proposed MPC method.
[73]	Perform techno-economical analysis of ESS with a wind farm to reduce volatility in the production with case study from Australia	Generic techno-economic model	Prevent ramp-rate violations	Found that regulatory frameworks for ramp-rates can significantly impact the economic viability of ESS, making them profitable.
[74]	Proposes algorithm that incorporates forecasting information to determine optimal power dispatch strategy for the BESS.	Optimal framework based on MPC with forecasting information	Max profit	Framework developed can be used to develop optimal power dispatch strategy for BESS-wind farm systems. The result can be used in planning to select optimal BESS capacity for a given power rating.
[75]	BESS installed with an R&D wind farm. It operated to provide two services, time-shifting, and regulation, to provide additional revenue	Logic rules for charge/discharge of BESS	Follow the predefined logic rules	Stacking services that resulted in additional revenue compared to just time-shifting. However, regulation provided 98 %, so it would be most beneficial financially to participate only in the regulating market.

[29]	Looked at RES and ESS integration for a large scale electrical grid (26 GW). Used Pakistan grid as a case study.	Model similar to HOMERs Energy Micropower Optimization Model but for large scale application	Min cost	Least cost combinations require the use of diverse renewable sources, installation of excess generation capacity, and ESS. Different combinations of storage can: bring the cost down, increase RES share, and reduce spilled energy.
[76]	Profitability of four bidding strategies for Li-Ion BESS coupled with wind farm participating in Iberian day ahead, intraday and tertiary reserve market	Non-linear optimization	Max profit	Simplified prediction models and non-linear optimization improves the operation of the wind farm with BESS support. The maximum theoretical benefit obtained with perfect information of forecasts
[77]	Techno-economic optimization of a large scale battery for four different cases	LP solved by heuristic procedure	Max profit	Use case with both participation in the spot market and balancing market provided a feasible configuration even with current battery prices
[78]	Find the optimal ESS rating to increase integration of wind farms by smoothing the output according to a power set point	QP solved by MPC	Optimal size of ESS to follow dispatch schedule	0.5 P/E ratio the best for wind power smoothing

3.1 Modeling of components

It is vital to understand the limitations and benefits of the earlier proposed methods to understand reasonable assumptions and models. Therefore, this section presents aspects of modeling the different components. Modelling of ESS is discussed in Section 3.1.1, wind farm modelling in Section 3.1.2 and market modelling in Section 3.1.3. How forecasting of data is handled, and models for forecasting in the different articles are presented in Section 3.1.4.

3.1.1 Energy Storage Systems

There have been several different ways to model ESS for renewable generation. The modeling process is essential when measuring the potential benefit of installing ESS, which is why previous approaches are discussed in this section.

Reference [63] studied the case where Compressed Air Energy Storage (CAES), coupled with a wind farm, was used so that the combined system could function as a baseload plant. To achieve this, [63] modeled the CAES as a fixed capacity where the combined system was meant to meet the desired output given by transmission constraints. The model included the effects of transmission losses between the wind farm and CAES. If the objective by installing ESS is to obtain the maximum profit, taking advantage of volatile electricity prices is often crucial. Operation as a baseload plant, as proposed in [63], can, therefore, be a poor choice. In [70], the operational characteristics included in the CAES model was: Efficiency, Charge power, Discharge power, Operating pressure range, Ramp rate, and Energy capacity. The lifetime/number of cycles was not included directly into the modeling, and neither was the self-discharge. Nevertheless, as the CAES system, in general, has a long lifetime, a high number of cycles, and low self-discharge, these features are less important to include in the model than for other types of storage.

In [75], a real 10MW R&D wind farm was used, with an installed BESS capacity of 1MW/2MWh, and a test period of one month. The BESS was operated with simple static rules for charging/discharging of the battery to achieve both time-shifting of energy supply and Automated Generation Control (AGC) response. It should be noted that although degradation was not included in the model for controlling the BESS in [75], it is, of course, present in the physical batteries installed. Hence, omitting it from the model might lead to unwanted battery operation, meaning that the static rules used might be too simple an approach for actual implementation. However, [75] did model the BESS with limitations for charge and discharge rates as a function of the SoC level. In particular, the authors in [75] found that the charge rate, which decreased with increasing SoC level, heavily limited the operation of the battery, and made it unable to perform the actions required in some instances of the simulations. Reference [51] modeled a Lead-Acid BESS using a simplified model developed by the authors in [79], which only includes the BESS storage dynamics. The BESS is in this simplified version modeled by a third-order linearized model. The chosen model was accurate enough for the primary purpose of the article, namely, to create a supervisory energy management control.

A generic ESS model coupled with a wind farm was proposed in [61], with a defined relationship between storage level and charging/discharging. Since it was developed as a generic ESS, it did not include features that, for some ESS might be prominent, such as self-discharge. The model would not be valid if the proposed method were used for a flywheel which has a very high self-discharge. However, as a case to show how ESS coupled with a wind farm, can contribute to less unused energy and a potential revenue stream, the simplified generic ESS model was satisfactory. Besides, although commented in the discussion section in the article, the ESS model lacked investment costs. This means that in the showcased revenue streams, showing a promising additional profit for installing ESS with a wind farm compared to only the wind farm, the actual cost of the ESS was not accounted for. As the authors in [61] also mentioned, at the price of ESS (in 2003), the comparison between additional grid investments and installing ESS often favors grid investments. This is due to the high ESS price at the time.

Reference [64] established a Linear Programming (LP) model of the hydrogen plant based on equations for electrical energy balance and flow of H_2 that could be used in the operation planning stage. In addition, excess production were sent to a dump load in [61] and [64]. The use of a dump load is a simplification that effectively results in loss of potential revenue. However, it is not a simplification that leads to a less realistic system, as it is the same as wind farm curtailment. I.e., that the production is reduced compared to what the wind farm can produce, as a result of agreements with the grid, environmental concerns, or control issues. Reference [68] modeled the ESS as a regulated power source. The regulated power source could absorb or supply power and was implemented with a charge/discharge scheme. The ESS model included power rating, energy rating, and efficiency. For a specific type of ESS, additional features like self - discharge and ramp rate should be included to give a more realistic model of a specific system.

Few of the earlier published work considers the response time or degradation of the chosen ESS, as can be seen in Table 3.2 while an increasing focus on this is found in the articles publicized in the more recent years. The common denominator for the proposed methods is that the model parameters are limited to the article's need. An example is found in [76], where the authors used a simplified method for degradation of the battery. In the article, degradation of the battery was modeled as a function of the Depth of discharge (DoD). Inclusion of degradation, response time, self-discharge, investment costs, and ramp rates for the storage types could potentially alter how each ESS is used. The level of complexity needed from the storage model, i.e., which parameters to include, depends on how the results obtained should be used. This can, for example, be as either an investment tool or to provide control moves for actual operation. Therefore, it is vital to include the parameters necessary for the use case of the ESS for the results to be valid. An example is shown in [75], where the charge rate of a BESS, which is a function of the chemical properties related to the SoC level, limited the use of the battery compared to the desired set-point. Hence, had this feature been omitted, the battery operation proposed could prove invalid for actual operation.

3.1.2 Wind farm

There are different ways to obtain the wind farm data used in the combined systems, either by using actual data or simulating the production.

In [70], one year of average output power at the grid interconnection from a 0.8 MW turbine with a time resolution of 10 minutes was used. Reference [75] also used real-life data from a 10 MW R&D wind farm and a simulation period of one month. In other studies, a generic wind farm model with identical wind turbines was used, [61, 69]. In particular, [61] assumed that the wind farm consisted of wind turbines with the same wind conditions where the production followed the characteristic input/output curve of a given wind turbine. Reference [62] modeled the wind farm as a stochastic quantity, represented as two hourly series: one for average wind speed and one for standard deviation. The algorithm then picks a random interval of these time series that represents a wind power scenario. Reference [65] used a linear wind model for the wind turbines, where the power output was in linear relation to the wind speed at hub height. This was then compared using Root Mean Square Error (RMSE) and chi-square with the power output curve of an actual wind turbine, resulting in very small deviancies (range 10^{-2} to 10^{-3}).

The main findings regarding wind power is that most of the articles use simplified models to predict wind power output. This is because the main focus of most of these articles is how ESS behaves with a fluctuating production. The inclusion of complicated production models would increase the computational effort required while not necessarily adding any additional benefit.

3.1.3 Electricity markets

How the chosen ESS can participate in the electricity market is vital in assessing the potential revenue which can be gained. It is, therefore, essential to know how the underlying electricity market has been modeled and should be modeled to reap the highest potential benefit in installing ESS. In this regard, it is especially interesting to look at the potential for revenue stacking, i.e., the potential for several revenue streams by, for instance, participation in several energy markets. A section concerning this is therefore included in Section 3.1.3.2.

3.1.3.1 Revenue stacking

Reference [75] used both the day-ahead and regulation market of PJM. The results showed that even though the PJM regulation market showed the highest revenue potential for ESS, it was insufficient to cover the cost of the chosen BESS for the 24-day trial. In [76], four market participation schemes were tested, were three of the schemes participated in the Iberian markets for day ahead, the first intraday and tertiary regulation. The authors found that the theoretical maximum revenue for participation in the three markets, obtained by perfect forecast information, showed an improvement of 52 % with the inclusion of BESS support compared to the reference case with the wind farm. In [64], the chosen ESS was hydrogen, where profit could both be earned by selling electricity produced by fuel cells (FCs) on the Nordic Spot market, which is a day ahead market, but where hydrogen was also used as a fuel. Unmet hydrogen demand was penalized, and hence revenue stacking in this sense could be interpreted as to maximize the combined revenue from selling electricity and meeting a hydrogen load demand.

3.1.3.2 Market structures

In [70], the proposed electricity market included a Time of Day Feed-in Tariff (TOD FIT) rate, i.e., a compensating scheme for both electricity consumption (TOD) and energy generation (FIT). This electricity market structure created higher price volatility and was used to make a decision scheme for whether the electricity price was on or off-peak. A charge/discharge scheme based on the electricity price was then created for the CAES, based on predictions of whether electricity would be worth more now or later. The Nordic Spot market was the market structure in [61]. In the Nordic Spot market, the bids are placed 12h (or more) before the actual delivery day, and discrepancies between bids and delivery typically result in reduced income. Reference [69] proposed a market model based on Italian regulation where correct hourly offers were rewarded with additional revenue, and penalties were given for deviance from the hourly delivery plan. Incentives for wind turbine installment were also included in [69].

Reference [73] tailored the ESS used to specifically reduce the number of ramp-rate violations, which, when it occurs, incur a penalty cost for the wind farm owners. Hence, ESS was not used to participate on a regular energy market, but rather to reduce the costs of ramp-rate violations. However, the authors found that by aggregating wind farms that are located far from each other, the need for ESS to mitigate ramp-rate violations decreases. This is because wind farms located far from each other have different production patterns, as the weather is highly local. Hence, the output from the aggregated farms is smoothed. However, the interesting find pertained to how regulatory frameworks can be paramount for creating economically viable ESS investments. It should also be mentioned that this study was conducted in an area in Australia with an extensive penetration of wind power (30 %). It could, therefore, pinpoint how regulatory framework in the future in other areas with increasing wind power penetration could provide opportunities for profitable ESS investments.

In [77], the battery modeled was used for different cases. In the first use case, the battery was used to reduce the peak of an industrial load since the battery paid a fixed amount for each kW used. However, this required battery prices below 200 EUR/kWh, which at present and in the near future is unrealistic according to prognosis found in [11]. In the second use case, the battery was used to reduce the peak infeed power from a PV system to 100 kW (infeed power above this incurs a cost for each kWh supplied following prosumer legislation in Norway [80]). Hence, the market structure proposed in the two first use cases did not result in a positive investment for batteries with the prices schemes used. However, in the third use case, the battery was allowed to trade in the balancing market for frequency containment reserves in Norway, FCR-N (normal operation), and FCR-D (disturbed operation). In this use case, the battery became profitable (positive NPV for the battery) for 1400 EUR/kWh, which means that it would be profitable with the price of batteries today. However, there were some limitations; fees required to participate in the FCR-N market were not included, and the battery model did not allow for interruptions in operations needed to charge/discharge battery or the penalties incurred.

3.1.3.3 Summary of electricity markets

As seen from Section 3.1.3.2, few of the authors include more than one market structure in their models. Including more markets could provide the potential for revenue stacking, i.e., increase the revenue from installing ESS. However, as shown in [75], it is not necessarily so, as the authors found out that for the highest economic benefit, the BESS should, in that case, only trade on the regulation market. But, as participating in both regulating activities and energy arbitrage provided additional technical benefits for the grid in [75], participation in several markets is still an area that needs further study. It is also worth noting that both in [77] and [51], ESS showed great potential when allowed to provide balancing power, either in terms of reducing ramp rate violations or by participating directly on a primary reserve (FCR-N) market.

3.1.4 Prediction models

In [61], the bids and sales were made on the Nordic day ahead market, Elspot, 12h ahead of time; thus, predictions for next days' production data were needed. An average wind speed equal for all hours was predicted using a simple algorithm that picked a random number from the normal distribution of wind speeds for the area. In [76], the forecasts for prices and the demand in the tertiary reserve market was found by extrapolation based on previous values for the same hour, within the most recent rolling window. Reference [69] used both predictions of weather and electricity prices. The average daily price forecast was predicted from hourly price forecasts based on data from the Italian day ahead market in 2009. Data sets for predicted wind farm production were made using the randomization of wind speed measurements. The wind speed measurements had a 5 minutes resolution and were collected from an existing wind farm in Southern Italy. These ways to obtain forecast and prediction data in the earlier part of this section are made by using average data or crude models. To obtain a more sophisticated prediction model than randomly picking a number from a data set, [71] and [65] assumed that reliable weather forecasts would be available. Hence, they chose a data set from an existing wind farm for use in the optimization model. Reference [75] used a rule-based system where there was no forecasting of price or production, hence the BESS strategy was determined based only on the current SoC and wind farm production.

As discussed in [69], even small deviations between actual and predicted production might lead to a significant reduction in revenue. It is, therefore, vital to obtain useful optimization tools for prediction models. Historical data of actual wind farm production for a given wind speed could be used in these models to obtain accurate forecasts.

3.2 Optimization

This section goes through the models and methods for optimization used in different stages of ESS and wind farm systems. In Section 3.2.1, the objective of adding ESS to a system is discussed. Section 3.2.2 defines the models used in the articles in Table 3.1 for sizing ESS, while the operation and planning of the ESS systems is shown in Section 3.2.3.

3.2.1 Objective

The objective for including ESS to a system varies, but can roughly be divided into three categories: economic, environmental or technical benefit. In [63], the main objective was to prove that ESS, coupled with wind farms, could function as conventional (and often fossil-based) baseload plants. This meant increasing the capacity factor of the combined system from 25-40 % to 80 %. Also, to show that wind farms and ESS were a better choice for the environment, a Life Cycle Analysis (LCA) was performed to showcase the environmental benefits of this combined system. The research showed that by operating as a baseload plant, the combined system was up to five times more efficient than the most efficient combustion technology and emitted less than 20 % of the least emitting fossil technology available [63] at the time. The objective in [61, 64] was to find the operation scheduling for the next day that would result in the maximum profit, given a set capacity and power of the proposed ESS and wind farm system. Maximum profit, but for optimization over a full year, was also the objective in [70]. In [69], the objective of potential economic profit was assessed using the Net Present Value (NPV) criterion. In [65], the objective was to gain as small deviancy as possible between the demand and supply of water, hydrogen, and electricity. Maximization of the combined revenue from participation in three different energy markets (Iberian day ahead, tertiary and intraday market) was the objective in [76], where the sum of the offered energy in the three markets was set as the maximum forecasted production of the wind farm.

As pointed out in [68] and shown in Table 3.1, previous studies focused mainly on either control of ESS or economic scheduling, leaving out ESS-grid interrelation issues. To remedy this, [68] proposed a method for optimal ESS design where the objective was both regulations of wind power to improve wind energy integration and grid voltage stability. In [68], Optimal Power Flow (OPF), which includes grid constraints in the optimization, was used to gain a reference value for the generation. Consequently, to assess more than just the economic benefit of ESS, a broader model that includes technical aspects in the objective function, is needed.

3.2.2 Sizing of energy storage systems

The optimal size of ESS for a given objective and problem has been found using different methods. The definition of ESS size/rating includes either the power rating in MW or energy storage capability in MWh.

The approach in [61, 69, 70] does not solve an ESS sizing problem per se but considers different ratings of ESS. Reference [70] ran the model for different sizes in steps of 1 MWh ranging from 1 MWh to 8 MWh and found the one which yielded the highest revenue. Reference [61] made a similar approach but also varied the power rating to showcase how this affected the system. In [69], two case studies with different rated ESS power were performed. Reference [65] and [75] used fixed sizes of both plants and storage systems. Reference [68] proposed optimization based on maximizing the net benefit of an Objective Function (OF). The OF included four terms: net profit, revenue obtained by selling energy from the ESS that would otherwise be lost, four benefit factors, and annual financial requirement of the ESS. The four benefit factors include revenue from environmental considerations, improved voltage stability, improved reliability, and wind capacity firming. These benefit factors can be challenging to quantify, but the main advantage of introducing them is that their effects are introduced directly into the optimization process. The problem was solves using *"direct calculation method"*, which in broad terms can be explained as solving the problem by a discretization of the OF and search of the function values.

