Electricity Market Bidding Strategies for Wind-Storage Hybrid Systems

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by

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in partial fulfillment of the requirements for the degree of Master of Science in Sustainable Energy Technology at Delft University of Technology

Student Number:	4388887
Project Duration:	December 15, 2020 - October 5, 2021
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Cover Image: Co-located battery storage at Vattenfall's Prinses Amalia wind farm.
Source: Alfen

Acknowledgements

First and foremost, I would like to thank Dominic and Mihir, the dynamic duo that made up my supervision team. I would like to thank Mihir for joining me on our journey down the rabbit hole of the Dutch electricity markets. I see a business opportunity in our page long emails, which could be bundled and successfully published as an edition of ”Electricity Markets for Dummies”. Furthermore, the fact that Mihir allowed me to work with him on my first publication and seeing him in action defending our work at the hybrid power systems conference was a true honour. Dominic’s guidance style set a genuine example on how to inspire, empower and make his students feel appreciated. His ability to listen to my troubles, zoom out, and make me see the bigger picture, whilst I was lost in a jungle of details, saved me from multiple ”is what I’m doing actually meaningful” crises. All of this guidance took place online, making it all the more admirable, and I’m looking forward to meeting you in 3D for the first time during my defense. The insights from Anton at Tennet and Dorine at Vattenfall proved very helpful to gain some real-world insights to cut through the overwhelming abundance of academic literature.

I probably could have written this thesis without the support of my friends and family, but it would have been a terrible year that would have driven me mad. I would like to apologize to all my friends from JC Ozon, for having to listen to me rambling on about the inner-workings of the electricity markets for the 7th time. I sincerely promise that my defense will be the last time and from that point on we can continue with our usual meaningless topics. Coming into the SET master as a 6th year in Delft, I didn’t expect to make a lot of new friends, but I’ve seldom been more wrong. Within three weeks the 4J’s gave my student life in Delft a new impulse, culminating in our attempt at rowing the Ringvaart, the only event that I welcomed being cancelled due to Covid. The sailing vacation that came in its place was a much better idea. Furthermore, my roommates have proven to be the best colleagues at our improvised stay-at-home-office. Although the Friday afternoon ”office” drinks turned to everyday afternoon drinks a couple of weeks too many. My parents deserve the largest thank you of all for 25 years of the best support anyone can wish for. Thinking of how to thank my parents was the hardest to to do whilst I’m sitting here writing these acknowledgements. Making jokes about your friends is easy enough, but how do you thank two people that gave you everything? Maybe I’ll think of a way after I finish my beer and finally hand in my thesis. Lastly, I would like to thank Eva-Britt for making the past thesis-covid-crisis year feel nothing like a crisis, but rather like one of the most enjoyable years of my life.

Gijs van Holthoon
Delft, 21 September 2021

Summary

The large-scale installation of wind energy will provide challenges, such as maintaining a stable grid, security of supply, and profitability of renewables. The unpredictable nature of wind energy will cause more imbalances between generation and consumption to occur, consequently increasing the demand for the balancing energy reserves that ensure the grid's stability. The intermittent nature of wind energy necessitates the ability to time-shift energy production from high to low periods of wind energy availability to retain the security of supply. Furthermore, generators can face imbalance costs due to errors in wind energy generation forecasts. They are already being confronted with the declining value of wind energy in energy systems with a high share of renewables. Storage capacity is widely perceived as a technologically possible solution to alleviate these issues. Additionally, storage capacity can be a carbon-neutral alternative to the traditional power plants that currently provide the required flexible generation and balancing energy. However, the lack of economic benefits is the missing link between the technical benefits and mass implementation of storage capacity.

This study explores whether operating storage, co-located with a utility-scale wind power plant, can solve these challenges while improving the bottom line for operators. Spot market arbitrage, providing balancing energy through the automatic frequency restoration reserve, and generator imbalance cost reduction are identified as possible strategies for operating storage that can add value whilst also alleviating the identified issues. Furthermore, this study explores if arguments for co-locating storage with wind energy to form hybrid wind and storage power plants exist or if the business case for operating storage is independent of being co-located. Three cases that respectively explore the potential of spot market arbitrage, providing balancing energy, and a combination of both, are defined. The cases are evaluated on their ability to generate enough revenue so that the combined wind-storage system becomes more profitable than a wind-only system. Additionally, the cases are subjected to a sensitivity analysis of investment costs, market forecasting errors, and storage degradation costs. Current storage costs of Li-ion technology are used as an example in the cases. Various storage sizes and power outputs, expressed in 1,4, and 8-hour storage systems, are explored.

In the first case, it was found that an 8-hour battery performs best when undertaking spot market arbitrage. Still, even with a perfect market forecast and no storage degradation costs, it will need at least a 65% decrease from current Li-ion storage costs to become profitable. The 8-hour battery outperforms the higher power batteries because the low volatility of the spot market doesn't warrant the higher costs of 1 and 4-hour batteries. In the second case, it was found that providing non-contracted balancing energy to the grid with a 1-hour battery provides a potential 5-fold increase in profitability compared to having no co-located storage. However, the sensitivity analysis to storage degradation costs ultimately makes the case less profitable compared to having no co-located storage. The lower sensitivity to degradation costs of the 8-hour battery cause it to outperform the 1 and 4-hour batteries. Providing contracted balancing energy showed less potential than non-contracted balancing energy before the sensitivity analysis. However, the contracted balancing energy scenario is less sensitive to storage degradation costs. It was found that a 4-hour battery providing contracted balancing energy performed best. However, this strategy was ultimately 20% less profitable compared to not operating co-located storage. In the third case, it was found that combining spot market arbitrage and providing balancing energy has no significant improvements compared to solely providing balancing energy. Furthermore, the results of the proposed strategies turned out to be independent of the storage being co-located. Therefore, no strong arguments for co-locating storage could be made here.

The business case for storage, as put forth in this project, might not exist today. However, strong clues exist that it will in the future. The predicted drop in costs of storage and the increased volatility in electricity markets will provide opportunities for the profitable operation of storage systems. When that time comes WPP operators should also be interested to operate these storage systems to further their goal of competing with traditional fossil fuel-fired power plants.

Contents

Acronyms

AC
Alternating Current.

aFRR
Automatic Frequency Restoration Reserve.

AS
Ancillary Services.

BESS
Battery Electric Storage System.

BRP
Balance Responsible Party.

BSP
Balance Service Provider.

DAM
Day Ahead Market.

ENTSOE-E
European Network of Transmission System Operators for Electricity.

FCR
Frequency Containment Reserve.

FFR
Fast Frequency Response.

HWSS
Hybrid Wind and Storage System.

IRR
Internal Rate of Return.

ISP
Imbalance Settlement Period.

LCoE
Levelized Cost of Energy.

MAE
Mean Absolute Error.

mFRR
Manual Frequency Restoration Reserve.

RES
Renewable Energy Sources.

RMSE
Root Mean Square Error.

SOC
State of Charge.

TSO
Transmission System Operator.

WPP
Wind Power Plant.

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Introduction

Wind energy has a large role in the transition to a world powered by renewable energies. In the Netherlands alone, installed offshore wind energy capacity will grow from 1 GW to 11 GW between 2019 and 2030 to provide 40% of all electricity (Rijksoverheid, 2020). However, large-scale installation is just part of the puzzle. Concurrently, the need for smart control strategies and system design arises to combat the drawbacks of wind energy as a major energy source. Consequently, combining wind energy with storage capacity has often been suggested to face the inherent technical challenges that face a Wind Power Plant (WPP) such as intermittency, grid stability, and security of supply.