Reference [76] used the net present value of the investment cost for a battery versus the present profit of the yearly benefit to obtain the optimal size of the Li-Ion battery. Reference [73] did not solve an optimization problem to find the optimal size of ESS, but instead used quantitative analysis to define the variability of the wind farm, which was then used to find the storage size necessary to prevent most ramp-rate violations. In [78], the main objective was to find the optimal ESS size that mitigates fluctuation for a wind farm, through the use of a double closed-loop control strategy. The ESS size that is most economical for meeting a given average fluctuation rate is chosen as the optimal in this instance.

The sizing problem of ESS can, as shown here, be solved using a range of different methods. The common denominator is that the objective by installing ESS is vital when deciding the ESS size. The difference between solving an optimization problem to find the optimal ESS size, and using a predefined value should also be highlighted. Simulations that are performed with an optimized size of ESS, which is tailored for a specific need, yields more accurate results for the given objective than using a predefined ESS size. Here again, it depends on the complexity of the system and the objective of the optimization. It can also be mentioned that the control or operation planning algorithms presented in a range of these articles well could be used on an existing system, meaning that the ESS is set. In these cases, solving the problem for the optimal size of ESS would have little value unless a further investment into ESS is planned.

3.2.3 Operation and control planning

Optimization of the operation of ESS in Table 3.1 is briefly presented and discussed in this section.

Reference [61] defined a daily operation planning scheme for a 24h running period. Reference [64] proposed a scheduling problem based on forecasts of the electricity price, production, and load, where a simple algorithm solved the on-off switching process of the electrolyzer and fuel cell. For the online operation, a variant of model predictive control (MPC) was used to obtain the control sequence for a specific time horizon N, which maximized the profit. Reference [69] proposed two different operation planning algorithms; technical and market. In the technical planning period, the algorithm used predicted the wind farm output and found which value the ESS should have to keep the output as constant as possible. Due to ESS limitations (minimum level of SOC, for instance), a Storage Fulfillment Index (SFI) was considered, and the optimization was run for each hour until acceptable values of the SFI(h) were found. The average daily price of the market-based planning stage was calculated from hourly price forecasts based on prices from the Italian Day-Ahead Market from 2009. It was assumed that the owner of the ESS/Wind farm system was a price taker. A delivery plan based on the price was proposed; the SFI(h) calculated and Storage Surplus Index (SSI) defined as another infeed ratio on the planned profile for each hour. These two different planning methods were then compared by running the model with an hourly resolution for a year to see which yielded the highest NPV. Reference [29] used an approach similar to that of the Hybrid Optimization of Multiple Energy Resources (HOMER) microgrid optimization model. Hence, the model provided the optimal hourly dispatch profile for load and generation. In [72], the objective was to find intraday operation for a PV and ESS system. Hence, the control planning period was limited to 4-5 h, which was solved using an MPC approach. The LP proved to have a solution which computational effort was low enough so that the MPC strategy could be used for the operation of a real plant given 4 min sample time.

To find the desired generator dispatch profile in [68], OPF was used. The resulting desired output profile was then used as the reference for the ESS operation. Reference [77] used a set of heuristic rules on an LP model of the battery to determine the operation, which yielded maximum revenue while minimizing the losses. In [70], the dispatching scheme, and model for selling energy was done in MATLAB for one year of operation using 10 minutes time-steps. Reference [65] had a minimization objective function, which included a total of six terms. Four terms were used for penalizing deviancies between acceptable water levels in the reservoirs and over-satisfaction/dissatisfaction in hydrogen and energy demand. Two terms were then used for the variable costs related to electricity production from either the hydroelectric generator or the fuel cell. The model then included constraints for storage capacities, plant capacities and activation, non-negativity constraints, and fuel cell constraints. The decision model is a quadratic problem with both binary and continuous control variables.

Here, the large span in how each problem is solved reflects how each has adapted or developed models that reflect the given objective they want to solve. For instance, [64] had as a goal to find the operation that yielded maximum profit and used a scheduling problem. At the same time, [68] wanted to show how ESS can contribute with static voltage stability (SVS) and hence used OPF for a more accurate grid model and inclusion of relevant grid constraints.

3.3 Summary

A brief overview of the methods and similarities between the reviewed articles and the chosen approach is shown in Table 3.2. The proposed method in this study is labeled

MT. The similarities between the proposed method and previous literature have been highlighted in green, where a deeper green highlights a stronger resemblance. Additional revenue has been shortened to add.rev and scheduling to sched. It should be noted that the self-discharge included in [75] was the amount of energy the battery system as a whole lost for the one month test period, translated directly into a loss of revenue. Hence, it was not included in the battery model but rather calculated based on the results of the operation strategy. Also, revenue stacking is in Table 3.2 defined as: *"the use of more than one market or one way to obtain revenue to provide additional benefit."*

Table 3.2: Comparison and summary of the literature reviewed

Article	Model	Solver	Category	Forecasts	Period	Type of ESS	Includes cost, degradation and self-discharge	Real-life case data	Revenue stacking [1]
[61]	Sched. prob.	DP	Add. rev.	Deterministic	24h	El. ESS	No, No and No	No	No
[62]	LP	PCPD IP [2]	Add. rev.	Stochastic	48h	HES	No, No and No	No	No
[63]	-	Excel	Red. emis.	Deterministic	2 weeks	CAES	Yes, No and No	Yes	No
[64]	Sched. prob.	MPC	Add. rev, H_2 demand	Based on WPPT tool [3]	24/48h	H_2 w/FC	No, No and No	No	Partly [4]
[65]	Constrained OF	Lingo 9.0	Meet demand	Deterministic	24h	PHS and H_2 w/FC	No, No and No	Yes	No
[66]	SIMULINK	MATLAB	Opt. ESS Size and Control	Deterministic	282 days	FBESS	Yes, No and No	No	No
[67]	OSIP [5]	-	Opt. ESS Size	-	Inf. horizion	Generic ESS	Yes, No and No	No	No
[68]	Size prob.	DCM [6]	Add. Rev and SVS	OPF for load profile	1 year	CAES	Yes, No and No	Yes	No
[69]	-	-	Integration of wind energy	Deterministic	1 year	Na-S-BESS	Yes, No and No	No	No
[70]	SIMULINK	MATLAB	Add. rev.	Deterministic	1 year	CAES	Yes, No and No	Yes	No
[71]	QP	MPC in MATLAB	Add. rev.	Deterministic	24h	BESS	Yes, Yes and Yes	No	No
[72]	LP	DD in MATLAB (MPC) [7]	Add.rev.	Deterministic	4-5 h	generic ESS	No, No and No	Yes	No
[51]	Convex prob.	MPC in MATLAB	Add.rev.	Deterministic	24 h	Lead-Acid BESS	Yes, Yes, and No	Yes	No
[73]	-	-	Red. costs	Deterministic	1 year	FESS, Li-Ion, NaS, VR FBESS, SC	Yes, No and No	Yes	No
[74]	OCP[8]	Dynamic programming	Add. rev.	Deterministic	24h	BESS	Yes, No and No	Yes	No
[75]	Static rules	Logic control	Add. rev.	No forecasting	1 month	BESS	Yes, No and Yes	Yes	Yes
[29]	Similar to HOMER[9]	-	Meet energy demand	Deterministic	1 year	Li-Ion, H_2 w/FC	Yes, Yes and Yes	Yes	No
[76]	NLO [10]	-	Add. rev.	Extrapolation rolling window	1 year	Li-Ion	Yes, Yes and No	Yes	Yes
[77]	LP	Heuristic rules	Add.rev.	Deterministic	10 years	BESS	Yes, No and No	No	No
[78]	QP	HQPR [11]	Opt. ESS Size and control	Deterministic	40 min - 2h	Generic ESS	Yes, No and No	Yes	No
				Authors choice					
MT	MILP	MGMS[12]	Add. rev.	Deterministic	20 years	Li-Ion	Yes, Yes and Yes	Yes	Yes

As Table 3.1 and Table 3.2 show, there have been numerous articles featuring case studies of different types of ESS coupled with wind farms or other volatile renewable production. The main findings in these articles are that it is hard to find economically viable options. There are exceptions to this, where the common denominator is that profit can be obtained by participation with regulating power, as seen in [73, 75, 76, 77]. Of the reviewed articles, only one has done optimization for a period longer than one year, i.e., that few take into consideration optimization for the lifetime of the project. It should, however, be mentioned that several, has used the annualized cost of the ESS in their calculations. It is also true that few take into account both costs, self-discharge, and degradation. However, several of the articles reviewed different types of ESS than the one chosen in this thesis. For instance, as PHS and CAES experience a very low self-discharge, and PHS has virtually no degradation, these features were not essential to include. However, as Li-Ion BESS is the chosen ESS in this thesis, it is vital to discuss these features and, to the extent possible, include these features in the proposed case study.

It should also be noted that most of the featured articles are concerned with economic optimization and thus neglects technical benefits (e.q. ancillary services) and moral concerns (like increase of renewable penetration or reduction of power shedding). Given the current legislation in the EU, where DSOs are prohibited from owning ESS [2], this is a natural choice, as the ESS proposed must be profitable for investors. In this regard, this thesis also follows the precedence of the articles presented, i.e., focuses on markets and features where the ESS is compensated economically for the services it provides. Hence, the area of study for this thesis is to maximize the revenue that can be obtained for a real case study of Midtfjellet wind farm with ESS. In this regard, the literature reviewed has shown that there are some gaps concerning the optimization period, ESS model, and revenue stacking. In the chosen optimization software for this thesis, PSS®DE, optimization for the lifetime of the ESS is possible, as well as a linear model for battery degradation; therefore, information on whether the system is profitable for its entire duration can be obtained. Thus, the case study presented in this thesis should aim to include revenue stacking by introducing several markets (primarily regulating markets), use a sophisticated battery model, and performance optimization for the lifetime of the project presented. This is seen Table 3.2, where the chosen approach, MT, objective is additional revenue, optimization for the lifetime of the project, inclusion of revenue stacking, and relevant parameters for Li-Ion BESS.

[1] PCPD IP: Predictor-Corrector Primal-Dual Interior Point method, see [62] for more details

[2] WPPT: Wind Power Prediction Tool, is explained in greater detail in [81]

[3] In a sense, as there was both a spot market and a penalty cost of unmet hydrogen demand

[4] OSIP: Optimal Storage Investment Problem, can be viewed in greater detail in [67]

[5] DCM : Direct calculation method [68]

[6] DD: Double Description algorithm based on [82], implemented in MATLAB

[7] OCP: Optimal Control Problem, DP: Dynamic Programming [74]

[8] Non-Linear Optimization, further explanation in [76]

[9] Hildreth's Quadratic Programming Procedure explained briefly in [78], MPC inner loop control in MATLAB

[10] MGMS uses a MPC approach [9]

Chapter 4

Method

This chapter details how the general optimization problem for the operation of a system containing a wind farm, load, and energy storage system (ESS) connected to a grid can be formulated mathematically. This is done to get an understanding of how the chosen program, PSS®DE, considers the system and how optimization is done. In this case, the optimization problem's objective is to maximize the revenue obtained by the system. The model of the system and the mathematical formulation of the optimization problem is presented in Section 4.1. A brief explanation of the Model Predictive Control (MPC) approach is also given in Section 4.2. This is done because the chosen PSS®DE dispatcher, MGMS, for solving the case study presented in Chapter 5 uses a method that is based on MPC principles. It is, therefore, vital to have a basic understanding of how the MPC algorithm works. The chapter is concluded with Section 4.3, which is comprised of the different features of the chosen optimization tool PSS®DE. The generic model for optimization is based on chapter 4 of my specialization project [3], but have been modified to a great extent. The modifications include adding a load to the model, including a multi-market structure and general improvements. Also, Section 4.2, concerning the MPC method, has been adapted from chapter 4 of my specialization project [3]. Section 4.3 is taken from chapter 5 of the specialization project [3] with minor modifications. An addition has also been made to the PSS®DE section to include the sizing optimizer, found in Section 4.3.3, a new feature used in the master thesis.

4.1 Optimization model

A generic optimization model for the operation of a wind farm, load, and ESS connected to an external grid is derived in the following sections. The indexing, summation, and general notation for the mathematical formulation of the optimization model follows the principles described in chapter 3 of [83].

4.1.1 Notation

Here the sets, parameters, constants and variables for the optimization model is declared.

4.1.1.1 Sets

T	-	Set of time period, indexed by t
N	-	Number of wind turbines, indexed by j

4.1.1.2 Constants

P^{LOSS}	-	Loss [MW]
η^{LOSS}	-	Loss associated with transition from mech. to el. power for one wind turbine [%]
η	-	Converter losses for one wind turbine [%]
$\eta^{AC/DC}$	-	Efficiency of battery converter AC/DC [%]
$\eta^{DC/AC}$	-	Efficiency of battery converter DC/AC [%]
η^{T}	-	Internal losses in central wind park transformer [%]
η^{C}	-	Internal losses in central wind park converter [%]
$P^{out,max}$	-	Maximum output power of battery [MW]
$P^{out,min}$	-	Minimum output power of battery [MW]
$P^{in,max}$	-	Maximum input power of battery [MW]
$P^{in,min}$	-	Minimum input power of battery [MW]
$P^{TC,max}$	-	Maximum transfer power of grid, both directions [MW]
$P^{TC,min}$	-	Minimum transfer power of grid, both directions [MW]
$P^{W,max}$	-	Maximum power from wind farm [MW]
$P^{W,min}$	-	Minimum power from wind farm [MW]
P^{TR}	-	Transmission losses from turbine to central converter [MW]
P^{TL}	-	Transmission line losses from grid to node [MW]

4.1.1.3 Parameters

P^{M}	-	Mechanical power of one wind turbine [MW]
P^{E}	-	Electrical output power of one wind turbine [MW]
P^{W}	-	Wind farm output power [MW]
P^{L}	-	Load power [MW]
C^{IMP}	-	Import price for power [EUR/MW]
C^{EXP}	-	Export price for power [EUR/MW]
SOC^{min}	-	Minimum SoC level [%]
SOC^{max}	-	Maximum SoC level [%]
$P^{E,min}$	-	Minimum electric output power wind turbine [MW]
$P^{E,max}$	-	Maximum electric output power wind turbine [MW]
P^{FFR}	-	Activation power for FFR reserves required by the grid [MW]

4.1.1.4 Variables

p^{out}	-	Battery output power [MW]
p^{in}	-	Battery input power [MW]
p^{ch}	-	Battery charge power [MW]
p^{dis}	-	Battery discharge power [MW]
soc	-	State of Charge of battery [%]
p^{imp}	-	Imported power fromDay-Ahead market [MW]
p^{exp}	-	Exported power to Day-Ahead market [MW]
$p^{\mathrm{F}imp}$	-	Imported power from FCR-N market [MW]
$p^{\mathrm{F}exp}$	-	Exported power to FCR-N market [MW]

4.1.2 System

The system with ESS, load, grid, and wind farm is as presented in Figure 4.1. The ESS in this model is a battery. The grid includes three different market models. The different components' investment cost is not included in this model but is considered an external element.

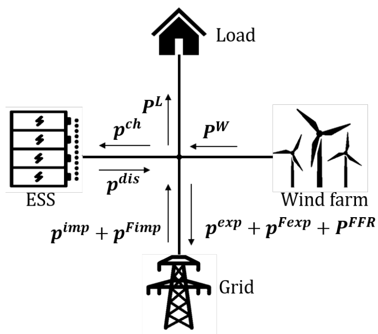


Figure 4.1: Generic model for a wind farm, load, ESS, and grid model showing in and output power flows. Grid icon by [18], ESS icon by [19] and wind farm icon by [20]. Load icon from Office 365 stock.

The input and output streams of power from the different components are given in Figure 4.1. Here, $p^{imp} + p^{\mathrm{F}imp}$ and $p^{exp} + p^{\mathrm{F}exp} + \mathrm{P}^{\mathrm{E}}$ are the imported and exported power from/to the grid, respectivly. P_{L} is the local load for the wind farm that is supplied by the system. p^{ch} is the charging to the battery from the system. p^{dis} is the discharge power from the battery to the system. P^{W} is the output power from the wind farm to the system.

4.1.3 Energy Storage System - Battery

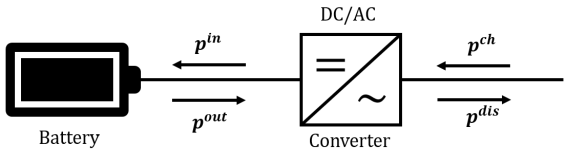


Figure 4.2: Model of battery with converter. Battery icon from Office 365 stock.

The chosen ESS for this model is a battery, which is connected to the node through a converter. Conversion from AC to DC power is needed to store energy in the battery. Hence, the power flows for charging, p^{ch}, and discharging, p^{dis}, passes through a converter before entering the battery, as seen in Figure 4.2. The relation between the input and output power of the battery with the discharge and charge power is as shown in Equation (4.1a) and Equation (4.1b). Here, $\eta^{\mathrm{AC/DC}}$ is the efficiency of the converter during charging and $\eta^{\mathrm{DC/AC}}$ during discharging. In addition, the applied power must lie within predefined upper and lower bounds in order to not damage the battery, as specified in Equation (4.1d) and Equation (4.1c) by $\mathrm{P}^{in,min}$, $\mathrm{P}^{in,max}$, $\mathrm{P}^{out,min}$, and $\mathrm{P}^{out,max}$.

$$p^{in} = \eta^{\mathrm{AC/DC}} \cdot p^{ch} \tag{4.1a}$$

$$p^{out} = \frac{p^{dis}}{\eta^{\mathrm{DC/AC}}} \tag{4.1b}$$

$$\mathrm{P}^{in,min} \leq p^{in} \leq \mathrm{P}^{in,max} \tag{4.1c}$$

$$\mathrm{P}^{out,min} \leq p^{out} \leq \mathrm{P}^{out,max} \tag{4.1d}$$

The State of Charge (SoC) of the battery, i.e., how much power it contains at time t, is a function of the SoC from the previous time step, $soc(t-1)$, and the input/output power, p^{in} and p^{out} for the current time step. Also, losses in the battery affect the SoC, here denoted as $\mathrm{P}^{\mathrm{LOSS}}$ and assumed constant. The SoC is important because it relates how much power the battery can deliver and receive at a given time step. The losses, $\mathrm{P}^{\mathrm{LOSS}}$, in Equation (4.2a) consist of the internal losses in the battery, and can consist of permanent losses, temperature losses or cyclic losses. Temperature and concerns regarding this can also limit the capacity. Lead Acid batteries are an example of a battery type that has an operational range that requires the temperature to be above a certain threshold temperature for a given SoC, as the battery might freeze and permanently damage the battery otherwise [84]. It is also important to note that the SoC band, SOC^{min} - SOC^{max}, of the battery is altered with the lifetime and use of the battery, due to degradation. I.e., the available capacity in the battery is lowered as a consequence of how the battery is used, the surrounding temperature, storage time, etc. The SoC band can also be set as a percentage chosen by the user, for instance, to stimulate a given battery use. The SoC as a function of input/output power, p^{in}/p^{out}, to the battery minus the losses, $\mathrm{P}^{\mathrm{LOSS}}$, and the SoC band are presented in Equation (4.2a) and Equation (4.2b).

$$soc_t = soc_{t-1} + p^{in} - p^{out} - \mathrm{P}^{\mathrm{LOSS}} \qquad t \in \mathrm{T} \setminus \{0\} \tag{4.2a}$$

$$\mathrm{SOC}_t^{min} \le soc_t \le \mathrm{SOC}_t^{max} \qquad t \in \mathrm{T} \tag{4.2b}$$

4.1.4 Wind farm

A generic wind farm can be modeled as the sum of the turbines in it, as shown in Figure 4.3.

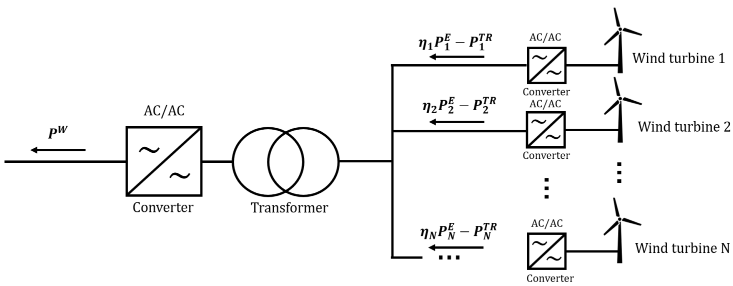


Figure 4.3: Wind farm model with converters. Wind turbine icon by [21].

A simplified mathematical formulation of the mechanical power of a wind turbine is found in Equation (4.3), gathered from [85]. The parameters in the equations are the tip speed ratio, λ, blade pitch angle, θ, rotor radius, R, wind speed, $v(t)$, mechanical power P^{M}, air density, ρ, and the power coefficient $\mathrm{C}_p(\theta, \lambda)$.

$$\mathrm{P}^{\mathrm{M}} = \frac{1}{2}\rho\pi\mathrm{R}^2 v(t)^3 \cdot \mathrm{C}_p(\theta, \lambda) \tag{4.3}$$

The electrical output from the turbine is a function of the mechanical power available minus losses in the generator. These losses can, for instance, be Cu losses in the stator and rotor windings [26]. In this model, the losses from conversion from mechanical to electrical power are aggregated to an efficiency coefficient called η^{LOSS}. The electrical output, P^{E}, then is as shown in Equation (4.4a). A maximum and minimum restrict the electrical output of each wind turbine, $\mathrm{P}^{\mathrm{E},min}$, and $\mathrm{P}^{\mathrm{E},max}$, as shown by Equation (4.4b).

$$\mathrm{P}^{\mathrm{E}} = \eta^{\mathrm{LOSS}} \cdot \mathrm{P}^{\mathrm{M}} \tag{4.4a}$$

$$\mathrm{P}^{\mathrm{E},min} \le \mathrm{P}^{\mathrm{E}} \le \mathrm{P}^{\mathrm{E},max} \tag{4.4b}$$

A converter scheme, as shown in Figure 4.3, can be used to control power output from the turbine. The dedicated converter losses for each turbine are represented by a converter efficiency loss, η. The output power from the entire wind farm is hence the aggregated sum of the electric power from the turbines times the efficiency of the converters, η, minus the transmission losses, P^{TR}, from the turbines to the central converter, as seen in Figure 4.3. It should be noted that for wind farms, the internal transmission losses are often small and negligible.

If the power is to be transmitted to an external grid, a transformation of the voltage can be necessary to gain the required output voltage or to reduce transmission losses. In this model, this is represented as a single central transformer. The input to the transformer is the aggregated input from all the wind turbines. The output is the aggregated input minus the internal losses in the transformer. This is in this model represented as an efficiency, η^{T}, included in Equation (4.5a). Wind farms often have a central converter to ensure that the power delivered is within the standard ranges, as specified by grid codes. Hence, the efficiency, η^{C} of this central converter is included in Equation (4.5a).

The wind farm output, P^{W}, is subject to limits regarding the maximum and minimum allowed output. The minimum value of the wind farm output can, in simple models, be set to zero. In more advanced models, the inclusion of how the wind farm can drain from the grid to run the power electronics (namely the converter) to, for instance, start up the wind farm, can be done. The maximum limit can be set according to the maximum production from the wind farm. The minimum limit hence becomes 0, as that is the lowest output the wind farm can yield if it is not allowed to draw power from the grid. The constraint with defined ranges with maximum, $P^{W,max}$, and minimum, $P^{W,min}$, values for the output power of the wind farm are given in Equation (4.5b).

$$P^{W} = \eta^{C}\eta^{T} \cdot \sum_{j=1}^{n} \eta \cdot P^{E}_{j} - P^{TR}_{j} \tag{4.5a}$$

$$P^{W,min} \leq P^{W} \leq P^{W,max} \tag{4.5b}$$

4.1.5 Grid

In this model, the grid contains three markets, each with its price and restrictions. The markets in the model are based on the Nordic day ahead market, FFR, and FCR-N market. Modeling a reserve market that complies with the FFR market's specifications presented in Section 2.4.3.3 requires that a given amount of power is reserved for use when needed. This can be modeled through raising the minimal SoC level, SOC^{min}, of the battery at the given instance. The required SoC level for a given FFR amount can be calculated using Equation (4.6). Here, SOC is the SoC level required in [%], O^{FFR} is the power in [MW] offered as FFR, F is the required delivery time for FFR in [h], and C is the capacity of the battery in [MWh].

$$SOC = \frac{O^{FFR} \cdot F}{C} \tag{4.6}$$

Hence, the required amount is ensured available if needed. The owner of the battery is compensated for reserving this capacity, and Equation (4.7) can be used to find the revenue obtained from FFR. Here, O^{FFR} is the FFR power that is offered in [MW], $\$_{FFR}$

is the price of FFR reserves in [EUR/MWyear] for the given scenario and R^{FFR} is the revenue from FFR for each year in [EUR/year].

$$R^{FFR} = \$_{FFR} \cdot O^{FFR} \tag{4.7}$$

If FFR is activated, the owner is compensated for the activated amount. Following the rules of the FFR market, it can only export to the grid during activation, denoted by P^{FFR}. The day ahead market has import and export power denoted as p^{imp} and p^{exp}, respectively. The FCR-N market has import and export power denoted as p^{Fimp} and p^{Fexp}, respectively. The capacity constraints for each individual market is not included, but rather the transmission constraint for the combined import and export to the grid. It is vital that the transfer capacity of the transmission line of the grid for import and export is not violated. This is ensured by imposing a constraint on the combined flow to and from the grid from the three markets. The minimum transfer capacity is denoted by $P^{TC,min}$ (set to zero here) and the maximum transfer capacity as $P^{TC,max}$.The import and export power and the grid transfer limits, are described by Equation (4.8). Besides, there are transmission losses on the transmission line between the grid and the other components, here denoted by a constant loss, P^{TL}. Transmission losses depend on parameters such as length, material, voltage, and transferred power of each specific line.

$$p^{exp} = P^{W} + p^{dis} - p^{ch} - P^{TL} - P^{L} - p^{imp} - p^{Fimp} - p^{Fexp} - P^{FFR} \tag{4.8a}$$

$$P^{TC,min} \leq p^{exp} + p^{Fexp} + P^{FFR} \leq P^{TC,max} \tag{4.8b}$$

$$P^{TC,min} \leq p^{imp} + p^{Fimp} \leq P^{TC,max} \tag{4.8c}$$

It should be noted that the bidding in the markets proposed has been simplified so that no time is required between the bids and actual power transfers.

4.1.6 Load

A load component is added to the system to model the internal load of the wind farm. The load is depicted in Figure 4.1. In this simple model, the load is assumed to draw only active power; i.e., it is purely restive and is limited to consuming power. This means that it at each time step has a given demand in this model. The load demand must be met, and as the load is connected in the same node as the other components, it is covered either through import from the external grid, ESS discharge, or wind farm production.

4.1.7 Objective function

The objective function states what the goal of the optimization should be. In this instance, the goal is to find the maximal revenue obtainable when operating a wind farm, load and ESS connected to an external grid. The external grid here provides the possibility of interaction with two markets, the Nordic day ahead and FCR-N market. The price of the exported and imported power for the day ahead market is denoted by C^{EXP}

and C^{IMP}, respectively. The price of the exported and imported power for the FCR-N market is denoted C^{FEXP} and C^{FIMP}, respectively. The revenue obtained from reserving capacity in the battery by raising the SoC-level for the FFR market is added as a constant to the objective function, denoted as R^{FFR}. The compensation if FFR is activated is denoted as C^{FFR}. It should be noted that R^{FFR} is calculated externally; i.e., it is not an explicit part of the optimization problem. The same is true for the compensation term for FFR reserves, $C^{FFR} \cdot P^{FFR}$, which is determined by external factors for activation. However, the two terms are included in the objective for completeness. Hence, the objective function is defined as the revenue from exported power minus the cost from imported power plus the revenue from the reserved power for the FFR market, as shown in Equation (4.10).

$$\max z = R^{FFR} + \sum_{t=0}^{T} \left(C_t^{FFR} \cdot P_t^{FFR} + C_t^{EXP} \cdot p_t^{exp} + C_t^{FEXP} \cdot p_t^{Fexp} - C_t^{IMP} \cdot p_t^{imp} - C_t^{FIMP} \cdot p_t^{Fimp} \right) \tag{4.9}$$

4.1.8 Mathematical formulation

The optimization problem can be viewed in its entirety in Equation (4.10).

$$\max z \quad = \quad R^{FFR} + \sum_{t=0}^{T} \left(C_t^{EXP} \cdot p_t^{exp} + C_t^{FEXP} \cdot p_t^{Fexp} + C_t^{FFR} \cdot P_t^{FFR} - C_t^{IMP} \cdot p_t^{imp} - C_t^{FIMP} \cdot p_t^{Fimp} \right) \tag{4.10a}$$

s.t

$$p_t^{exp} = P_t^{W} + p_t^{dis} - p_t^{ch} - P_t^{TL} - P_t^{L} - p_t^{imp} - p_t^{Fimp} - p_t^{Fexp} - P_t^{FFR} \quad \forall t \in T \tag{4.10b}$$

$$P_t^{W} = \eta_C \eta_T \cdot \sum_{j=1}^{N} \eta_j \cdot P_{jt}^{E} - P_j^{TR} \quad \forall t \in T \tag{4.10c}$$

$$soc_t = soc^{(t-1)} + p_t^{in} - p_t^{out} - P_t^{LOSS} \quad \forall t \in T \tag{4.10d}$$

$$p_t^{in} = \eta^{AC/DC} \cdot p_t^{ch} \quad \forall t \in T \tag{4.10e}$$

$$p_t^{out} = \frac{p_t^{dis}}{\eta^{AC/DC}} \quad \forall t \in T \tag{4.10f}$$

$$
\begin{aligned}
\mathrm{P}^{\mathrm{TC},min} \leq \quad & p_t^{imp} + p_t^{\mathrm{F}imp} && \leq \quad \mathrm{P}^{\mathrm{TC},max} && \forall\, t \in \mathrm{T} && (4.10\mathrm{g})\\
\mathrm{P}^{\mathrm{TC},min} \leq \quad & p_t^{exp} + p_t^{\mathrm{F}exp} + \mathrm{P}_t^{\mathrm{FFR}} && \leq \quad \mathrm{P}^{\mathrm{TC},max} && \forall\, t \in \mathrm{T} && (4.10\mathrm{h})\\
\mathrm{P}_j^{\mathrm{E},min} \leq \quad & \mathrm{P}_{jt}^{\mathrm{E}} && \leq \quad \mathrm{P}_j^{\mathrm{E},max} && \forall\, t \in \mathrm{T}, j \in \mathrm{N} && (4.10\mathrm{i})\\
\mathrm{P}^{\mathrm{W},min} \leq \quad & \mathrm{P}_t^{\mathrm{W}} && \leq \quad \mathrm{P}^{\mathrm{W},max} && \forall\, t \in \mathrm{T} && (4.10\mathrm{j})\\
\mathrm{SOC}_t^{min} \leq \quad & soc_t && \leq \quad \mathrm{SOC}_t^{max} && \forall\, t \in \mathrm{T} && (4.10\mathrm{k})\\
\mathrm{P}^{in,min} \leq \quad & p_t^{in} && \leq \quad \mathrm{P}^{in,max} && \forall\, t \in \mathrm{T} && (4.10\mathrm{l})\\
\mathrm{P}^{out,min} \leq \quad & p_t^{out} && \leq \quad \mathrm{P}^{out,max} && \forall\, t \in \mathrm{T} && (4.10\mathrm{m})
\end{aligned}
$$

The expected solution to this optimization problem is to find the import and export power to the grid, p^{exp},$p^{\mathrm{F}exp}$, p^{imp} and $p^{\mathrm{F}imp}$, and the charge/discharge schedule, p^{dis}, p^{ch},p^{in}, and p^{out} for the battery, that yields the maximal revenue for the objective function.

4.2 Model predictive control

In this section, the general principle of MPC is discussed, along with a brief presentation of advantages and disadvantages with the MPC method.

4.2.0.1 Description of Model Predictive Control principles

The optimization model in Equation (4.10) can be solved by using several algorithms. In this section, the linear MPC with a receding horizon approach is explained, and its benefits and disadvantages are discussed. In short terms, the MPC principle is to use a model of the system to predict future states and find the optimal control input to the system. The general MPC method is sensitive to unmodelled dynamics and process disturbance [73]. One way to overcome the issues related to this is to use the receding horizon policy [86]. The receding horizon MPC principle for an optimization problem is shown in Figure 4.4.

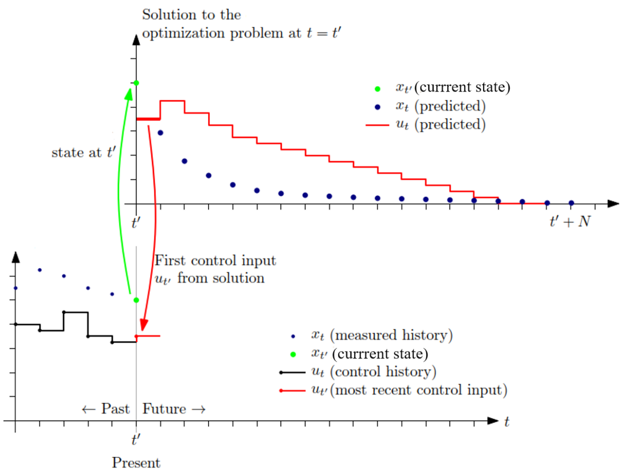


Figure 4.4: MPC principle (based on Figure 4.1 from [8])

As shown in Figure 4.4, only the first control move is implemented, thus ensuring that the newest available information is used when calculating the next step of the control. The objective of control in this model is to obtain the highest possible value of the objective function through charge/discharge of the battery and interaction with the different markets. The MPC algorithm is explained in the pseudocode in Table 4.1.

Table 4.1: Linear receding horizon MPC algorithm (adapted from algorithm 4 [8])

MPC algorithm
for t = 0, 1, 2, ... **do**
Get the current state of the system x_t
Solve an optimization problem on the prediction horizon from t to t + N
where x_t is set as the initial condition of the system
Apply the first control move u_t from the obtained solution on the system
end for

As shown in Table 4.1, the receding horizon means that the MPC uses the newest state measurements in the system when solving the optimization problem. This yields more accurate results for forecasting and control input compared to other controllers (for instance, Proportional-Integral-Derivative (PID) controllers [87]).

4.2.1 Advantages and disadvantages with Model Predictive control

The advantages of MPC include that constraints can be put on both input and output variables, that it is useable for both Single Input Single Output (SISO), and Multiple

Output Multiple Input (MIMO) systems and that it finds the optimal solution (if it exists) [87].

The main disadvantage of MPC is that it requires an accurate prediction model of the states that are to be controlled. The constrained optimization problem that must be solved at each instance can result in a high computational effort, making the MPC a slow method of control that might be unsuitable for fast process applications [72]. With MPC, there is a trade-off between the control/prediction horizon and the accuracy of the control, as an increase in the number of prediction steps can cause the prediction error to proliferate. Once the receding horizon strategy is used, only the first of the control move is implemented. Hence, it adjusts the control in each time step, making it robust regarding disturbances.