The growth of wind energy in the Netherlands exemplifies a larger trend. Grids will face higher penetrations of Renewable Energy Sources (RES) in the future and will have to deal with the concomitant grid stability issues. Major questions exist on how grid stability can be ensured in grids powered by 100% RESs. These issues can currently still be resolved by traditional large-scale power plants, which offer the bulk of balancing services to the grid. In line with the energy transition, it can be expected that these fossil fuel-fired plants will not be around in the future to provide this balancing energy and safeguard grid stability. The addition of storage capacity to the grid is one possible answer to alleviate this problem. The expected growth in wind energy capacity makes WPPs an interesting option to be co-located with this storage capacity. Combining storage with an intermittent WPP to form a Hybrid Wind and Storage System (HWSS) is not a novel idea. Multiple studies into control strategies for HWSSs have shown numerous technical benefits, such as aiding grid stability (Choi et al., 2016),(Thorbergsson et al., 2013).

The Dutch Transmission System Operator (TSO), Tennet, is acutely aware of these grid stability issues. Utility-scale pilots are being conducted with industry partners that operate aggregated storage and renewables. The pilot aims at testing their capabilities when it comes to providing balancing energy. The first results conclude that renewables combined with storage are technically perfectly able to deliver balancing energy and that the balancing energy market is open to parties operating these types of hybrid power plants (Tennet, 2021).

The case for storage from a technical standpoint is clear. However, whether adding storage is also beneficial in an economic sense is still a topic of debate. The lack of economic benefits might be the missing link between the technical benefits and the mass implementation of storage technology alongside RES. This study examines possible strategies through which combining storage and RES results in an economically beneficial outcome.

The growth of RES on the grid is portrayed as the cause of the problem, and storage has been identified as a possible solution. The question remains where the required storage capacity will come from. The grid will need storage in the future, but it is not said that this storage capacity necessarily has to come from the operators of RES. Operators of RES can be part of the solution when operating co-located storage. Whether they choose to operate storage will partly come down to if co-location is economically beneficial for them. However, it will also partly come down to a second question. Does co-location of storage alongside RES provide a better business case than stand-alone storage systems? This study will analyze the cases for a HWSS to analyze if co-location benefits exist or if the business case for storage is not influenced by co-location.

In the remainder of the introduction, the driving developments and concepts that have been touched upon above will be discussed in further detail culminating in the definition of the research objectives. The report is further structured in a background chapter on electricity markets followed by the methodology, 3 results sections, and finally, the conclusion and recommendations. Parts of this research have already been published in a conference paper, (Mehta et al., 2021) attached in the Appendix.

1.1. Designing for Profitability

In 2018, Vattenfall won the first subsidy-free wind farm tender in the Netherlands, thereby marking the start of offshore wind energy becoming commercially competitive with traditional energy sources (Rijksoverheid, 2019). Vattenfall believes they can make a profit from this wind farm because the costs have dropped significantly in the past decades. As of 2021, wind energy is on the brink of surpassing fossil fuels in Levelized Cost of Energy (LCoE), as shown in figure 1.1.

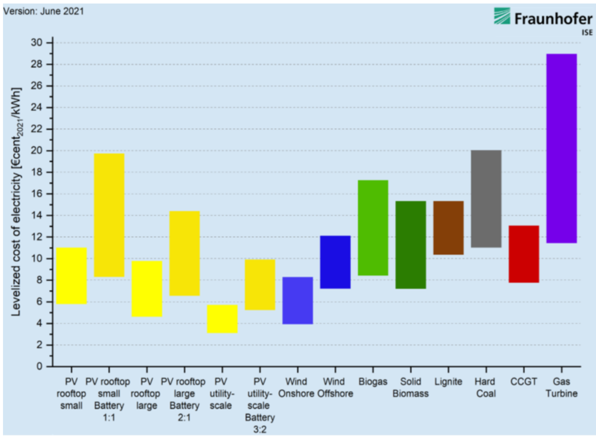

Figure 1.1: LCOE of various energy sources in Germany as of 2021. (Fraunhofer ISE, 2021)

Predating this development, wind farms were subsidized and designed with the lowest LCoE in mind. This was the dominant parameter determining tender and subsidy allocation. With subsidies out of the picture, wind turbine producers and asset owners will shift from winning subsidies based on LCoE to profitability as the dominant design parameter. Accordingly, commercial entities looking to invest in subsidy-free offshore wind will be looking for methods to boost their profitability.

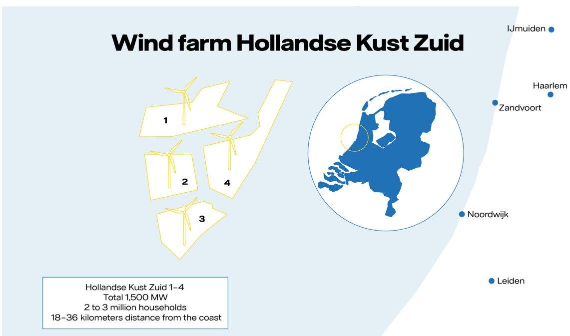

Figure 1.2: Location of the first subsidy-free wind farm. Source: Vattenfall

Increasing profitability can be done in many ways. Industry trends show continuous growth in the size of wind turbines, continuing cost reductions, and market incentives for RES. Future growth of WPP goes hand in hand with their ability to continue this development towards becoming cost-competitive with traditional energy sources.

The intermittent nature of WPP might be one of the biggest inhibitors for this evolution. This is where co-location of storage can come in. If profitable strategies for co-locating storage can be found, then not only can the profit be boosted, but it could be done while solving one of the biggest inhibitors for RES.

The fledgling profitability of WPPs, and RES in general, is already being jeopardized by the declining market value of renewable generation. Energy systems with high RES penetrations have shown declining wholesale energy prices (IEA, 2021). Simultaneously, the price volatility is expected to increase significantly for these same systems (CE Delft, 2020). The profitable operation of storage systems is correlated with the volatility of the market that they operate in. Therefore, the expected increases in price volatility motivate exploring storage technology as a way of increasing the profitability of HWSSs. The methods through which co-location of storage might provide potential to increase profitability for WPPs will be introduced in the coming section.

1.2. Co-location of Wind Energy and Storage

In this section, the revenue-generating mechanisms of storage systems are reviewed. In the introduction, the question was raised whether storage should be co-located or not. Currently, WPPs worldwide already operate co-located storage but not for the reasons suggested in the introduction. These systems are mostly operated for safety considerations. On-site storage can keep control of the turbine's braking and yaw systems in the event of a grid loss. Furthermore, storage can be operated for black start and low voltage ride through purposes. Since the main purpose of these systems is for emergencies, they tend to be idle most of the time. This existing storage capacity can be employed for the mechanisms that will be discussed below.

The main uses of storage can be categorized as either making profits in the energy and ancillary service market, enabling grid adequacy for grid operators, or providing firm generation levels for RES developers. These storage services have different sizes, potential values, and market types which will shortly be discussed to identify interesting applications of a HWSS. The different storage services are correlated with a type of user, i.e. Transmission System Operator (TSO), storage operators, consumers, and generators. The discussion will be limited to storage services that are of interest to generators as this project looks into HWSSs. This section touches upon many topics that are explained further in chapter 2.