4.3 PSS®DE

Power System Simulator for Distributed Energy (PSS®DE) is a tool that Siemens AG has specifically developed for the sizing and evaluation of Distributed Energy Systems (DES). PSS®DE takes user-defined configurations and then simulates a plant's performance over its designed lifetime. For the Midtfjellet case study presented in Chapter 5, PSS®DE is the chosen optimization program. How the program models the different components and how the optimization is done is, therefore, aspects that must be presented. The modeling of the relevant system components is presented in Section 4.3.1, while the different dispatchers and the chosen dispatcher for the optimization are shown in Section 4.3.2. A tool for finding the optimal size of different components is then presented in Section 4.3.3. Also, how the results can be viewed and evaluated using Key Performance Indicators (KPI's) in PSS®DE is presented in Section 4.3.4. A comparison between PSS®DE and a similar optimization tool, HOMER PRO (main), is also done to highlight the disadvantages and advantages of PSS®DE. This comparison is presented in Section 4.3.5. Note that the content in this section is based on the manual for PSS®DE [9].

4.3.1 Modelling of system components in PSS®DE

The different system components relevant for the model in Chapter 5 are presented in this section.

4.3.1.1 Energy storage systems

In PSS®DE, an Energy Storage System (ESS) is modeled as a battery and a converter. Optionally a container with Heating, Ventilation, and Air Condition (HVAC) can be added to the ESS model.

4.3.1.1.1 Batteries

Li-Ion batteries are currently the only battery type supported in PSS®DE. Of the Li-Ion battery, there are eight different types to chose from, each specified by a different price, efficiency, and C-rate. The battery model can be explained based on Figure 4.5.

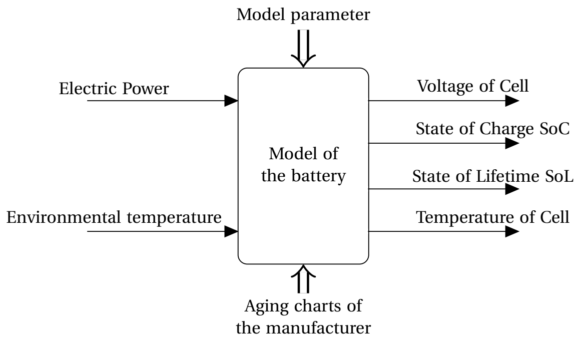


Figure 4.5: PSS®DE model of battery [9]

Figure 4.5 shows how the battery gets the input of electric power and environmental temperature and calculates different battery states to be used in the simulations. The converter of the storage system also restricts the power conversion, while the container model simulates the performance of the heat, ventilation, and air condition system. When the battery is discharging, the power set point in kW is positive, and thus the power setpoint is negative when the battery is charged. Parameters that are included in the battery model is; resistance (function of temperature), losses, initial values (SoC and temperature), aging calendric lifetime and aging cycling cycle-life, End of Life (EoL) capacity, Aging costs, etc. For additional parameters and explanations, see [3].

4.3.1.1.2 Converter

A converter is used to convert between AC and DC power. Among others, the parameters included in the converter model are power rating, efficiency, and failure fraction for both AC/DC and DC/AC. It is important to note that different components cannot share a converter. Also, the converter must be connected to another component to be included in the modeling.

4.3.1.1.3 Container

The container encapsulates the converter and battery and includes an air condition, ventilation, and heating system. The container is modeled with different parameters, volume, lifetime, and economics, as well as relevant parameters for the HVAC system, like temperature, inverter efficiency, and power consumption.

4.3.1.2 Wind farm

To model a wind farm, there are essentially two options in PSS®DE. Either, each turbine can be modeled individually, or data showing the production data for a wind farm or turbine can be provided for the simulations. If the wind farm is modeled with individual turbines, PSS®DE can consider the following technical parameters: Hub height, Losses, lifetime, installation delay, replacement strategy, failure fraction, short circuit current, operating reserve, ramp rate, rated power, and the number of turbines. If a specific converter is used, this can also be included through the Dedicated Converter alternative, where losses and limits of the converter can be defined. Also, economic parameters can be defined for the wind park, such as O&M costs.

4.3.1.3 Grid

Energy exports from the grid are sent to an undefined anonymous external grid, while the grid is modeled as an Independent Power Producer (IPP) with a grid-component for imports. Each off-taker or IPP has an assigned tariff at which it sells to the grid. Parameters both for import and export of power and the price of electricity can be defined.

4.3.2 Dispatchers

PSS®DE offers different algorithms for power dispatch optimization, presented in Table 4.2. In addition to this, different dispatcher parameters must be specified, for in-

Table 4.2: Power dispatch optimization algorithms in PSS®DE [9]

Algorithm	Source	Speed	Description
MILP_Etb	Native PSS®DE	Medium	Single step, economic optimization
Greedy/Greedy2	Native PSS®DE	Fast	Single step, heuristic (rules) mirroring MILP_Etb
MGMS	Spectrum Power 7	Slow	Multi step, economic optimization
MGC	SICAM	Fast	Single step, heuristic (rules)
Local control	-	Fast	Single step, heuristic (rules)

stance, time step size, if blackouts are allowed, parameters that define generator redundancy, the briding duration for batteries, smoothing of generator curves, incentives, and costs related to the components of the project. The local control dispatcher simulates a local control routine for each component in the system where there is no common dispatcher or controller for the system. Therefore, it is unsuitable in this specific project and is not explained in greater detail here. Besides, Micro Grid Controller (MGC) is not relevant for this project. MILP_Etb and Greedy/Greedy2 are single step dispatchers, meaning that they have no sense of time and can only use the information available at each time step. Micro Grid Management System (MGMS) offers multi-step economic optimization based on the Model Predictive Control (MPC) principle and hence yields an optimal solution. The main drawback of the MGMS dispatcher is that it requires a high computational effort and has a long solving time. This can make it unsuitable for large configurations or if a significant amount of simulations are needed. The MGMS method is explained in more detail in Section 4.3.2.1.

4.3.2.1 Micro Grid Management System

Micro Grid Management System (MGMS) uses an MPC approach for effective power dispatching with a prediction horizon of 24 hours. The time step can be set by the user and is by default set to 15 minutes. The triggering interval for MPC optimization can also be set by the user but is initially set to happen after each 15 min interval. MGMS support all the available dispatcher features in PSS®DE. Special features include a linear decrease in the MILP model's cost by setting the discount factor to 0.99. This is done to avoid symmetries in the MILP model. As the details of the specific MGMS algorithm is not available for this thesis, the general principle of a receding horizon MPC is explained in Section 4.2.

4.3.3 Sizing optimizer

The sizing optimizer in PSS®DE is a tool based on a prototype optimization algorithm that can be used to determine a suitable initial configuration. The prototype algorithm is based on the tool, Multi-modal energy system design (mm.esd). Mm.esd is a sizing algorithm that both optimizes the design and dispatch of an energy system concerning costs and emissions. In the solver, the user can adjust the weight of three different weight factors to account for different objectives. The three different weight factors are cost, primary energy, and CO_2. An overview of how the solver treats the different weight factors is shown in Table 4.3.

Table 4.3: Three weight factors in PSS®DE Sizing optimizer

Weighting factor	Minimization objective	Additional information
Cost	TOTEX	Replacement costs not considered
Primary Energy	Primary energy consumation	Consideres the efficiency of each technology and seeks to minimize how much resources are consumed to produce the required energy. Does not considerer renewable sources.
CO_2	CO_2 production	User defines how much CO_2 the different units produces for each kWh

4.3.3.1 Solver Constraint Integer Programs

The sizing optimizer uses Solver Constraint Integer Programs (SCIP) 6.0 as the solver. SCIP is a solver that can both solve mixed-integer programming and mixed integer nonlinear programming problems. According to the developers, it can offer detailed information into the solver and total control of the solution process [88].

4.3.4 Evaluation of the results

In this section, how evaluation of the obtained results can be done in PSS®DE is presented.

4.3.4.1 Key Performance Indicators

To evaluate the results based on the users' preference, PSS®DE has created a range of key performance indicators (KPIs) for each system component that can be used to compare different configurations. There exist different KPIs both for each component and the combined system. For instance, there is a KPI for the expected lifetime of a battery component and a KPI for the Net Present Cost (NPC) for the project lifetime. The user selects relevant KPIs in the results tabular.

4.3.5 Comparison of PSS®DE with similar optimization tool

Table Table 4.4 was created to display how PSS®DE, compares to a similar optimization tool for DES, HOMER PRO (main), for selected parameters.

Table 4.4: Comparison of optimization tools for DES, PSS®DE and HOMER PRO (main)

Parameter	PSS®DE	HOMER Pro (main)
Commercially available	No	Yes
Sizing Optimizer	SCIP 6.0 [1]	Numerical optimization
Dispatcher types	MGC, Local control, MGMS, Greedy/Greedy2 and MILP_Etb	Two
Dispatch strategy	Min. cost or min emission	Lowest cost grid power demand limit for each month
Sensitivity analysis	Yes	Yes
Optimal control dispatcher time horizion	24 h	48 h
Financial evaluation	KPI's	NPC
Battery types	8 types Li-Ion	Zinc, Vanadium, Generic Battery model
Battery degradation	Yes	Additional module needed
Different power markets	Demand charges, UK triads, User-specified, Balancing, Contracted and German Tariff	Grid power price. Need additional module for inclusion of demand charges
Simulation time step	1-60 min	1-60 min
Results	Sensitivity, Optimization, Economics	Sensitivity, Optimization, Economics
Results year-by-year	Yes	Additional module needed
Hydrogen equipment	Load, Electrolyser, Tank, Valve, Compressor, Turbine, Fuel cell, Export	Additional module needed, which includes: Tank, Reformer, Electrolyzer, Load and Fuel cell

As can be seen from Table 4.4, one of the disadvantages of PSS®DE, is the lack of a commercial version. Besides, it is still in development, meaning that the program occasionally crashes and that different components are added and removed with new updates. This also means that the equipment available is limited. For instance, there are only 8 standard battery types, all of the type Li-Ion. As is clear from Table 4.4, one main advantage by using the PSS®DE software is that the standard version includes all packages, whereas the HOMER PRO requires additional packages for special features. In addition, more features exist for modeling of hydrogen production, transportation, electricity generation, and consumption. PSS®DE also offers numerous KPIs for the user for which different configurations can be compared based on critical features for a specific application, case study, or project. Also, it has a graphical tool to compare different configurations, and the ability to run hundreds of variations of parameters on the same system at once, which can be used to showcase advantages with different design choices. Besides, the different dispatcher types can be used for different purposes, where faster algorithms can be used to run a large number of simulations.

Chapter 5

Case Study

In this chapter, a case study is presented with a model in PSS®DE for the wind farm owned by Midtfjellet Vindkraft AS, denoted as "Midtfjellet wind farm." Choices pertaining to the case study presented, along with a description of the Midtfjellet wind farm, are therefore shown in Section 5.1. The scenarios that are simulated are presented in Section 5.2. The defined models and relevant parameters are then presented in Section 5.3, along with a discussion of key design choices and presentation of the time series used and the chosen simulation parameters. To showcase how the chosen program, PSS®DE, works, a verification is carried out as described in Section 5.4. Modeling of the FFR market is shown in Section 5.5. The chapter is concluded with a summary in Section 5.6, which also details how the simulation process is carried out.

5.1 Description of Midtfjellet wind farm

Midtfjellet wind farm is comprised of a total of 55 turbines, 34 turbines of type N90 and size 2 MW, 10 turbines of type N100 and size 2, and 11 of type N117 and size 3.6 MW, situated on Midtfjellet at Fitjar, Stord municipality, Norway. This means that it lies in the NO5 price area for Elspot and regulating prices [42]. The production is 433.7 GWh on average since the installation of building stage III. Stage III started production in August of 2018 and consisted of the 11 3.6 MW [89]. The wind farm is connected to the external grid through a 10 km 300 kV line to Børtveit, which has a rating of 800 MVA [89]. Assessing the possibility of a positive business case with ESS investment for this wind farm is the main objective for this thesis; to do this, a techno-economic optimization on a model of the wind farm, ESS, load, and grid is carried out. The reasoning behind the specific model built for the case study (i.e., choice of revenue streams and technical aspects) is explained in the following sections.

5.1.1 Choice of energy storage system

As previously explained, with an increase in wind power integration, the need for ancillary services grow due to the intermittent wind power production. Therefore, it is interesting to look at which ESS can be used to combat and mitigate the different issues related to volatile production for the particular case study of Midtfjellet.

Wind farms are often decoupled from the grid by the use of power electronics, and when decoupled, they do not participate with inertia when a frequency disturbance occurs ([27], page 632). Hence, in areas dominated by wind farms, there might be an increasing need for fast-acting frequency reserves. As shown in Table 2.3, Li-Ion battery energy storage systems (BESS) are particularly suited for frequency regulation and were explored further in regards to ESS for the Midtfjellet wind farm. The benefits of Li-Ion BESS are presented below. Firstly, Li-Ion BESS are tried and starting-to-be mature technology. Secondly, with the EV market driving the prices down, the costs of Li-Ion batteries have decreased significantly, and it is likely that the prices in the future decrease further. Thirdly, it is likely that the future grid codes can demand more from the production units in terms of ancillary services, which require a fast response time, which Li-Ion BESS can provide. Fourthly, Li-Ion (and other BESS) offer scalability and portability that other forms of ESS, like CAES and PHS, lack. Li-Ion BESS were also proven in [73] to outperformed other storage types (FES, VR FBESS, NaS, for instance) in terms of having the fastest payback period for the reduction of ramp-rate violations from wind farms. Besides, the FFR pilot of 2018, proved that batteries could provide this service because of their fast response time [48].

Hence, based on the above reasoning, it has been decided to include small Li-Ion BESS as the proposed ESS for the case study of the Midtfjellet wind farm.

5.1.2 Ancillary services

In this section, relevant ancillary services are discussed as to which is applicable for the Midtfjellet wind farm. As DSOs cannot own the ESS in Norway, as explained in Section 2.5.3, it is vital that ESS projects are economically viable. Therefore, the focus for ancillary services, in this case, has been to find ancillary services suited for Li-Ion BESS where there is a potential revenue stream. As shown in Table 2.3, Li-Ion BESS are particularly suited for frequency regulation. This is mostly because of the rapid response time. In Norway, participation in balancing markets is the way to participate with frequency regulation. Of the available balancing markets in Norway, Li-Ion is best suited for the primary and FFR market, as these require faster response time and accept lower bid sizes than the other balancing markets. As found in the specialization project, it is difficult to achieve a positive net present value (NPV) for Li-Ion BESS integrated with a wind farm when only participating in one market [3]. It was therefore considered essential for obtaining a positive business case that revenue stacking through participation in several markets was attempted.

5.1.2.1 Fast containment reserves

Based on the reasoning above, it has been decided that the market structure for normal Frequency containment reserves (FCR-N), as explained in Section 2.4.3.2, is to be implemented in the case study. There is, however, one modification on the bid volume in the FCR-N market. In this case study, this is not restricted to 1 MW intervals as specified in Section 2.4.3.2, but can have any number within the defined max/min range. This is a simplification done because of restrictions in the program but can be explained in a real case as if the system was part of a virtual power plant. In a virtual power plant, bids are aggregated with other producers to comply with the bid requirements. This simplification is similar to the approach for the FCR-N market in [77]. Li-Ion batteries can, by participation in the FCR-N market, prevent frequency swings.

5.1.2.2 Fast frequency reserves

The market for fast frequency reserves (FFR) is a new market that is yet to be implemented, but the rules in the demo version in 2020 can be used as a reference framework. The FFR market in the demo version yields revenue to stand as a reserve, as well as compensation for activated production. As it demands very fast-acting reserves for short time intervals (0.7-1.3 s activation and activation times of 5-30 s [47]), it is well suited for Li-Ion batteries and other battery types. It should here be noted that it is assumed that FFR reserves cannot be part of another bid volume, which complies with the rules in other electricity markets. The FFR market is implemented by Statnett mainly to cope with decreasing inertia as a result of increasing wind farm production [90].

5.1.3 Price of Li-Ion Battery Energy Storage System

It is decided that the high and low prices of Li-Ion BESS for 2020 would be taken from [10], as these were higher than the ones in [11] and hence would yield a more conservative result. The prices in 2020 was then decided to be 6000 NOK/kWh (high) and 4000 NOK/kWh (low). Converting this to EUR/kWh, the 2020 prices are set at 372.68 EUR/kWh and 474.4 EUR/kWh.

Following the reasoning in Section 2.5.4, it has been decided that two price scenarios, high and low, should be created for the price of Li-Ion BESS in 2030. These prices should be based on the mean price between the results found in [11] and estimates from NVE in [10]. The high price scenarios for Li-Ion BESS are the mean between the high estimates of [11] at 301.79 EUR/kWh and the high estimate of [10] at 304.55 EUR/kWh. The average of this, and thus the resulting price for the high price of Li-Ion BESS in the 2030 scenario, is 303.17 EUR/kWh. The low price scenarios for Li-Ion BESS are the mean between the medium estimates of [11] at 184.82 EUR/kWh and the low estimate of [10] at 202.68 EUR/kWh, which is 193.93 EUR/kWh.

The prices for Li-Ion BESS used in the different scenarios are summarized in Table 5.1

Table 5.1: Price of Li-Ion BESS for the different scenarios in the case study, based on [10] and [11]

Price scenario	Short name	Price [EUR/kWh]
Li-Ion High 2020	H20	474.4
Li-Ion Low 2020	L20	372.68
Li-Ion High 2030	H30	303.17
Li-Ion Low 2030	L30	193.93

5.1.4 Change in market prices

Based on the theory presented in Section 2.5.2, it was decided that an increase in the electricity price in all the Norwegian energy markets could occur in the future. How large this increase is can be uncertain; however, based on the historic trends presented, an attempt has been made to predict future prices. It should be noted that the balancing power prices could decrease if large ESS investments are made [77]. However, the balancing prices could also increase if there is a large investment in renewable energy sources (RES) with volatile production without sufficient stabilizing power. Hence, the future balancing prices could both increase and decrease, according to how the future investments into RES and ESS are.

As argued, the future electricity price is uncertain. Therefore, it was decided that the scenarios should include both a decrease and an increase in the electricity price. Based on the historical trends, a 115 % increase in the Elspot and regulating power price has occurred in the last 20.5 years. Assuming that the price projection from 2020 to 2030 follows the same historical trends, this would mean an increase of 56.01 %. Adjusting for inflation, this increase would be 22.34 %. In the proposed price scenarios, these values are rounded to a 50 % (historic) and 25 % (inflation-adjusted). A scenario with a 25 % decrease is also included, as well as the same prices as for 2018. Hence, the resulting price scenarios for this case study are 0.75, 1.0, 1.25, and 1.5 times the prices of 2018.

It is also decided that the prices should be decreased/increased flatly for all the markets (FCR-N, DA, and FFR), to minimize the number of scenarios required. It is unlikely that the future price changes would be entirely symmetric across these markets. However, this simplification is seen as reasonable given that it minimizes the amount of scenarios and the uncertainty of future electricity prices.

5.1.5 Revenue stacking

Revenue stacking is to be explored in the different scenarios to properly ascertain how the different markets can be used to make ESS investment more profitable. This means that different combinations of the chosen power markets are simulated, to find out which combination that yields the highest potential revenue. All simulations can trade at the day ahead (DA) market, and hence combinations including either the FCR-N or FFR market or both are explored. This is further detailed in Section 5.2.

5.2 Simulations

In this section, an overview of the simulations performed for the scenarios in the case study is presented. Scenarios for both the current price of Li-Ion BESS, in 2020, and future predictions for the price of Li-Ion BESS in 2030, as well as different energy prices, are presented in Section 5.2.1 and Section 5.2.2 respectively.

5.2.1 Simulations for 2020 scenarios

The simulations that are performed for 2020 are summarized in Table 5.2.

Table 5.2: Simulations to be performed for 2020 scenarios

Case name	Short name	Values	Unit
Price of Li-Ion	H20 / L20	474.4/ 372.68	[EUR/kWh]
Day ahead market	DA	Elspot price 2018 NO5	[EUR/MWh]
Fast frequency reserves	FFR	FFR price 2020 demo project	[EUR/MW]
Fast containment reserves	FCR-N	FCR-N price 2018 NO5	[EUR/MWh]

The simulations are shown, in order to clarify how they will be carried out, in Figure 5.1.

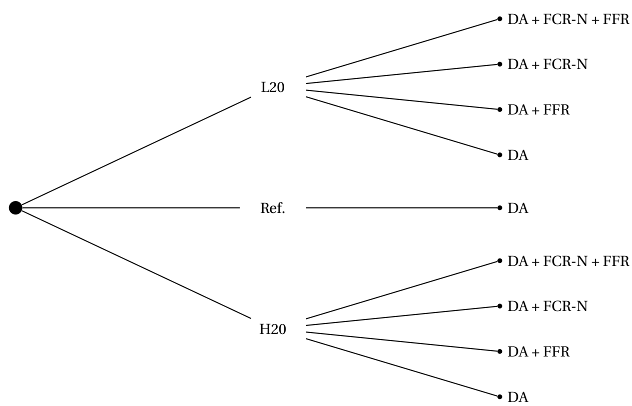


Figure 5.1: Simulation tree depicting the different 2020 scenarios

As can be seen from studying Figure 5.1, there are a total of eight scenarios and one reference case, denoted Ref., that are run for the 2020 case study of Midtfjellet.

5.2.2 Simulations for 2030 scenarios

The simulations that are performed for 2030 are summarized in Table 5.3.

Table 5.3: Simulations to be performed for 2030 scenarios

Case name	Short name	Values	Unit
Price of Li-Ion	H30/L30	303.17 / 193.93	[EUR /kWh]
Day ahead market	DA	0.75, 1, 1.25, 1.5 of Elspot price 2018 NO5	[EUR/MWh]
Fast frequency reserves	FFR	0.75, 1, 1.25, 1.5 of FFR price 2020 demo project	[EUR/MW]
Fast containment reserves	FCR-N	0.75, 1, 1.25, 1.5 of FCR-N price 2018 NO5	[EUR/MWh]

The structure of how the simulations are performed is depicted in Figure 5.2.

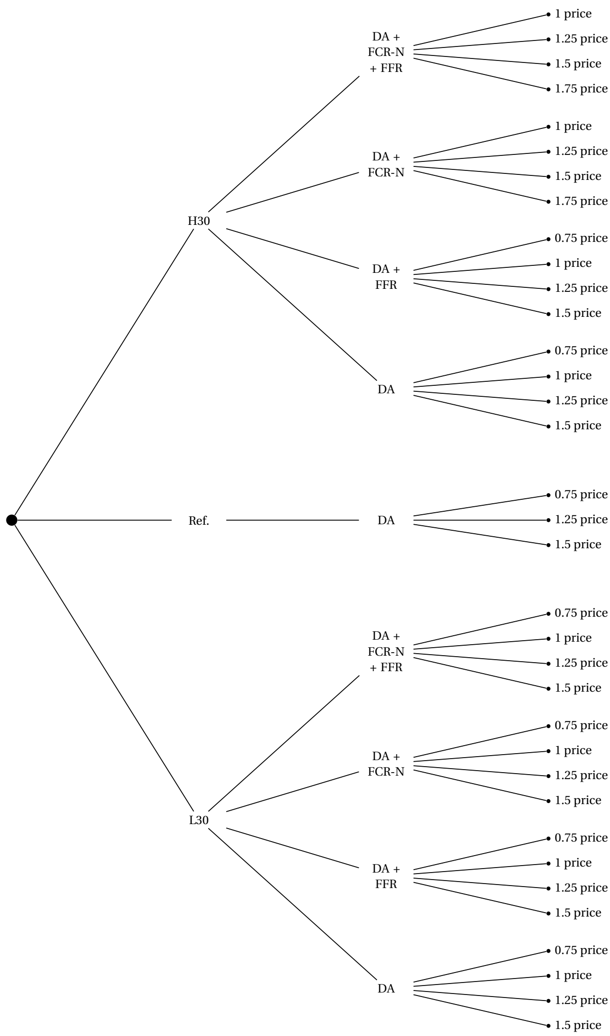


Figure 5.2: Simulation tree depicting the different 2030 scenarios

As can be seen from Figure 5.2, there are a total of 32 scenarios and three reference cases, denoted Ref., to be simulated for the future case study of Midtfjellet, as the reference case with 1.0 price in the DA market is the same as simulated for the 2020 reference case.

5.3 Definition of models in PSS®DE

In this section, the models of Midtfjellet wind farm and Li-Ion BESS configuration in the chosen optimization program PSS®DE is presented. First, a model including the wind farm, DA market (modeled as an external grid), and the internal load is presented as a reference case study. This reference case can then be used to compare the benefits of adding Li-Ion BESS and new markets. Then, a base case where the reference model is expanded to including Li-Ion BESS is defined. The full model, including two markets, FCR-N and DA, is shown, for use in the relevant scenarios.

5.3.1 Reference model

The reference model consists of an external electrical grid, labeled the DA market, to which an electric load and wind park are connected, as shown in Figure 5.3.

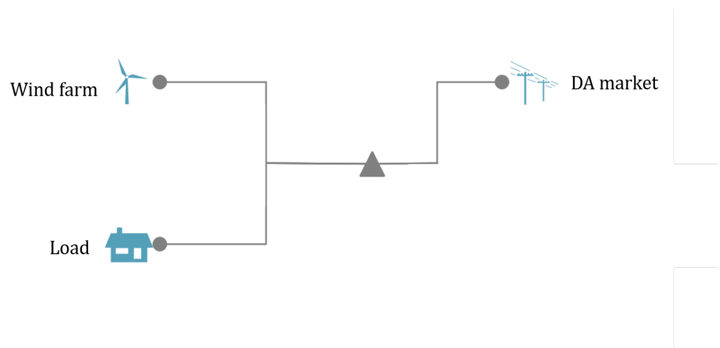


Figure 5.3: Reference case model set-up in PSS®DE, icons from PSS®DE

The most important parameters for the grid and wind farm is given in Table 5.4. Note that the reference model presented here was also used in verification of PSS®DE. The parameters not listed here are kept at their default values.

Table 5.4: Wind farm, load and DA market parameters for Midtfjellet wind farm case study

Component	Rated power [MW]	Lifetime [years]	Max imp./exp. power [MW]	Graph
Load	-	20	0.6	-
Wind farm	149.6	20	-	Figure A.1
DA Market	200	50	200	Figure A.2

The chosen limit for the DA market, at 200 MW, as can be seen from Table 5.4, is set well within the boundaries of the line (rated at 800 MVA). This is done to ensure that the transferred power stays well within these limitations, while it is still high enough to transfer power from the wind farm even at peak capacity. This reference model is used as the reference case in the simulations described in Section 5.2.

5.3.2 Li-Ion Battery Storage System model

The definition of the Li-Ion BESS model is that a Li-Ion BESS unit is included in the reference model. This configuration is shown in Figure 5.4.

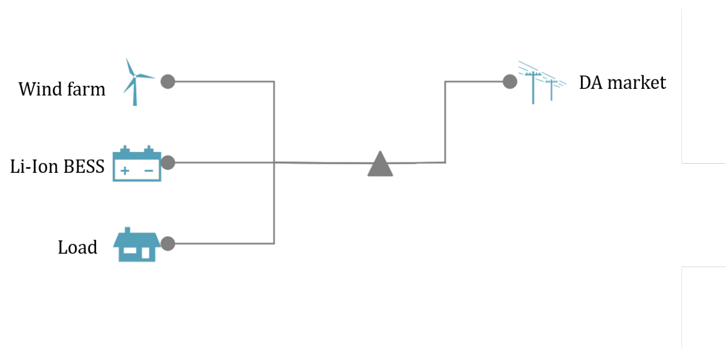


Figure 5.4: Li-Ion BESS included in model set-up in PSS®DE, icons from PSS®DE

The parameters for the Li-Ion BESS are given in Table 5.5.

Table 5.5: Parameters of the Li-Ion BESS for Midtfjellet wind farm case study

Parameter	ESS (with container)
Rated power [MW]	4.02
Energy [MWh]	1.668
Reference lifetime [years]	10
Converter efficiency [%]	95
SoC Min/Max [%]	0/100 or SoC to fit FFR req.
EoL capacity [%]	70
Initial state of charge [%]	80
Replacement strategy	No replacement

This Li-Ion BESS model is used for the simulations that include the DA and FFR market in Section 5.2. When the FFR market is modeled, the time series raising the SoC level at the required times to the correct value are used as input for the Li-Ion BESS.

5.3.2.1 Choice of ESS size

As can be seen from Chapter 3, finding the optimal size of an ESS is a difficult task and depends on the purpose of the ESS installment, as well as the type, cost, and other parameters of the chosen ESS. In this thesis, the focus has been on the inclusion of additional balancing markets, which could provide increased network stability through frequency containment and new revenue streams for the owners of Midtfjellet Vindkraft AS. Hence, the size of ESS should be tailored to fit these needs while also adhere to the goal of finding a positive business case.

As discussed in Section 4.3.3, there is a sizing tool available in PSS®DE, for the sizing of new components. This sizing tool was used to see the recommended Li-Ion BESS size for the given case study. However, as the sizing tool does not yet support wind farm components, the wind farm had to be modeled as individual turbines. Wind speeds with a resolution of 10 min from August 2018 to August 2019 provided by Midtfjellet was used as input for the wind farm. Also, the load profile and Elspot prices for 2018 was used as input to the sizing optimizer. The objective of the sizing optimizer was set to minimize the cost. As could be expected from the results found in the specialization project [3], the resulting case showed that large Li-Ion BESS investments were not desirable. The dispatcher recommended installing a Li-Ion BESS with an energy rating of only 7 kWh. However, this did not take into account possible revenue from other markets, of which the Li-Ion BESS was needed to participate. As found in [73], it was possible to obtain revenue by installing ESS that relative to the wind farm size is small. The authors in [73] found that a 3-4 MW battery would limit most ramp rate violation for a 165 MW wind farm. Building on this argument, and adding that the internal load of the wind farm is not higher than 1 MW, it was, therefore, decided that the Li-Ion BESS unit should have a power rating of approximately 4.0 MW for the Midtfjellet wind farm of 149.6 MW.

Following the conclusion of the power rating, the ESS power/energy ratio must also be decided. To participate in the FFR market, a large power/energy ratio is desirable. This is because to participate in the FFR market, the duration is short (5-30 s [47]), but the price is paid per kW available, and hence a larger power rating means increased income from FFR. The largest ratio of the Li-Ion batteries available in PSS®DE is 2.4, and this battery was therefore chosen for this project. Following the natural scaling of the selected battery type, the resulting Li-Ion ESS has a 4.02 MW power rating, which results in an energy rating of 1.668 MWh.

5.3.3 Market model for Frequency Containment Reserves

To model the FCR-N market, an extra grid is added to the Li-Ion BESS model. This configuration is shown in Figure 5.5, where the FCR-N market has parameters, as described in Table 5.6.

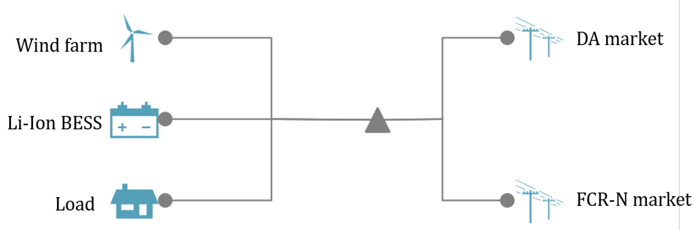


Figure 5.5: Full model set-up including FCR-N market in PSS®DE, icons from PSS®DE

Table 5.6: FCR-N market parameters

Component	Rated power [MW]	Lifetime [years]	Max imp./exp. power [MW]	Graph
FCR-N market	1.668	50	1.668	Figure A.3

The FCR-N market is modeled in the same fashion as in [77]. This means that the Li-Ion BESS, or load, is paid per MWh for import and export of power. The import and export prices are set according to the prices provided by Statnett for 2018 [23].

Modelling the FCR-N market as an extra external grid is not without limitations. It both raises the computational effort required and is not an accurate representation of the actual case. However, as the maximum limit of the FCR-N market combined with the DA market is still well below the 800 MVA rating of the power line (even with a low power factor), it is considered an acceptable simplification. As the balancing market function in PSS®DE was limited at the time of simulation, the solution to include the

FCR-N balancing market was to model it as a separate grid. The computational time increased by 32 % with this extra grid added, but this increase was seen as acceptable as it enabled inclusions of the FCR-N market. This FCR-N model is hence used when the simulations that include the FCR-N market in Section 5.2.

As can be seen in Table 5.6, the FCR-N market has been modeled to fit the battery energy limit at 1.668 MWh. This is because it is improbable that a wind farm, with its volatile production, would be allowed to bid on a reserve market. It is modeled both as up- and down reserves, i.e., the internal load can use the FCR-N market to cover its consumption, thus earning money by covering internal needs. From the data of the available volume (in MW) in the FCR-N market of 2018, the volume requested was below 1.668 MW in NO5 in just 4 hours. Hence, it was decided that a flat 1.668 MW limit would be an appropriate way to model the available FCR-N reserves. This would both spare computation time and provide results that mimic real-life demand to an acceptable degree.

5.3.4 Time series

The wind farm was simulated with a wind farm chart with normalized output power adapted from the real-life output of the Midtfjellet wind farm in 2018, which was provided by Midtfjellet Vindkraft AS. The normalization of output power means that the table includes production values compared to the wind farm's rated power. For the Midtfjellet wind farm, which has a size of 149.6 MW, a production of 100 MW would yield a normalized value of 0.668.

The price for power exported/imported from the wind farm/ESS/lead to the DA market was given by the Elspot prices for NO5 from 2018, while the price for power Exported/imported from the wind farm/ESS/load from the FCR-N market was given by the prices for FCR-N reserves in NO5 in 2018. These time series graph's can be viewed in Appendix A.2, with the DA price, FCR-N price, SoC-levels and normalized wind power output power depicted in Figure A.1, Figure A.3, Figure A.4 and Figure A.2 respectively.

The time series and which component they are used for is presented for clarification in Table 5.7. The names of the components are referred to Figure 5.5.

Table 5.7: Time series and input sources for the different components in the case study of Midtfjellet wind farm

Component	Parameter	Input	Source
DA market	Import/Export price [EUR/MW]	Elspot prices 2018 NO5	Nordpool [59]
FCR-N market	Import/Export price [EUR/MW]	FCR-N prices 2018 NO5	Statnett [23]
Li-Ion BESS	SoC Level [%]	FFR requirements	Calc. in Section 5.5 based on FFR req. [47]
Load	Load demand [kW]	Extrapolated from load profile Aug. 2019	Midtfjellet Vindkraft AS
Wind farm	Normed output profile	Adapted from 2018 production profile	Midtfjellet Vindkraft AS

It should be noted that the load profile for the wind farm is based on one month, Aug. 2019, as that was the data available. What this load is, have not been disclosed. Still, if it is a load demand related to the daily operation (and not to provide a seasonal load such as heating or related to extraordinary switching events), it is reasonable to assume that the load would follow a similar pattern throughout the year. The load profile from Aug. 2019 has therefore been extrapolated to cover the entire year. In addition, it should be noted that Midtfjellet wind farm was expanded from 110 MW to 149.6 MW capacity 10. August 2018. This was a result of building stage III, as 11 NREL 3.6 MW turbines were included in the wind farm. This can be viewed in Figure A.2, where there is a significant increase in production after this date.