Energy arbitrage or energy time-shift gives the system flexibility to sell power in the day-ahead or intra-day electricity markets when it is most profitable to do so or to operate off-grid. Large storage sizes are required, and potential values of co-location are low (Wind Europe, 2017). Work has been done to prove that adding storage to WPPs can improve their revenue generation capability by 10% (Das et al., 2019) when operating an arbitrage strategy. Simplified battery models were used and the settling algorithm was forced to sell all the stored energy within one day. Optimal operation of HWSSs has been studied and control schemes have been proposed that attempt to lower costs of the hybrid system (Wang et al., 2018). Studies using NYISO data from 2010-2013 on the revenue potential of a HWSS have shown that the investment costs of current battery systems were too high to be recouped through spot arbitrage and capacity market revenues (Jafari et al., 2020).

The potential for Day Ahead Market (DAM) arbitrage depends on the price volatility. Higher price fluctuations allow storage operators to make higher revenues. The DAM price curve on a representative day is predominantly influenced by the daily load/demand profile and the generation sources. Peak loads occur in the morning and evening and drive up the price. This can be seen in figure 1.3. Other factors influencing the DAM price are weather conditions and the consequent solar and wind energy generation. The influx of solar power on the grid can push prices down during the day, and during times of high wind production, DAM prices have been negative in Germany. This is caused by fossil fuel-fired plants whose costs of shutting down are higher than selling the energy at negative prices. The normal, load-dominated price cycles repeat daily and hint that performing DAM arbitrage will likely consist of a maximum of 1 or 2 discharge cycles per day.

Figure 1.3: Example of DAM price for the Netherlands, 8-8-2021. Source: EPEX-Spot

Ancillary services are fast-reacting energy reserves that aid the grid in maintaining a stable frequency. Frequency reserves are sold in Frequency Containment Reserve (FCR), Automatic Frequency Restoration Reserve (aFRR), or Fast Frequency Response (FFR) markets, where each market has a different purpose and characteristics. At this stage of the project, these markets will be jointly referred to as 'frequency markets' for simplicity. Frequency markets require low storage sizes and offer high potential values of co-location (Wind Europe, 2017).

Per the 1st of September 2020, Tennet has restructured the frequency regulation markets in the Netherlands. Previously, these ancillary services were privately contracted by Tennet. In the new system, the services will be auctioned, with the auction being open for all BSPs (Tennet, 2019). This is partly driven by the technological advancements of Tennet's mobile communication network (Tennet, 2020). Previously, dedicated leased lines were necessary to provide the data connection between the BSP and Tennet. In the new system, communication is possible over mobile networks, significantly lowering the entry barriers for new BSPs. This opens up the market to new and smaller-scale BSPs. This is part of the effort of Tennet to move towards a decentralized grid. Furthermore, bidding frequencies for balancing energy have been increased from monthly to daily or even hourly depending on the type of balancing energy. It has been shown that higher bidding frequencies can positively influence the business case for distributed energy sources providing balancing energy (Poplavskaya & de Vries, 2019).

Adding storage to intermittent RES has the positive technical effect that it can be employed for frequency regulation for the grid. Control strategies to provide these services to the grid have been suggested and proven to enhance the system's stability (Choi et al., 2016),(Thorbergsson et al., 2013). However, these studies did not look into the effect on revenue or profitability of a HWSS.

The opening of the frequency regulation market by Tennet is interesting for HWSS as it has been shown that BESS can be profitable in performance-based frequency regulation markets (Xu et al., 2018) even when taking battery aging costs into account. Whilst this was performed for a battery-only model operating in the frequency market, it still shows potential for the HWS where the battery is part of a system that operates in all energy markets with an intermittent RES as it's source. Layered operation in energy arbitrage, balancing and frequency markets has been proven to be profitable in the case of a grid-tied BESS in the UK energy market. (Gundogdu et al., 2019).

The voltage control ancillary service is linked to frequency control, which sells reactive power to the grid to maintain voltage levels. These ancillary services require only small storage sizes and have a high value of co-location. Additional ancillary services are the black-start capacity to re-energize the grid in the event of a black-out. This requires a large storage size and has a medium potential value

(Wind Europe, 2017).

Grid adequacy storage services for generators are curtailment reduction and imbalance reduction. Storing electricity when the wind power would have been otherwise curtailed due to overproduction minimizes energy losses and has a high potential value for small storage size (Wind Europe, 2017). Using storage for imbalance reduction allows the HWSS operator to avoid imbalance penalties that occur when produced energy deviates from the day-ahead bid due to imperfect wind power forecasting. This, too, has high potential value for low storage sizes (Wind Europe, 2017). In the future, ramping control and smoothing of energy output may also emerge as a service. However, currently, no market exists for these services.

System adequacy for generators pertains to selling future capacity in a capacity market to TSOs to balance demand and generation. Seasonal storage is also an option, but just as capacity markets, this requires large storage sizes and has a low-value potential (Wind Europe, 2017).

It is important to note that multiple services can be combined to complement each other. A storage operator can layer operations across these services by flexibly allocating storage capacity between these services. Value stacking is what occurs when this layering of services gives rise to additional revenue generation. Complex optimization strategies have to be developed to combine these services to result in the highest value-stacking. The economic performance of the HWSS then depends on the operational control strategy. Among others, the strategy depends on local market design, which dictates the number of markets and their specific characteristics.

The significant revenue addition of arbitrage and the high potential of frequency markets makes these two interesting candidates for this report. The potential of these mechanisms has been researched in a previous master thesis and was shown to be profitable for a stand-alone storage system (Hugenholtz, 2020). Whilst also providing valuable insights, this work contains missing elements and modelling errors. Therefore, this thesis will attempt to verify these results and build upon them by including imbalance mitigation from the perspective of a HWSS operator. Imbalance mitigation is the only service listed above that specifically requires co-location. The other services show low potential or are not mature yet.

1.3. Objectives

Combining storage with a WPP is an interesting opportunity to further the cause of making WPP cost-competitive with traditional energy sources. The opening of the frequency market combined with WPPs becoming revenue-driven are developments that motivate researching new strategies for adding revenue for HWSS operators through co-location of storage. The use of storage in combination with intermittent RES is an extensively researched field. However, there is a lack of a comprehensive case study for HWSSs comparing the various storage services, incorporating the layered operation of storage services, and incorporating forecasting errors.

Looking at the developments discussed above, the area of interest for this project starts to take shape. The combination of these developments points to a need of developing strategies for co-located storage to maximize profits for HWSS operators in light of new market design. Frequency services have been discussed as the possible way to achieve this as the value potential for storage in the newly reformed frequency markets is high.

In this project, onshore wind in the Netherlands is used as a case study. Whilst the developments and concepts in the introduction are valid globally; they are particularly clear in the Netherlands. Nevertheless, the goal of this project remains to find universally applicable learnings.

The project aims to explore if strategies exist that will improve the business case of HWSS and the factors influencing the same. The main objective of this project then becomes:

'To gain insights into optimal control strategies for a hybrid wind and storage power plant bidding in different energy and ancillary markets, and to quantitatively analyze the economic value of co-locating

storage for WPP developers.'

Sub-objectives are defined to outline the goals of this project further. The sub-objectives are divided into objectives that determine which requirements must be met to answer the main objective and objectives that analyze how the outcome of the main objective is influenced by the system design. The latter sub-objective pertains to performing sensitivity analyses of system parameters such as forecasting error, storage size, storage type, and wind turbine size.

i) *Analyze the economic performance of utility-scale HWSSs by utilizing optimal bidding strategies and forecasting methods in day-ahead and balancing markets.*
ii) *Analyze the economic performance of utility-scale HWSSs by utilizing optimal bidding strategies and forecasting methods in ancillary services markets.*
iii) *Develop bidding strategies that layer HWSS operation in energy and ancillary services markets and analyze if this leads to value stacking benefits.*
iv) *Perform a sensitivity analysis of the revenues with respect to the system's technical parameters and storage* costs.

1.4. Scope

The system researched in this project will initially consist of onshore utility-scale wind farms and battery storage technologies. If deemed interesting, the scope can be broadened to other storage technologies. However, alternative storage solutions must adhere to the fast discharge and ramp rate criteria for operating in ancillary services.

A case study will be developed for the specific market conditions of the Dutch energy and ancillary services markets. Additionally, the approximate system sizing and location will resemble current onshore wind projects in the Netherlands.

It is outside this project's scope to develop novel weather or market price forecasting methods. The goal is to implement an existing method for both parameters. The goal of implementing these forecasting methods is to simulate the nonperfect forecasting that operators of real-world HWSS will face.

The HWSS is assumed to be a price-taker. The bids placed by the system are deemed small enough not to affect the market price. Furthermore, it is assumed that all placed bids are activated.

2
Electricity Markets

To identify possible approaches for adding value through co-location of storage and wind energy a basic understanding of the manner in which electricity is traded is needed. The goal of this section is foremost to describe the electricity markets. In the introduction, strategies and value-adding scenarios for HWSSs were defined. In this chapter, the detailed working of the markets that allow for these value-adding scenarios is discussed. Readers that have a background in electricity markets can choose to only read the last section of this chapter as it contains several assumptions, simplifications and motivations that are relevant for the methodology of this project. The other sections contain background knowledge and no crucial arguments, motivations or results are made in these sections pertaining to the research objectives.

Before reviewing the different markets it is relevant to point out that there are differences between so-called capacity markets and energy markets. In a capacity market, the generator is remunerated for offering power capacity to the market regardless of whether this capacity is activated. The generator's bid in a capacity market consists of the promise that it will have an X amount of power capacity in MW available during a defined time span. Remuneration is delivered through the capacity price in €/MW/hour. In an energy market, the generator is remunerated for the energy it has delivered to the grid. The generator's bid consists of the promise that it will deliver the bid amount of energy during a defined time span. Remuneration is delivered through the energy price in €/MWh. Alternatively, it is also possible that an electricity market has a combined capacity and energy remuneration system.

In this chapter, the actors in the markets are discussed, followed by reviews of the DAM, Imbalance and Frequency markets. Since the geographic focus of this study is primarily on the Netherlands, the given description of electricity markets is valid for the Dutch Electricity Markets as of September 2021.

2.1. Stakeholders and Actors

The electricity market harbours many actors and stakeholders that all have their roles in maintaining a stable power supply. The three most relevant actors for this project will be discussed in this section.

The Transmission System Operator (TSO) owns and is responsible for the operation and maintenance of the high voltage grid infrastructure. Alongside maintaining the physical infrastructure the TSO is responsible for the stability of the grid. Electricity is a peculiar commodity because transport is instantaneous and it cannot be stored by the grid. These properties give way to the concept of grid stability. To retain stability on the grid there must always be a real-time balance between generation and consumption. Failure to do so leads to instability, which in turn can cause failure of the grid. Generally, grid infrastructure operates with AC power. The physical property associated with stability for AC grids is the grid frequency. The grid frequency is amongst others determined by the grid voltage. Simplified, it can be stated that whenever there is more consumption than production the grid frequency will drop and vice versa. The TSO aims to keep the grid frequency stable at the 50 Hz frequency set for the entire synchronous European connected grid. Balancing of generation and consumption on the grid is facilitated by multiple intertwined electricity markets. These various electricity markets are the topic of the next sections.

An entity that operates in the electricity market is called a Balance Responsible Party (BRP). A BRP can be a consumer, generator or both. A BRP must submit its E-program to the TSO. The E-program contains the scheduled operation of the BRP. The E-program is established by the energy trades that the BRP has made in the electricity markets. For instance, a generator cannot push energy into the grid without having first sold that volume of energy to a consumer in a market. The scheduled operation of the BRP must correlate to the energy trades it has made.

BRPs will often deviate from their E-program due to incorrect weather forecasting, breakdowns and load spikes amongst others. Whenever this occurs the E-programs of all BRPs are no longer balanced. To maintain balance on the grid balancing power is needed. Balancing power is provided by a Balance Service Provider (BSP). BSPs offer balancing capacity to the TSO. The TSO can employ this capacity whenever the grid is in a state of imbalance. The TSO procures this balancing energy via auctions or contracts which will be discussed in detail in section 2.4. BSPs must go through a pre-qualification process before they can offer balancing energy. This ensures that they are able to meet the demands required by the TSO to provide balancing energy. These demands consists of, amongst others, a certain ramp rate, response time and the ability to accurately follow set points, for generation or consumption, provided by the TSO. The interactions between the BRPs, BSPs, and the TSO on the balancing market is shown in figure 2.1.

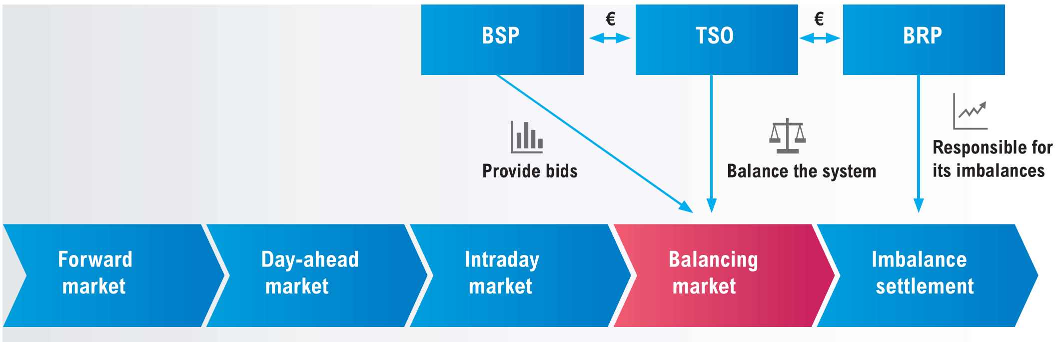

Figure 2.1: Balancing market sequence in electricity markets (ENTSO-E, 2018)

2.2. Day-Ahead Market

The Day Ahead Market (DAM), also called spot market, is an energy market where generators and consumers trade energy a day before the delivery period. At 12:00 generators and consumers have to submit their bids for each period of the day. For the DAM the period is one hour. These bids contain the amount of energy that the generator/consumer expects to produce/consume and the price at which they are willing to trade energy. The bids for each period are placed on a bid ladder and cleared based on the merit order approach. The merit order approach entails that generators are activated in ascending order based on their marginal cost of energy production. The generation bids and demand line are plotted against one another and at the point the lines cross the market price is set. Consequently, the price of the most expensive bid that needs to be activated to fulfil the demand becomes the market price. Every generator receives the market price for their produced energy, regardless of if they bid their energy at a lower price. This system has incentives for generators to bid their marginal cost of energy production. The merit order approach is visualised in figure 2.2