5.3.5 Simulation parameters

For this thesis, the simulation and dispatcher parameters in PSS®DE were chosen as depicted in Table 5.8.

Table 5.8: Simulation and dispatcher parameters for PSS®DE and the case study of Midtfjellet wind farm

Parameter	Value
Project lifetime	20 years
Simulation	Entire lifetime
Dispatcher	MGMS
WACC	8 %
Time step size	3600 s

As shown in my specialization project [3], the reason for simulation over the entire lifetime is to get as accurate results as possible, even though it significantly increases the simulation time compared to, for instance, extrapolation from year one values. Hence, it was chosen to simulate for the entire lifetime, also in the thesis work, see [3] for further details. Note that the input data was based on data from one year, 2018; this means that wind power production and available energy have the same values for all years. As the thesis has as the main goal to see if there exists a positive business case for Midtfjellet Vindkraft AS, accuracy and economic optimization are the primary goals. Hence, the MGMS algorithm is chosen, and, since the MGMS utilizes the MPC approach if a solution to the given dispatch exists, it is optimal. The MGMS approach follows the principles explained in Section 4.2, and solves the optimization problem of power dispatch for each hour of each day for the lifetime of the project, with MPC retriggering intervals of 15 min.

The project lifetime of the project is set to 20 years, based on an approximate lifetime of 25 years the installed wind turbines installed in the different building stages (44 2MW turbines installed in 2012 and 11 3.6 MW turbines installed in 2018). Note that the salvage value of the Li-Ion battery is added at the end of the simulations. The time step size is set to the default value of 3600 s. The difference between 3600s timesteps and 60 s timesteps is discussed further in Section 5.4. The WACC is set to the default value of 8 %, and it should be noted that a change in WACC would influence the results. A higher value of WACC often implies a greater risk of the project and results in a lower net present value for the project of a firm [91]. Hence, a higher WACC could yield a more conservative result.

5.4 Verification of program

To verify that the results obtained by PSS®DE reflect real-life data, a verification based on actual revenue results provided by Midtfjellet for one month, August 2019, was conducted. The verification method proposed is to use the real measured data from Midtfjellet for this month together with Elspot price data from Nordpool as input to the program, and verify that the program's output resembles the revenue obtained by Midtfjellet. The simulation parameters, inputs and reference base case modelled in PSS®DE is as shown in Table 5.9, Table 5.10 and Figure 5.3 respectively.

Table 5.9: Simulation and dispatcher parameters for the verification

Parameter	Value
Project lifetime	1 year
Simulation	Entire lifetime
Dispatcher	MGMS
WACC	8 %
Time step size	3600 s & 60 s

Table 5.10: Input data for the verification of PSS®DE

Component	Input	Source
DA market	Elspot prices Aug.2019 NO5	Nordpool
Wind farm	Normalized production data Aug.2019	Midtfjellet Vindkraft AS
Load	Internal load demand for Aug. 2019	Midtfjellet Vindkraft AS

Note that the verification is carried out both for the standard 3600 s time step, and with 60 s time step. This is to look at how increased accuracy in the optimization reflects in the results versus the extra computational effort needed.

5.5 Modelling of fast frequency reserves

A method has been developed for simulation of participation in a future Nordic fast frequency reserves (FFR) market. The FFR market is explained in greater detail in Section 2.4.3.3. The method proposed to secure FFR is to raise the SoC level of the Li-Ion BESS, hence reserving parts of the battery capacity for FFR reserves as needed, as discussed in Section 4.1.5. The price from the demo version conducted by Statnett for FFR in 2020 is used. Hence, the price used for FFR reserves is 17 623.33 EUR / MW, see Section 2.4.3.3. For the simulations explained in Section 5.2, this base price serves as the reference value for FFR reserves. It was also decided that the calculations for the FFR market should be discounted and by using monthly cash flows.

FFR profile reserves need in the demo version to be available in the hours 22-7 on weekdays and all hours on weekends from 1. May - 30. September. The level of SoC needed for participation in the FFR market must be calculated. As the decided battery power is 4.020 MW, and there are special requirements for delivery of only 5 s FFR (see [47] for further details), it was decided that the minimum delivery time of 30 s should be chosen. Hence, with a period of delivery of at least 30 s, the required SoC level was calculated to 0.02008 MWh = 2%, using the equation in Equation (4.6). The SoC level should be raised to 2 %, where the available power for FFR participation is the power of the battery, 4.02 MW, at the time slots defined by Statnett. A time series raising the required SoC for the specified hours was created in Excel as input for the Li-Ion BESS in PSS®DE. The time series in graphical form for this SoC level is found in Figure A.4.
The calculation of additional revenue (cash flow) from the FFR market is found using Equation (4.7) to be 70845.79 EUR/year for the 4.02 MW Li-Ion BESS. As can be seen by Equation (4.7), the revenue from FFR market participation both depends linearly on the price for offered availability, and the amount of power provided as FFR reserves. The cash flow is thus the same for each year. This cash flow is then divided by the number of months that FFR reserves are required. Here, the period is from May to September, which yields 5. I.e., the cash flow in these months, CF_m, is 14 169.16 EUR.

To find the discounted cash flow (DCF), the monthly WACC must also be calculated. The chosen yearly WACC is 8% (see Table 5.8). The monthly WACC can be calculated, as shown in Equation (5.1). Equation (5.1) is based on the equation for an effective rate of interest found in [92]. Here WACC_m is the monthly WACC, WACC is the annual WACC, and n is the number of months in a year.

$$\text{WACC}_m = (1+\text{WACC})^{\frac{1}{n}} - 1 = (1+0.08)^{\frac{1}{12}} - 1 = 0.006434 = 0.6434\% \tag{5.1}$$

To get the appropriate value of the FFR participation, the DCF is found, as shown in Equation (5.2), which is based on the DCF equation found in [93]. Here, N is lifetime of the battery with the given SoC level in [months] (rounded) obtained from PSS®DE simulations, WACC_m is the monthly WACC, calculated by Equation (5.1) to be 0.6434 %, and CF_m is the monthly cash flow in [EUR].

$$\text{DCF} = \frac{\text{CF}_m}{(1+\text{WACC}_m)^1} + \frac{\text{CF}_m}{(1+\text{WACC}_m)^2} + \ldots + \frac{\text{CF}_m}{(1+\text{WACC}_m)^\text{N}} \tag{5.2}$$

The reason for the monthly discounting, as opposed to yearly, is that it is assumed that the FFR market price is paid each month, and hence the results would be less accurate if the FFR was discounted for a year when they are paid each month. The DCF is calculated for each scenario that includes FFR and added as a discounted revenue stream obtained by the inclusion of the Li-Ion BESS.

5.6 Case study summary

In this chapter, the different models and simulations that are to be carried out have been shown. To clarify how the simulation process is conducted, and specifically how the FFR results are included, a summary is presented here. To clarify the simulation process, i.e., which parts are done in PSS®DE and which are added later (FFR), a flow diagram is found in Figure 5.6.

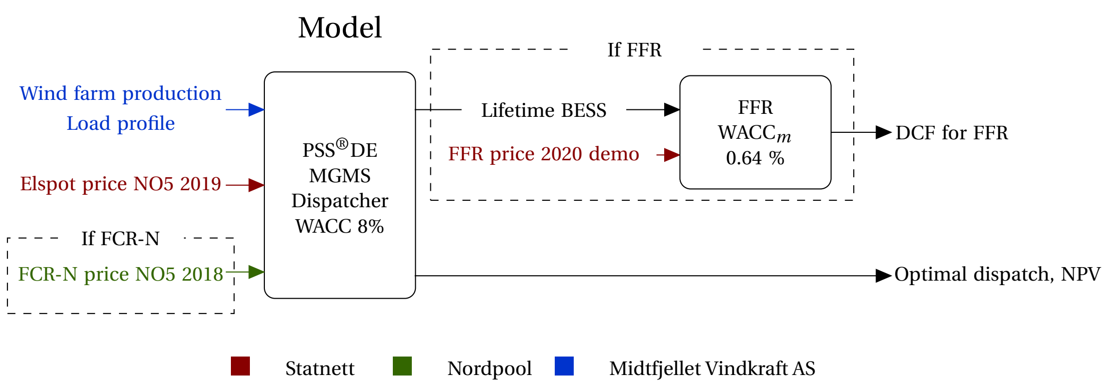


Figure 5.6: Simulation process

As can be seen from Figure 5.6, the optimal dispatch is found through optimization in PSS®DE. The results from PSS®DE yields the specific operation of the combined system and overall NPC. By using the average expected lifetime of the battery from the PSS®DE results, the revenue from the FFR market is calculated using Excel. Hence, the aggregated results of the PSS®DE and FFR calculations show how the ESS model can participate in the DA, DA + FFR, DA + FCR-N, or DA + FCR-N + FFR markets. These can then be compared to the reference case with the wind farm, which is only allowed DA market participation in this case study. The sources for the input data is also shown in Figure 5.6.

To summarize, a total of 44 scenarios are conducted in the case study, while the separate verification process requires one simulation. This translates to a total of 45 simulations in PSS®DE. The simulations are carried out using a HP zBook computer, that has an Intel®Core™ i7-6820HQ CPU @ 2.70GHz 2.71GHz and 16 GB RAM and is running the PSS®DE version V3.1.0.3488. The results of the scenarios are presented and discussed in Chapter 6.

Chapter 6

Results

In this chapter, the simulation results from running the cases presented in Chapter 5 in PSS®DE are presented along with discussion. To gain an overview of how the results can be interpreted, a brief explanation is given in Section 6.1. Then, the verification of the program is displayed and discussed in Section 6.2.1. After this, graphs depicting the optimal dispatch schedule for an arbitrary day from PSS®DE simulations are shown in Section 6.2.2. Finally, the results and subsequent discussion from running the different scenarios is presented in Section 6.2.3 and Section 6.2.4. It should be noted that the import and export values given is the mean value over the 20 years of simulation. I.e., import/export might be different in different years, but the mean value of the 20 years is used in the graphs presented here. The raw data for the results presented can be found attached to the thesis in the excel file labeled "Appendix_B1_LE_Master_thesis_2020.xlxs"

6.1 Interpreting the results

For the reader to understand how the results from PSS®DE and the fast frequency reserves (FFR) calculations should be interpreted, the following section outlines how the chosen Key Performance Indicators (KPI's) should be viewed. What the different KPI's represents, and which values are desirable/undesirable from an economic or technical perspective are described below.

6.1.1 Discounted Cash Flow

The discounted cash flow (DCF) is calculated for the FFR market using the method specified in Section 5.5. The resulting DCF is the revenue obtained from the participation of the Li-Ion battery energy system (BESS) in the FFR market, discounted for future cash flows with the chosen WACC. Hence, for a project where the investment of the battery is accounted for in PSS®DE, DCF is here equivalent to net present value

(NPV). It can, therefore, be added to the NPV calculated by PSS®DE, to obtain the combined NPV.

6.1.2 Net Present Value

Net Present Cost (NPC) is the system cost in EUR for the entire lifetime of the project and is the given output from calculations in PSS®DE. It outlines how much a given project would cost, taking into account the Weighted Average Cost of Capital (WACC), which is chosen to be 8 %. To simplify how the results can be read, and particularly concerning the fact that the NPV is calculated for the FFR market, the NPC results from PSS®DE are converted to NPV values by multiplication of minus one. It is desirable to have a positive NPV, as this implies that the proposed project is profitable. When comparing two results, the highest NPV thus belongs to the most profitable project.

6.1.3 Imported and exported energy

The imported and exported energy from the grid is given in kWh for each hour of the simulations, aggregated to annual values in the tabular results. Each hour, import or export of energy to the grid has a cost in EUR/kWh, where a negative cost implies a revenue earned for either import or export of power.

6.1.4 Energy content

The energy content, in kWh, is given for the Li-Ion BESS and reflects the amount of energy stored in kWh for each hour of the simulations.

6.1.5 Power set point

A negative power set point means that the component is importing power, while a positive power set point means that the component is exporting power. The power set point of a component is given in kW for each hour of the simulations.

6.2 Results

In this section, the results from the verification , 2020 and 2030 scenarios is presented and discussed in Section 6.2.1, Section 6.2.3 and Section 6.2.4 respectively. A small demonstration of the operational output from the simulations is presented in Section 6.2.2.

6.2.1 Results of verification of PSS®DE

To confirm that the software runs as intended, the reference case simulation results are verified using real revenue data provided by the Midtfjellet wind farm for August 2019, as described in Section 5.4. Due to secrecy clauses, the actual data is not published in their entirety here, only the relative difference in percent between the provided revenue output from Midtfjellet and the revenue output calculated by using PSS®DE. The results of this verification are presented in Table 6.1. Note that the results are rounded to two decimals accuracy.

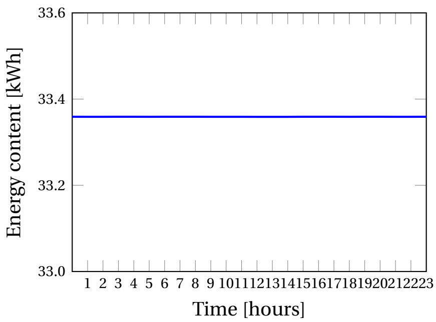
Table 6.1: Percentage change between PSS®DE simulations and data provided by Midtfjellet Vindkraft AS

Time step	**Production** [%]	**Revenue** [%]	**Export energy price** [%]	**Load** [%]	**Import energy prices** s> [%]
3600	-1.65	-1.62	-0.18	1.92	1.15
60	-1.45	-1.42	-0.18	-1.90	-2.37

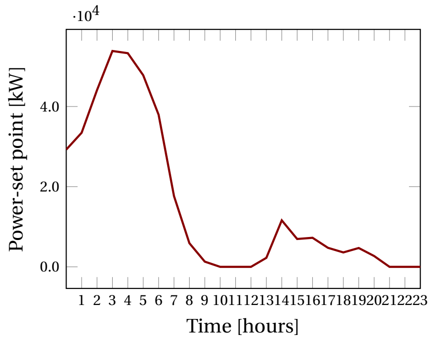
As can be seen, there are small discrepancies between the simulated values and the production data for August 2019 provided by Midtfjellet Vindkraft AS. The results show that the 60s time steps with 60s re-triggering of MGMS yield slightly better results regarding differences in production. However, this an almost negligible difference, and considering the wast increase in computational time (1 min vs. 28 min for a one-year simulation), it was decided that 3600 s time steps would yield accurate enough results while keeping the computational effort to a reasonable level. The import price of energy is further from the data provided in the 60s time step scenario. This is probably because a more accurate prediction of wind farm production results in less imported energy from the grid since the wind farm then can provide the required load. It should also be noted that the loads are overestimated slightly (increased compared to input), and production is underestimated (lower than Midtfjellet results) for the case with 3600 s time steps. Hence, it could be argued that the results obtained from PSS®DE are more conservative than the real-life results. As the errors are small, it should also be noted that they could be due to round off errors in the program. Therefore, it is concluded that the differences are small enough that their impact on the overall results of the case study is negligible.

6.2.2 Operational output

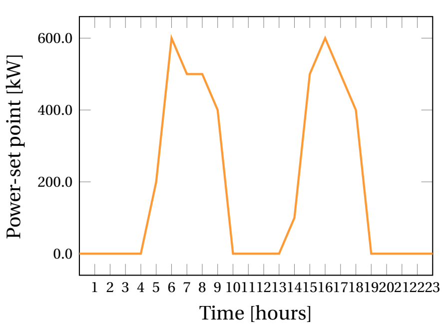
To demonstrate how the operation data provided by the program looks the graphs from a day in Figure 6.1 after a simulation of "L30 - DA + FCR-N + FFR" is presented. The graphs show the power-set point of the load, wind farm, day ahead (DA) market, as well as the battery's energy content on an arbitrary day, 05.06.2028 (year 10 of the simulation).



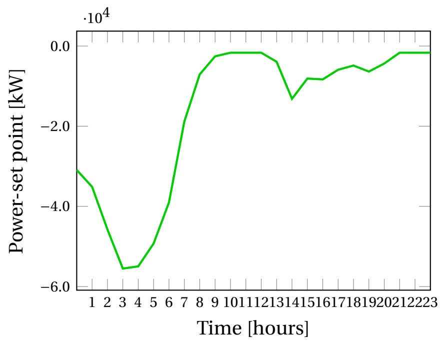
(a) Energy content Li-Ion BESS



(b) Power set-point wind farm



(c) Power set-point load



(d) Power set-point DA market

Figure 6.1: Operational output on 05.06.2028 for the different components from PSS®DE for L30 - DA + FCR-N + FFR simulation

From Figure 6.1a, it is apparent that the battery has a stable energy content, set at the 2 % = 33.36 kWh level required for FFR participation. Hence, the battery is not charged/discharged notably this day, but rather stays at a flat rate required by the SoC settings. As can be seen from Figure 6.1b and Figure 6.1d, the power-set point of the wind farm and the DA market are almost completely complimentary. I.e., all of the wind farms production is exported to the DA market, while the load is covered by import from the market for normal frequency containment reserves (FCR-N). To further show this, Figure 6.2 has been created, which has been made using the inverted power-set point for the DA market to show how the two graphs coincide.