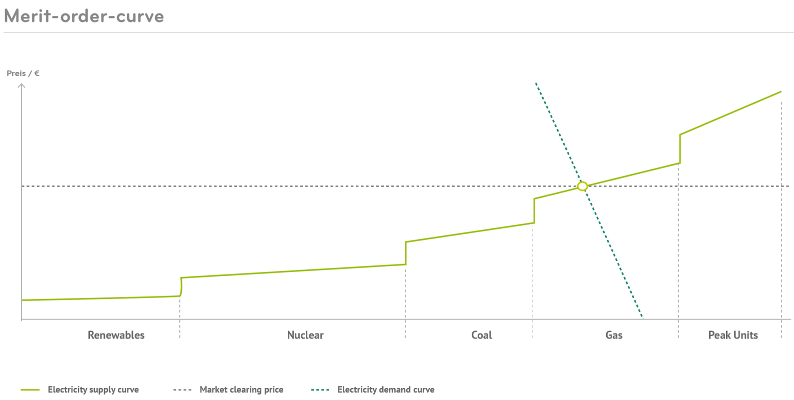

Figure 2.2: The merit order curve for the DAM. Source: NextKraftwerke

The DAM auction is organized by EPEX Spot, a company that handles DAM trades for most parts of northwestern Europe. By participating in the DAM a generator or consumer becomes a Balance Responsible Party (BRP). The BRP's accepted bids for the next day are called its E-program. Every BRP is committed to their submitted E-program on the day of delivery. If every BRP delivers on their E-program then there is a balance between supply and demand. Deviations from the E-program are settled in the imbalance market.

2.3. Imbalance Market

In the previous section the E-program was introduced. An E-program contains the BRP's production or consumption schedule for the coming day. Since the bids for the DAM need to be submitted one day ahead, BRPs make a prediction of how much energy they will produce/consume the next day. Errors in these predictions lead to deviations from the BRP's E-program. Whenever this happens the BRP is in a state of imbalance as it is not upholding its e-program. These deviations lead to imbalances between supply and demand in the DAM. To keep the grid in balance these imbalances need to be resolved. When a grid-wide imbalance occurs the TSO activates balancing energy. This balancing energy can be in the form of up-regulation or down-regulation depending on whether there is, respectively, a shortage or surplus of energy on the grid. The balancing energy is provided by the BSPs that are activated by the TSO. The TSO passes on the cost of the balancing energy onto the BRP that is causing the imbalance. Whenever a BRP is in imbalance the imbalance volume is measured at the BRP's grid connection. The imbalance volume is settled between the BRP and the TSO according to the imbalance price. The direction of payment depends on the imbalance price, whether the BRP is a surplus or shortage and on the regulation state of the grid. A detailed overview of this can be seen in figure 2.3.

During ISP with	Imbalance position BRP	Imbalance Price	Direction of payment
Regulation state 0	BRP shortage	P_{mid} (+)	BRP → TSO
		P_{mid} (-)	TSO → BRP
	BRP surplus	P_{mid} (+)	TSO → BRP
		P_{mid} (-)	BRP → TSO

During ISP with	Imbalance position BRP	Imbalance Price	Direction of payment
Regulation state +1	BRP shortage	P_{up} (+)	BRP → TSO
		P_{up} (-)	TSO → BRP
	BRP surplus	P_{up} (+)	TSO → BRP
		P_{up} (-)	BRP → TSO

During ISP with	Imbalance position BRP	Imbalance Price	Direction of payment
Regulation state -1	BRP shortage	P_{down} (+)	BRP → TSO
		P_{down} (-)	TSO → BRP
	BRP surplus	P_{down} (+)	TSO → BRP
		P_{down} (-)	BRP → TSO

During ISP with	Imbalance position BRP	Imbalance Price		Direction of payment
Regulation state 2	BRP shortage	$P_{up} \geq P_{mid}$	P_{up} (+)	BRP → TSO
			P_{up} (-)	TSO → BRP
		$P_{up} < P_{mid}$	P_{mid} (+)	BRP → TSO
			P_{mid} (-)	TSO → BRP
	BRP surplus	$P_{down} \leq P_{mid}$	P_{down} (+)	TSO → BRP
			P_{down} (-)	BRP → TSO
		$P_{down} > P_{mid}$	P_{mid} (+)	TSO → BRP
			P_{mid} (-)	BRP → TSO

Figure 2.3: The direction of payment for Imbalance Scenarios. Source: Tennet

The regulation state of the grid is a parameter that portrays whether the grid is a surplus, shortage or both during an ISP. Tennet defines four numbered regulation states, 1, -1, 0 and 2. Regulation state 1 means that during the ISP only up-regulation has been activated. Regulation state -1 means that during the ISP only down-regulation was activated. Regulation state 0 means that any imbalance on the national grid was solved through international interconnectors and no balancing energy was activated in the Netherlands. Regulation state 2 means that both up and down-regulation capacity has been activated during the ISP. The imbalance price during regulation state 2 depends on what the mid-price in the merit order was. The mid-price is the average of the price of the highest down-regulation bid and the lowest up-regulation bid. These bids are placed by the BSPs. The working of this bidding process and how the imbalance price comes about is explained in the next section.

In general, a BRP is rewarded if it is helping the grid remain stable and is punished whenever it is worsening the grid's stability. For instance, if the grid is in a surplus then the imbalance prices tend to be low. If simultaneously, the BRP is in a shortage, it will need to buy this shortage volume on the imbalance market but due to the low price levels this won't cost them too much. The BRP is helping solve the surplus on the grid by being in a shortage compared to its placed bid. Alternatively, if their is a shortage on the grid, the imbalance price tends to be high. If simultaneously, the BRP is in a surplus it will receive this higher imbalance price for the surplus volume. The BRP is helping relieve the shortage on the grid by producing more than it had bid. Therefore, being in imbalance with its placed bid is not necessarily bad for the BRP. A BRP that operates co-located storage has controllable flexibility to add or subtract for its DAM bid. By doing this, the BRP provides a form of frequency support, thereby limiting the amount of balancing energy that needs to be provided by BSPs.

2.4. Ancillary Services

Ancillary services is a term that encompasses multiple services that can be offered to the grid. For the purpose of this study, the term will be used as a synonym of frequency support. Frequency support is a term used to describe the ways in which balancing energy is activated to retain a stable frequency on the grid.

The balancing energy activated by the TSO to maintain the balance on the grid is provided by BSPs. This balancing energy is subdivided into four types that can be differentiated by their respective response times and bid sizes. Figure 2.4 graphically shows the different types of balancing energy. Whenever there is an imbalance between generation and consumption on the grid, the frequency deviates from the 50 Hz norm. In the case of Figure 2.4 the frequency drops at t0. The first type of balancing energy to be activated by the TSO is the Frequency Containment Reserve (FCR). These are fast-reacting energy reserves that are automatically controlled by the TSO to stabilize the dropping frequency. The systems providing the energy reserves need to be able to ramp to 100% of their capacity within 30 seconds following the activation command. If the frequency deviation is not resolved within 30 seconds by activation of the FCR alone, then the next type of balancing energy is activated. The Automatic Frequency Restoration Reserve (aFRR) consists of energy reserves that can be automatically controlled by the TSO and that can ramp to 100% of their capacity within 5 minutes following the activation command. The aFRR has a larger volume and will attempt to restore the frequency to the reference value. If the imbalance persists, the Manual Frequency Restoration Reserve (mFRR) replaces the aFRR and is expected to have a full activation time of 15 minutes. mFRR cannot be controlled automatically but has to be manually activated. Tennet contracts 1 GW of up-regulation and 760 MW of down regulation mFRR capacity. The activation of these three balancing products happens constantly and is part of the day to day operation of a stable grid. However, imbalances caused by unexpected outages of larger power plants can be so severe that balancing energy is needed on time frames longer than 30 minutes. For these situations, the TSO employs the Restoration Reserve (RR). These are often old power plants that have been mothballed, or kept on standby, for this purpose instead of being demolished.

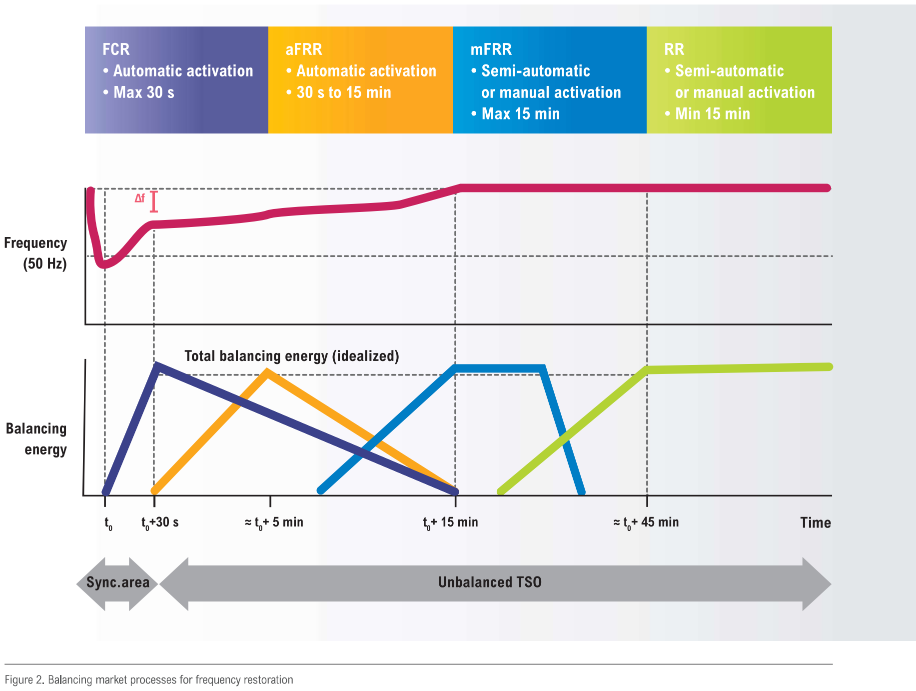

Figure 2.4: Activation order of the various types of balancing energy(ENTSO-E, 2018)

FCR is procured by the TSO in an auction. This auction is organised daily, together with other TSOs in the European Network of Transmission System Operators for Electricity (ENTSOE-E). FCR is a capacity market and the TSOs in the ENTSO-E are obligated to contract a certain amount of FCR depending on their partial production in the ENTSO-E. This amount is based on a reference incident of a 3000 MW shortage or surplus. The Dutch grid accounts for around 4% of energy production in the ENTSO-E. Therefore, for its Dutch operation, Tennet has to contract 4% of the reference incident which comes down to approximately 115 MW of FCR capacity. At least 30% of this contracted capacity must be located within The Netherlands. FCR is offered in a resolution of 4-hour blocks.

The aFRR is procured by the TSO in a daily auction and has a resolution of one ISP, i.e. 15 minutes.The aFRR market is a combined capacity and energy market. The TSO is obligated to contract a minimum amount of aFRR capacity for each ISP. This amount is based on deterministic, stochastic and probabilistic analyses and is approximately 300 MW in The Netherlands. The contracted BSP offering the aFRR must be located in The Netherlands.

The aFRR market is split in a capacity auction and an energy auction. The capacity auction is held at 12:00, one day ahead of delivery. The capacity contracts are asymmetric. This entails that up and down-regulation capacity are contracted separately. For instance, a BSP can offer 4 MW of up-regulation capacity but only 1 MW of down-regulation capacity. BSPs that are awarded a capacity contract have an obligation to bid at least the amount of the contracted capacity in the aFRR energy auction for each ISP in the one day contract length. Essentially, contracted aFRR means that the TSO buys an obligation to bid capacity in the aFRR market from the BSP

Instead of contracted aFRR, BSPs can also choose to provide non-contracted, also called ”free bid”, aFRR. Free bid aFRR allows BSPs to offer capacity for only a certain number of specific ISPs in a day. This is in contrast to the bidding obligation that contracted BSPs have for each ISP. Free bid aFRR suppliers can also change their offered capacity size up till half an hour before the delivery ISP whereas contracted bid aFRR suppliers are bound to their contract.

The aFRR energy auction works on the merit order method. For each ISP, the BSPs submit their energy price for their offered capacity. So a bid for an ISP contains the capacity size, for instance 1 MW, and the energy price in €/MWh. For each ISP, the bids are placed on a bid ladder, ordered from cheap to expensive, based on their energy price. No differentiation is made between contracted and free bids on the bid ladder. When an imbalance occurs, the bids that are cheapest to activate for are activated first by the TSO. The most expensive bid that has been activated during the ISP determines the imbalance price. All BSPs who’s bids have been activated receive, or pay, this imbalance price, regardless of what the energy price was for their own bid. For up-regulation bids, the cheapest price is the lowest price. For down-regulation bids, the cheapest price is the highest bid price. An example of a bid ladder for an ISP is shown Figure 2.5.

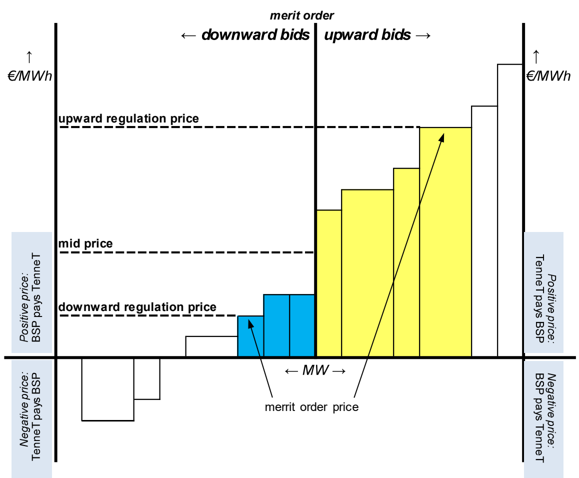

Figure 2.5: The merit order curve for the imbalance price. Source: Tennet

The purpose of the differentiation between contracted and free bids stems from the TSO. The TSO is required to have a minimum amount of balancing capacity in reserve. Therefore, this minimum amount is contracted day ahead to ensure that there is enough balancing energy available. Contracted bids offer this security. Alternatively, free bid aFRR offers more competition in the energy prices on the bid ladder which brings the costs of the balancing energy down. BSPs that are willing to offer contracted capacity are rewarded with a capacity remuneration alongside their energy revenues whilst free bid aFRR suppliers only take part in the energy revenues.