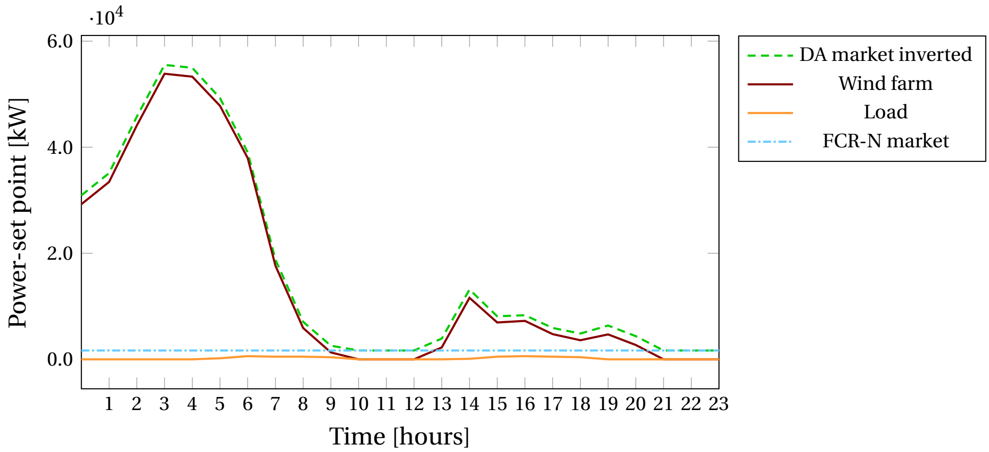


Figure 6.2: Power-set point in kW on 05.06.2028 for the load, wind farm, DA market and FCR-N market from PSS®DE for L30 - DA + FCR-N + FFR simulation

The power set point of the FCR-N market is included in Figure 6.2, and as can be seen, it was at a flat 1.668 MW import through the entire day. Since imported power provides a revenue, the dispatcher tries to import as much as possible from the FCR-N grid. The imported power from the FCR-N market is used both to cover the load demand and is transferred and sold at the DA market. This is especially apparent in Figure 6.2 in the time from 10-12 h and 21-23 h, where the load demand is zero, and the DA market minus the FCR-N import matches the wind farm production perfectly. In this regard, the transfer happens directly at the node, meaning that the power is never stored in the battery and then sold. This is natural, as storing the power would lead to losses and degradation. The model used in this thesis has a limitation on the power flow equation, which enables this interaction to occur. However, if such transactions are legal, it is beneficial for the battery to behave in this manner, as it would imply an increased revenue without the degradation costs associated with storing power.

In addition, it is worth noting that the operational data obtained for this scenario had a solving time of 50 min with the computer and PSS®DE version specified in Section 5.6. Hence, the current model is not suitable for online operation.

6.2.3 Result of 2020 scenarios

In this section, the results from running the 2020 scenarios presented in Section 5.2.1 are displayed.

6.2.3.1 Net present value

Figure 6.3 displays the percentage change in NPV for the simulations performed compared to the reference case of 2020. The aggregated NPV from PSS®DE and the DCF calculations for the FFR market in Excel is shortened to Agg. NPV.

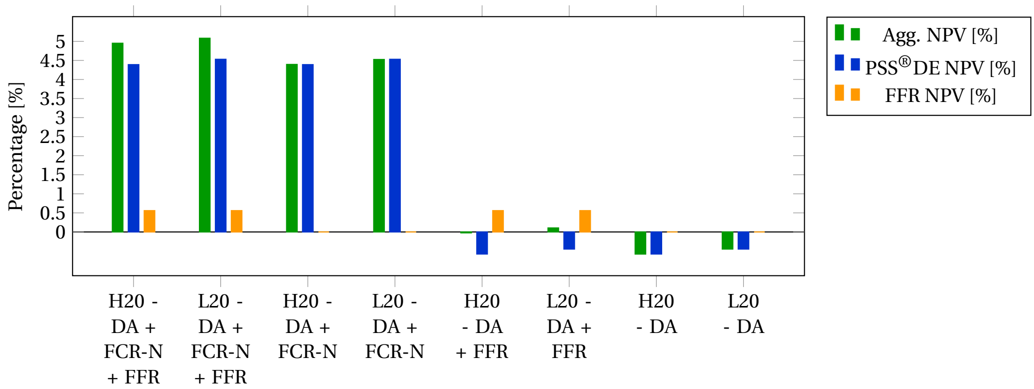


Figure 6.3: Percentage change in aggregated NPV from PSS®DE and FFR compared to the reference case for 2020 scenarios

As can be seen from Figure 6.3, the scenarios which include the FCR-N market all provide an increase in NPV compared to the reference case. The scenario containing the low Li-Ion price with the FFR market also has a slight increase in NPV compared to the other cases, while the other three cases; "H20 - DA + FFR," "H20 - DA" and, "L20 - DA" all have a decrease in NPV compared to the reference case.

6.2.3.2 Frequency Containment Reserves

Here, the most important results from the FCR-N market is presented. As there is no export to the FCR-N market, only import, the results presented is limited to the imported power, which can be viewed for the relevant configurations in Figure 6.4.

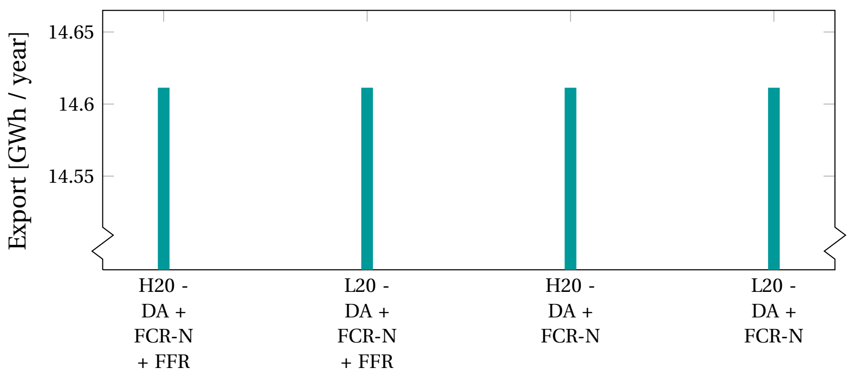


Figure 6.4: FCR-N import power in GWh / year with DA, FFR and FCR-N prices of 2018

As can be seen by Figure 6.4, there is virtually no change in the FCR-N import between the different FCR-N scenarios, with a 0.0001 % increase when the FFR market is included. Hence, the price of the Li-Ion BESS does not affect the import from the FCR-N market.

6.2.3.3 Day ahead market

Here, the results from the DA market after running the 2020 scenarios are presented. Both imported and exported energy is show.

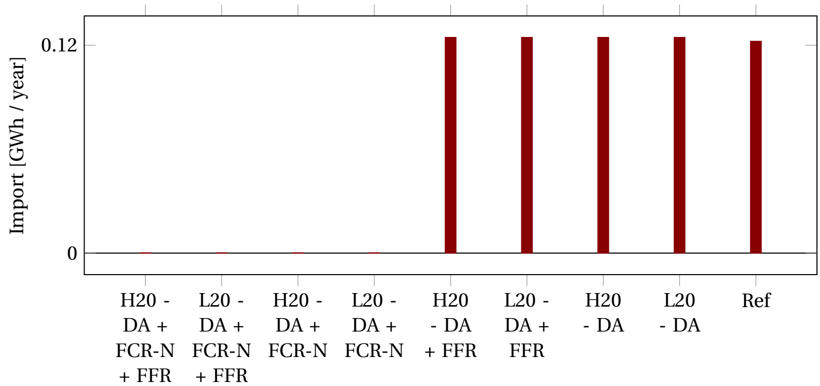


Figure 6.5: DA market import power in GWh / year with DA, FFR and FCR-N prices of 2018

It is apparent from Figure 6.5 that when the FCR-N market is included, the import from the DA market drops to virtually zero. This is because importing from the FCR-N market is paid, so it is more beneficial to import it from there than import it at a cost from the DA market.

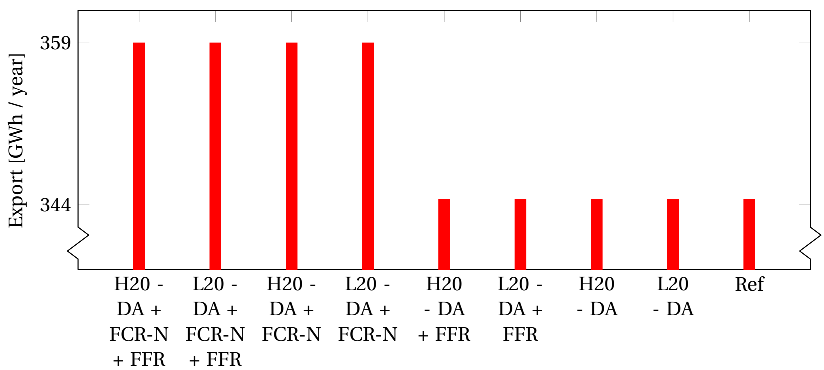


Figure 6.6: DA market export power in GWh / year with DA, FFR and FCR-N prices of 2018

As can be seen from Figure 6.6, there is an increase of exported power to the DA market when the FCR-N market is included in the simulations. This is because the import from the FCR-N market is traded on the DA market. It is also clear from Figure 6.5 and Figure 6.6 that the price of the Li-Ion BESS does not affect the amount of imported or exported power from the DA market.

6.2.3.4 Summary of 2020 scenarios

The main conclusion that can be drawn from the results of the 2020 simulations is that for the model and simulation program used, it is possible to obtain a positive business case with the current prices of Li-Ion BESS. This is both true for the inclusion of the other markets for FCR-N, FCR-N and FFR, and only FFR (valid only for the low price of Li-Ion BESS). However, note that the results are based on prices in 2018 for FCR-N/DA, and the FFR prices from 2020. Hence, a different pricing regime could alter the results. Besides, it is worth mentioning that the Li-Ion BESS is used very little in each instance, and hence has an unrealistically long-anticipated lifetime, up to 28.89 years. If the Li-Ion BESS had to be charged and discharged, for power transfer between the FCR-N and DA market to occur, this would alter the lifetime of the Li-Ion BESS. It issues related to the modeling of the FCR-N market are discussed further in Section 6.3.

6.2.4 Results of 2030 scenarios

In this section, the results from running the 2030 scenarios presented in Section 5.2.2 are shown.

6.2.4.1 Net present value

In this section, the results of NPV are presented for the 2030 scenarios. The NPV is aggregated from PSS®DE and the FFR calculations in Excel. The resulting NPV for each scenario, with a percentage increase compared to the reference case, is presented in-Figure 6.7.

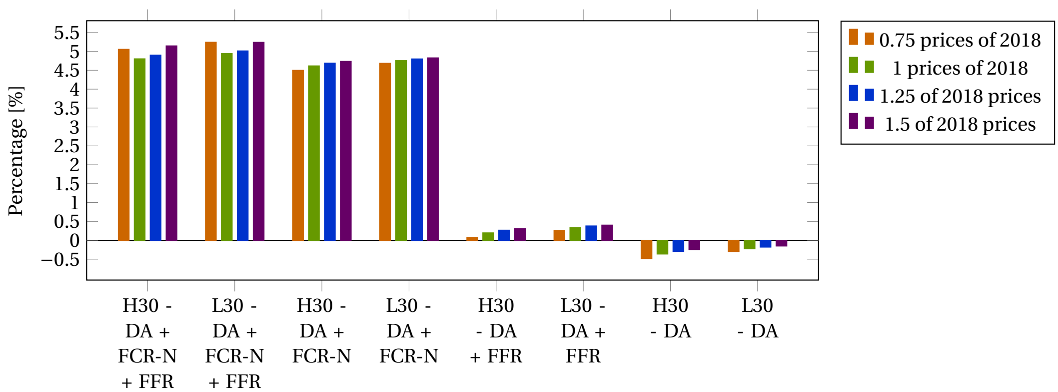


Figure 6.7: Percentage change in aggregated NPV from PSS®DE and FFR compared to the reference case for 2030 scenarios

As can be seen from Figure 6.7, there is a slight increase of NPV relative to the reference case for the different electricity price scenario, except when all markets are included. This can be attributed to the fact that for 0.75 times the electricity price scenario, the revenue from the FFR market has a bigger impact on the NPV, as the NPV from PSS®DE is lower. For the price scenarios of Li-Ion in 2030, both the high and low prices yield a positive NPV for all market structures except for the DA market only scenarios. This is expected based on the 2020 results, as the high price estimate for Li-Ion batteries in 2030 is lower than the low price in 2020, and the low-priced Li-Ion battery with 2020 electricity prices also provided a positive NPV.

6.2.4.2 Frequency containment reserves market

In this section, results from the FCR-N market for the 2030 scenarios are presented. The imported energy in annual values for the different scenarios and price of electricity is presented in Figure 6.8.

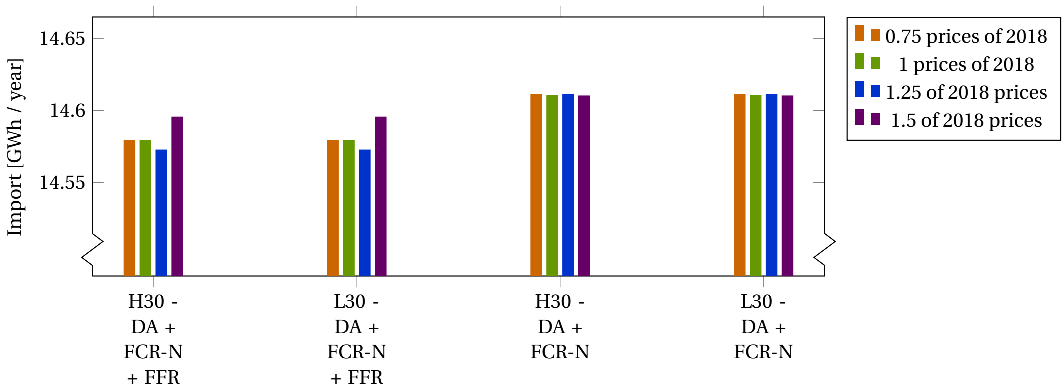


Figure 6.8: FCR-N import power in GWh / year with DA, FFR and FCR-N prices as described in 2030 scenarios

As can be seen from Figure 6.8, there is not a big difference between the different price scenarios concerning the amount of imported energy from the FCR-N market. Neither is there a large difference between the scenarios, including and excluding the FFR market. The difference in the 1.5 electricity price scenario is a decrease of only 0.10 %. Hence, it can be argued that the FFR market's inclusion does not impact the import to the FCR-N market noticeably. This is similar to the results obtained for the 2020 scenarios.

6.2.4.3 Day ahead market

In Figure 6.9, the changes of export for the simulations containing the FCR-N market versus the reference case are presented. The cases that include the DA market and the FFR market are omitted from the graphs. This is because their change relative to the reference case is in the range of -0.003 - -0.004 %, which is a negligible decrease.

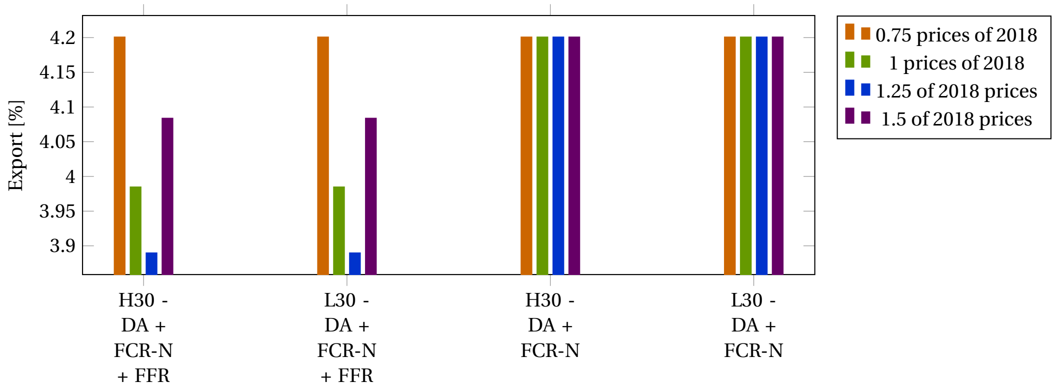


Figure 6.9: Percentage change in DA market export power compared to reference case for 2030 scenarios

As can be seen from Figure 6.9, the amount of exported power to the grid as a result of adding the FCR-N market increases with a value between approximately 3.9-4.2 % compared to the reference case for all the electricity price scenarios. This increase in export is because the import from the FCR-N market is sent directly to the DA market (when not used to cover the load demand). In Figure 6.8, there is a 0.1 % decrease in FCR-N import when the FFR market is included, and this also results in a decrease in the exported power to the DA market, as seen in Figure 6.9.

6.2.4.4 Summary of 2030 scenarios

There is not much difference in the simulation results when the electricity price is changed. Compared to the reference case, almost all projects are still profitable; with a slight increase in NPV relative to the reference case, the higher the price of electricity is in the different markets, except when all markets are included. This follows the same reasoning that was shown in the 2020 scenarios. The main trends for the 2030 scenarios are that the highest NPV is obtained when all the markets are included and that the FCR-N market is more profitable than the FFR market. The main difference between the 2020 and 2030 scenarios is the slight increase in NPV, mainly due to the lower prices of Li-Ion batteries. It is also apparent that increasing or decreasing electricity prices would result in a small improvement in NPV for the scenarios where all the markets (FCR-N, DA, and FFR) are included.