The mFRR is procured by the TSO via contracts instead of auctions. Because mFRR's main use is emergency backup the minimum bid size is 20MW. Suppliers of mFRR receive a fixed energy price of 200 €/MWh above the spot price for activated up-regulation and 100 €/MWh below the spot price for activated down-regulation. The role of Replacement Reserve shown in figure 2.4 is also covered by the mFRR in The Netherlands.

2.5. Assumptions and Simplifications

A simplified version of the Dutch electricity markets has been presented in this chapter. In this section, the simplifications and assumptions that have been made will be listed and shortly discussed.

Several electricity markets have been left out of the consideration for this project. Bi-lateral and over-the-counter energy trading are forms of energy trading where two parties enter into an agreement to trade energy outside of the power exchanges. This form of energy trading mostly occurs for risk management or project financing purposes. Since these trades are not part of an open bidding auction they are not considered in this study.

Intra-day trading is an electricity market that allows generators and consumers to trade energy on the same day as the delivery. The intra-day market allows for continuous energy trading up to half an hour before delivery. Generators and consumers can use intra-day trading to compensate for unforeseen changes in power production or consumption. For instance, if a WPP operator unexpectedly loses production due to a broken turbine they can buy the missing energy in the intra-day market to minimize the deviation from their submitted E-program that would otherwise have occurred. Intra-day trading is an interesting option for storage operators to explore in future research. The continuous trading nature of the intra-day made it complicated to include this market in the modelling of this project and was therefore left out of scope.

Balancing energy or frequency support can be provided through FCR, aFRR, and mFRR. In this project, only aFRR is explored. Exploratory talks about the subject of this project with Tennet and Vattenfall have provided the insight that the FCR market is currently overly saturated. This can be explained by the relatively small size of the market. Additionally, these talks pointed out that the FCR market is already being serviced by carbon-neutral sources whereas providers of aFRR are more often fossil-fuel orientated. Therefore, these industry players had more interest in the subject of providing aFRR with a HWSS due to the larger market size and possibilities of gaining carbon emission reductions. Furthermore, because the FCR market is a capacity market, the actually activated amounts of energy are not published. Modelling of the activation of FCR would require frequency data and the so called ”droop curve” that Tennet uses to activate FCR. This data is not available on the ENTSOE-E transparency platform or on Tennet's own data services. The minimum bid size of 20 MW for mFRR as well as the requirement to have the capacity available the entire day makes the mFRR out of reach of current storage size projects. Due to the large size, low reaction times, and infrequent activation of mFRR, Tennet expects this service to be provided by hydrogen fuel cells in the future.

The aFRR market currently has a minimum bid resolution of 1 MW. In this project this restriction is not included for simplicity. The placed aFRR bids are assumed to always be activated when the regulation state matches the bid direction. The considerations that BSPs employ to optimize their aFRR energy bid price are out of scope for this project. The modelled system is assumed to be a price taker in both the aFRR and DAM markets.

3 Methodology

In this section, the methodology to achieve the research objectives is discussed. Ideally, a full-size test setup should be built and operated over many years to gather data and achieve the stated objectives. Of course, this lies far outside the available resources for a simple master thesis project. Therefore, this research is restrained to computer simulations, the setup of which will be discussed in this section.

To illustrate the interest the energy sector has in this type of powerplant, it is noteworthy to mention that as of 2020 there is a utility-scale pilot hybrid power plant active in the Netherlands, the Haringvliet Hybrid Powerplant, owned and operated by Vattenfall and seen in figure 3.1. Here Vattenfall has invested into experimentally researching the possible benefits that hybrid power plants may hold, including operational strategies for optimal operation of battery storage alongside RES.

In the following sections an overview of the general system, model and forecasting method will be given, followed by an overview of the case definitions and their case-specific changes to the model.

Figure 3.1: Aerial Photo of the Haringvliet site. Source: Vattenfall

3.1. Modelling Setup

The modelling setup is an expansion of the setup used in a preliminary study (Mehta et al., 2021)(See Appendix A). Factors such as system assumptions, data sources and general model overview are unchanged from the preliminary study. Therefore several figures and tables in this section stem directly from this preliminary study.

3.1.1. Model Overview

The modelling in this study can be roughly separated into two parts, a bidding and a control part. The bidding part is an optimization scheme that aims to maximize revenue by placing bids in an electricity market. The subsequent flows of energy are handled by the controller part based on the placed bids and current market prices, regulation states and wind energy production. The bidding block is activated only in timesteps when bids must be submitted whereas the controller is active in real-time. The modelling setup works in discrete timesteps. The timestep of all simulations is set to one ISP or 15 minutes. An overview of the general modelling setup is shown in figure 3.2. The bidding block takes wind forecasts, market forecasts and the State of Charge (SOC) of the storage system as input values to determine the optimal bids. If the model is active in multiple markets, multiple bidding blocks will be active. This will be illustrated in section 3.1.3. The controller determines the flows of energy and takes the placed bids, current market and current SOC as inputs. The controller decides whether bids placed by the optimizer are fulfilled and sends this information back to the markets to calculate the resulting revenue.

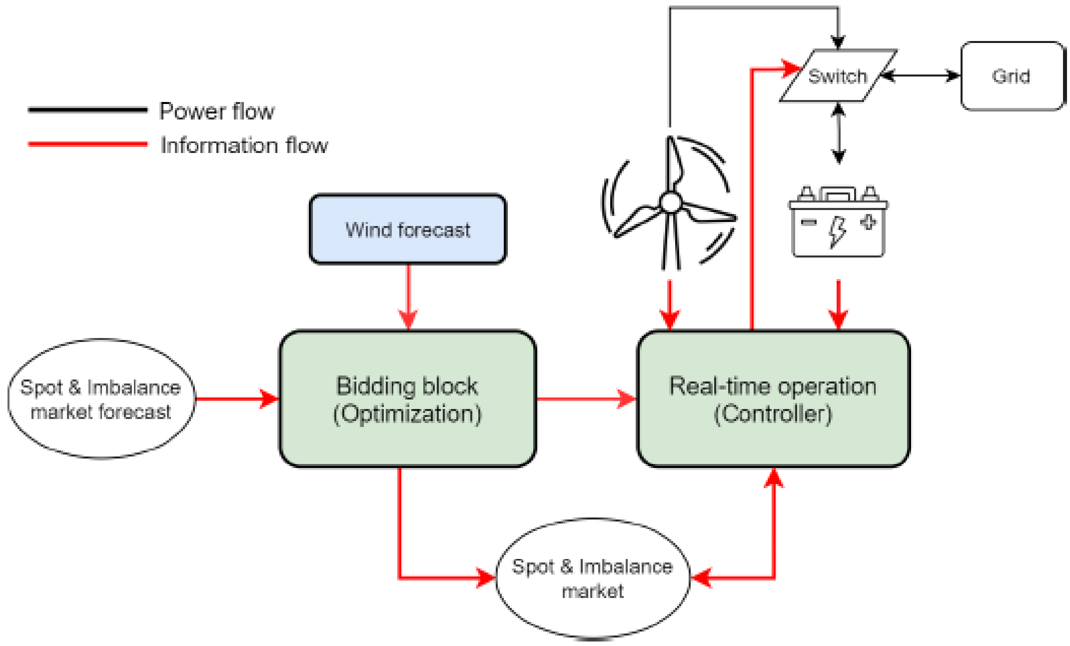

Figure 3.2: Model overview (Mehta et al., 2021)