6.3 Discussion of the results

Following the main findings in the specialization project, it was important to include new revenue streams to make a battery profitable for a wind farm [3], as changing different battery parameters (SoC, EoL) did not impact the resulting NPV to a great extent. The results from the master thesis support this, showing that a Li-Ion BESS investment with only DA market participation yields a decrease in NPV. Hence, it is apparent that revenue stacking is vital to gain profitable ESS projects within the 10-year limit in these scenarios. The main results from the inclusion of two markets are that they both increase the NPV, and when looking at projections for 2030, all electricity price scenarios showed an increase in NPV when including the FCR-N or the FFR market. It is essential to emphasize that the wind farm probably would not be allowed to participate in these markets without the Li-Ion BESS. Hence, the extra revenue gained from these markets would not be possible without the Li-Ion BESS.

Regarding a comparison between the 2020 and 2030 scenarios, it is apparent that the main difference lies in the price of Li-Ion BESS. As the prices of Li-Ion BESS decreases from 2020 to 2030, the scenario where DA and FFR participation is allowed changes from a negative NPV to a positive NPV compared to the reference case. The results show that even with 2020 prices, there exist positive business cases for a Li-Ion BESS investment, given that participation in the FCR-N and DA market is allowed. When the 2030 scenarios are considered, all scenarios, including two or more markets, yield an increase in NPV compared to the reference case. Hence, a 4.02 MW / 1.688 MWh Li-Ion BESS unit can yield an increase in revenue for the case study presented, given the assumptions taken.

As is seen from the 2030 scenarios in Section 6.2.4, the variable that impacted the NPV value the most was changing the electricity price. The relative increase in NPV for the different electricity price scenarios was around 0.1-0.4 %. The relative difference between the different prices for the Li-Ion BESS was around 0.1 % increase in NPV for the low price scenarios. This could be explained by the fact that the electricity price is a uniform increase in all three markets. Hence, the gain in NPV is aggregated from the FCR-N, DA, and FFR market. It could be interesting to explore scenarios where only one of the electricity prices changed compared to 2018 values and see how price changes in different markets affect the NPV.

It should be noted that the dispatcher considers the input time series as perfect information; hence real variables and forecasted values coincide (wind production, load profile, DA price, and FCR-N price). This means that the battery operation in this model might be unrealistically good at following the set rules.

The largest issue is the modeling of the FCR-N market. As all transfers happen at one node, the power from the FCR-N market is directly traded to the DA market, which might not be legal. This could have been solved if the FCR-N market had been incorporated in a different node than the DA market, meaning that it would have to trade with the Li-Ion BESS/wind farm/load for any transfer of power to the DA market. However, as the program is limited to one such node, including this possible improvement was not possible. The FCR-N market model also affects the results of the FFR market. This is because the DCF is calculated using the anticipated lifetime of the battery from PSS®DE. Hence, a constraint that states that the battery must be charged and then discharged for transfer between FCR-N and the DA market could heavily alter this lifetime through degradation. Thus, the estimates for FFR revenue could, in this example, have been unreasonably high. The simulations with the FFR market showed only a slight improvement in NPV. Therefore, it is essential not to conclude that inclusion of FFR would lead to a positive business case, but rather to look at it in terms of a potential increase compared to only DA market participation.

Another thing that the model lack is taxes and feed-in prices related to import and export of energy. As these would have impacted the overall revenue obtained from selling at the different markets, a lower NPV improvement than shown would have to be expected if these were included. However, the inclusion of taxes and feed-in prices would significantly increase the model complexity. Hence, for this type of study, the computational effort would be unreasonable high compared to the additional insight gained.

The results show promising trends for ESS investments when they participate in balancing markets, with NPV improvements of 4-5 % when given perfect information. As Li-Ion BESS provides access to these balancing markets, it is interesting for further study to explore case studies using forecasted data. The main conclusion is, therefore, that revenue stacking can help provide a positive business case for Li-Ion BESS, and would be interesting to explore further.

Chapter 7

Conclusion

This thesis presented different benefits of installing an Energy Storage System (ESS) with a wind farm (or other volatile production) through an extensive theory chapter, a literature review, and a real case study of a proposed Li-Ion BESS for Midtfjellet wind farm. Previous literature was found to have had a primary focus on economic benefits. At the same time, the theory chapter concludes that there are several technical features and ancillary services that ESS can provide.

The case study conducted used the data from Midtfjellet wind farm and future scenarios for 2030 with both different electricity prices, and the development of the Li-Ion BESS price was created. The scenarios included using a multi-market model, with participation in one or more of the selected power markets. The power markets used was the Norwegian day ahead, FCR-N, and FFR market. Optimization of 44 scenarios and one verification was carried out in PSS®DE, an optimization program for distributed energy systems (DES) developed by Siemens AG.

The main results from the case study show that a 4.02 MW / 1.688 MWh ESS unit can provide additional revenue for the Midtfjellet wind farm of 149.6 MW in 2020, if it can participate in several markets, i.e., through revenue stacking. For the 2030 scenarios, the results show an even greater increase in NPV when Li-Ion BESS and revenue stacking is included. The results from the case study hence support previous findings in the regard that regulating power markets improve ESS profitability.

The future price of electricity did not alter the results to a great extent. Even with a decrease in the prices compared to 2018, the high price 2030 scenario for Li-Ion BESS with multi-market participation was profitable. However, the multi-market model used in the case study allowed for direct interaction between the different markets. This might have yielded unrealistically high revenues, as the cost of losses and degradation in the battery was not accounted for. Hence, the future development of the thesis should explore the possibility of a more accurate multi-market model.

Chapter 8

Future work

This chapter presents areas in the master thesis, which could be expanded in future work. Besides, the feasibility of the different areas is discussed. It should be noted that some of these are case-specific, and hence is not relevant for other case studies than the one presented, while others are broader and include improvements to the overall method presented. Some of the topics presented coincide with those in Chapter 9 of my specialization project [3].

8.1 Improvements to the case study

In this section, general improvements to the conducted case study is presented and discussed.

8.1.1 Input

The accuracy and resolution of the given input could be improved in the future development of this thesis. Regarding the input data for this particular case study, the load profile data was extrapolated from one month of data. Therefore, an improvement could be to collect a more accurate load profile for a whole year of operation. This would effect both the reference case and the scenarios, and would thus not alter the relative difference in net present value to a great extent. Another improvement could be to gather data using a statistic pick from several years of input data. Using a pick from different years could provide information as to how sensitive the results are. Hence, it could provide valuable information as to whether the proposed ESS investment would be profitable given different demands and prices than seen in 2018. The increase in resolution would also increase the computational effort required. Hence it should be explored for options with lower time horizons or where long computation times are not an issue. It should also be mentioned that the tool used, PSS®DE, is not meant to be used for hourly operational control, but rather as an investment tool. This is supported by the fact that simulations have to be done for at least a year of operation.

8.1.2 Modeling

The simulations on the multi-market model introduce issues regarding the validity of the results. The ESS in this case study is not used as the markets are allowed to trade and interact with each other directly. This is because the use of the ESS would incur a cost both because of losses and degradation. A possible way to remedy this could be to include more nodes in the configuration, so that the two markets could not trade without passing through the system containing the load, wind farm, and ESS, or to impose constraints on import/export between the two grids. However, as these features are not included in PSS®DE, it was considered out of scope for the thesis. Also, it could be mentioned that adding more nodes could increase the complexity of the optimization problem to such a degree that it becomes either unfeasible or has a too high computational effort required for it to be a useful tool. The accuracy of how the different components are modeled could also be improved. For instance, the battery model could be made more accurate, particularly concerning battery degradation. But, as degradation of a battery is a highly nonlinear process, improvements in accuracy could here result in a substantial increase in the computational time required and possible in-feasibility of the optimization model. Forecasting models to predict both prices and demand could have been developed or used to a greater extent in this thesis.

8.1.3 Scenarios

For the scenarios, more sophisticated models for predicting the future prices of electricity and Li-Ion BESS could have been developed or explored. In addition, the price increase of electricity could have been tailored to each specific market, instead of using a flat increase/decrease for all the markets.

8.2 Other aspects

In this section, other aspects that could be explored in further development of this thesis is briefly presented.

8.2.1 Different type of energy storage system

Li-Ion BESS was chosen as the ESS in this master thesis. However, as seen in Chapter 2, other types of ESS can be used for wind power integration. For the specific case study of Midtfjellet, one ESS that could be explored further could be hydrogen. Hydrogen could be suitable both since water is easily available for electrolysis, the wind farm is situated on an island, and for use as a fuel in the ferry line that connects the island of Fitjar to the shore.

8.2.2 Transportation

As the case study of Midtfjellet lies on an Island with a connected ferry line, it would be interesting to include how this ferry could be converted to either an electric or hydrogen ferry. Other forms of either hydrogen or electricity transportation could be also be explored, for instance, for buses, trailers, or other vehicles.

8.2.3 Energy storage systems versus grid investments

In cases where a grid investment for an increase of capacity is needed, it can be interesting to look at how this compares to an ESS investment. This could both be as an investment deferral, postponing a necessary investment, or as an option to the grid improvement. Although the authors in [61] found that grid investment was cheaper than ESS investment in their case, the article is from 2003. Hence, ESS versus a grid improvement could prove more profitable with the current prices of ESS. This would be an especially interesting topic for case studies where grid improvements are particularly costly, for instance, on islands where underwater cables are necessary. As the wind farm considered in this thesis is situated on an island, the topic of grid improvements versus ESS investment is, therefore, particularly interesting.

8.2.4 Technical aspects and ancillary services

Technical aspects or ancillary services that could be provided by installing ESS could be explored further in the case study presented. This could, for instance, be regarding the static voltage stability or reactive power improvements. For this, another tool than PSS®DE is needed, as it is not suited for these kinds of evaluations.

8.2.5 Grid codes

The relevant grid codes for ESS and a wind farm of Midtfjellet size could have been discussed further. Particularly regarding how grid connection would be possible, and the requirements of the joint operation of the ESS and wind farm for such a connection to be possible.

8.3 Summary

As seen by the parts in this section, there are several ways this work presented in the thesis could be developed further. The future development that is seen as yielding the most considerable improvement would be to achieve an accurate multi-market model. An accurate multi-market model could be used to find the real economic benefit of ESS installment. Gaining this information could help find suitable ESS investments, which again could be used to improve RES integration, ultimately resulting in a greener, smarter, and more agile grid.

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Appendix A

Appendix

A.1 Comparison method for different energy storage systems

The comparison method is based on the performance of the given ESS in each category. The best performance, defined below, is given value 5, while the worst is given value 1. If no information is found for a specific ESS type for a given parameter, the score is set to zero. The other ESS is then weighted against the ESS with the worst and best performance.

- **Discharge time**: long discharge time yields higher score
- **Response time**: low response time equals high score
- **Efficiency, power rating, specific power, lifetime, number of cycles and specific energy**: The higher the value, the higher score
- **Self discharge**: lowest levels gets highest score
- **Maturity**: Mature technology yields a score of 5, developed a score of 3 and developing a score of 1.
- **Geographical location**: The more flexible the storage is, the higher score it yields.
- **Capital cost**: Lower cost equals higher score

A.1.1 Energy storage systems weight matrix

The weight matrix based on the method in Appendix A.1 is shown in Table A.1.

Type	Discharge time	Response time	Efficiency	Power rating	Energy rating	Spesific power	Spesific energy	Num. Cycles	Lifetime	Capital cost	Self dis-charge	Location	Maturity
PHS	5	1	4	5	5	0	0	5	5	5	5	1	5
FC	5	3	1	3	4	0	5	1	4	3	5	2	1
FESS	2	5	4	1	2	5	3	1	3	2	1	5	5
LA	2	5	4	3	2	3	2	2	3	4	4	3	5
Lit Ion	4	5	3	4	3	4	4	2	3	3	4	3	3
VRB	3	4	3	2	3	3	2	4	3	3	4	4	3
SC	1	5	5	1	1	5	2	1	2	3	2	5	3
SMES	1	5	4	4	1	0	2	0	1	1	3	5	3
CAES	5	1	2	4	5	0	1	4	4	5	4	1	3
NaS	2	5	4	2	4	3	4	3	3	3	3	5	3

Table A.1: Weighting matrice for different ESS types based on method in Appendix A.1

A.2 Time series

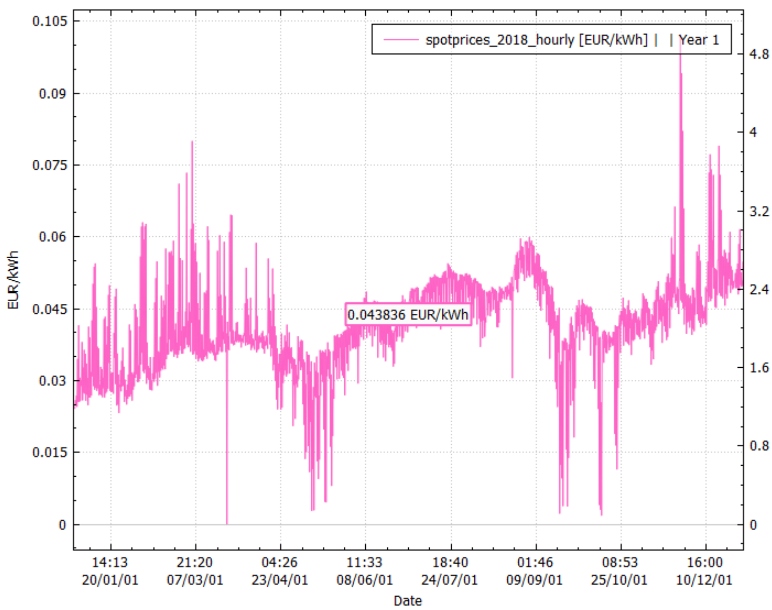

Figure A.1: Hourly 2018 Elspot prices for NO5 [22]

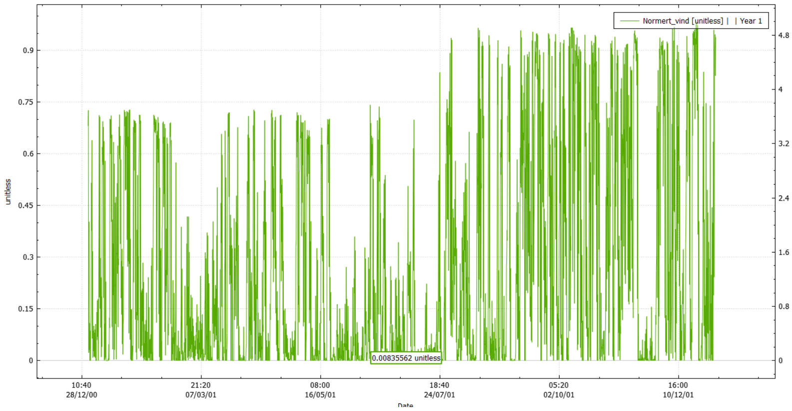

Figure A.2: Hourly normed power vs. rated power for the wind farm

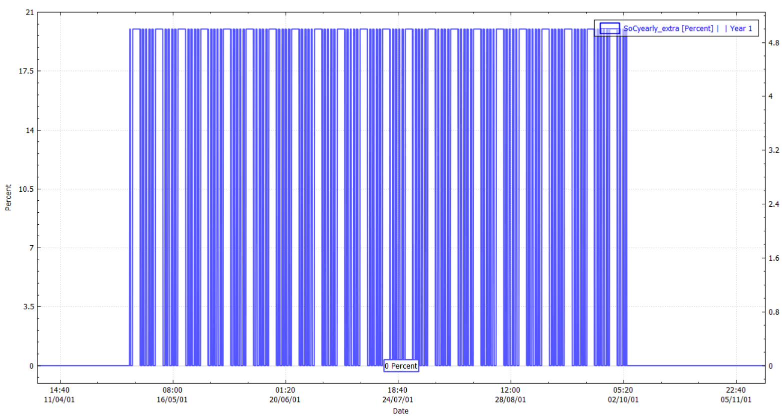

Figure A.3: SoC rules to secure FFR reserves

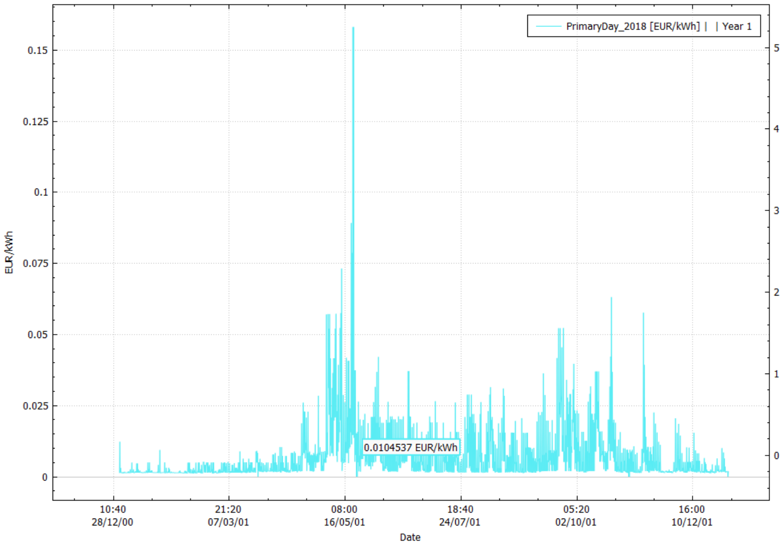

Figure A.4: Hourly FCR-N prices NO5 2018 [23]

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