The bidding blocks will optimize for revenue. However, the cases will not be compared against one another on their revenue alone. Similar to the preliminary study, the figure chosen in this study to evaluate the economic feasibility of a particular configuration is the Internal Rate of Return (IRR). This is the rate at which the Net Present Value (NPV) of a project is zero, as shown in equation (3.1), where Cf_n represents the cash flows over the years and C_0 represents the initial investment. The lifetime of the WPP was assumed to be 20 years. Reliable data sets are hard to come by for a 20 year period. Therefore, the model will be based on data from 2019. The model will produce the revenue at the end of the year based on this data. The cash flow used in the IRR calculation is assumed to be the same for every year in the project life time and is based on the outcome of the model for the year 2019.

$$0 = NPV = \sum_{n=1}^{N} \frac{Cf_n}{(1+IRR)^n} - C_0 \tag{3.1}$$

The IRR values for different wind-storage configurations have been normalized with the wind-only case. In this case, an IRR lower than 1 does not mean the business case has a negative value or isn't profitable. It simply means that the case is not as profitable as the wind-only case. Thus, by comparing the IRR values of different cases, the better performing case can be identified.

3.1.2. System Overview

In this section, the sizing of the system, as well as the used data sources, are discussed. All data sources used are temporally correlated and are for the year 2019. The objective of this studywas to investigate utility-scale HWSSs. The sizing of the WPP is given in table 3.1. The assumptions are based on the Siemens Gamesa G128-5 turbine.

Table 3.1: Assumptions related to wind energy generation

	System assumptions	
	Turbine P_{rated}	5 MW
	Turbine D_{rotor}	128 m
Wind	Turbines	6
	Total installation costs	$1870/kW
	Operation and Maintenance Costs	$55/kW/year
	Lifetime	20 years

Wind forecasts, as well as actual wind production, are based on the open-source data platform of the European Network of Transmission System Operators for Electricity (ENTSO-E). The error as a function of the installed capacity is shown in figure 3.3. The wind forecast or wind production is converted to power production through equation (3.2). The Power coefficient (C_p) and drivetrain efficiency (η_{dt}) are also based on the Siemens Gamesa G128-5 turbine.

$$P(v) = 0.5 \cdot C_p(v) \cdot \rho \cdot A_{rotor} \cdot v^3 \cdot \eta_{dt} \tag{3.2}$$

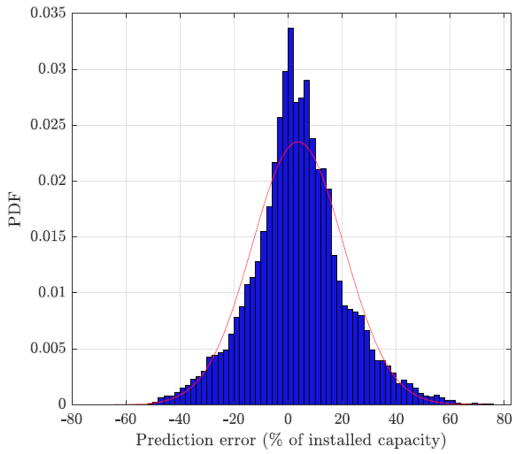

Figure 3.3: Offshore wind forecast error. (Mehta et al., 2021)

The model will be indifferent to the storage technology and only needs a ramp rate, size and price as input parameters for the storage system. While the focus of the study is not on researching the potential of one specific storage technology an example technology is still needed for the case definitions. Li-ion battery storage is used as an example technology in the cases investigated in this study. The assumptions for this technology are shown in table 3.2. The battery costs are based on the International Energy Agency's cost estimate for Li-Ion batteries as of 2017 (IEA, 2019). The storage system is characterised by the maximum volume of energy it can contain and its power output. The power output is expressed in the number of hours the battery takes to fully charge or discharge. For example, if the maximum stored energy volume is 10MWh, then the 1-hour variant has a maximum power output of 10 MW, the 4-hour variant has a maximum power output of 2.5 MW, and the 8-hour variant has a maximum power output of 1.25 MW.

Table 3.2: Assumptions related to storage

Storage assumptions	
Storage type	Li-ion
Duration	1,4 & 8 hour battery
Energy costs	$ 165/kWh
Power costs	$ 125-365/kWh (duration dependent)
Round-trip efficiency	90 %
SOC limits	0.3 - 1

3.1.3. Optimization Setup

In the previous section, the general working of the model was discussed. In this section, the optimization operations shown in figure 3.2 by the green blocks will be discussed in further detail.

All simulations are executed in MATLAB ® and the defined optimization problems are solved with the MATLAB ® linear programming solver. The more computationally expensive simulations are executed using parallel processing techniques. The exact definition of the optimization problems differs per case and the case-specific conditions are shown in section 3.2. All optimization problems are subject to various general constraints that mostly pertain to the battery operation. These constraints are shown in equation (3.3). Here $E_{charge}(t)$ and $E_{discharge}(t)$ is the energy charged and discharged to and from the storage system. E_{batt} represents the total energy volume of the storage system. The (dis)charged amount of energy cannot exceed the ramp rate. The third equation constrains the storage system to either discharge or charge within an ISP. In the final equation, the SOC limits are set.

$$
\begin{aligned}
&E_{charge}(t) \leq Ramp\ Rate \\
&E_{discharge}(t) \leq Ramp\ Rate \\
&E_{charge}(t) * E_{discharge}(t) = 0 \\
&SOC(t+1) = SOC(t) + \frac{E_{charge}(t) - E_{discharge}(t)}{E_{batt}} \\
&0.3 \leq SOC(t) \leq 1
\end{aligned}
\tag{3.3}
$$

The objective functions of the optimization problems are set to maximize revenue. Decision variables are the bids placed in each market per ISP and the operation of the switch that controls if the wind energy flows directly to the grid or is stored. Two approaches to execute the optimization problems are used depending on the case or scenario. In scenarios that bid in a single market and operate under the assumption of perfect forecasts, the optimization can be executed for the whole year at once. This is possible because the perfect forecast assumption ensures that what the optimization block thinks will happen is exactly the same as what will happen in reality. As a consequence, the real-time controller block can execute the placed bids perfectly without having to intervene in the planned system operation.

In scenarios that operate with an imperfect forecast or in scenarios that operate in two or more markets, the optimization cannot be run for the entire year at once. The cause and solution of this issue will be discussed based on two examples. Scenarios that operate in two markets face the issue that the execution of the bidding block for the second market changes the SOC trajectory that is expected by the bidding block of the first market and, consequently, this changes the SOC at the start of the new bidding period of the first market. For instance, the DAM arbitrage bidding block is executed first for day D. Activation of the bids placed by this bidding block throughout the day will determine the SOC value at the end of the day. Let's assume that the bidding block finds the expected SOC at the end of the day to be 0.5. Subsequently, the aFRR bidding block is executed and the ensuing activated aFRR bids combined with the DAM bids alter the SOC at the end of the day to 0.6. Then the DAM arbitrage optimizer for D+1 should use 0.6 as the starting value for the SOC and not the 0.5 it had expected itself. Therefore, the optimizations cannot be executed for the entire year at once but must be executed one after the other for each day of the year. This example is visualised by the flowchart in figure 3.4.

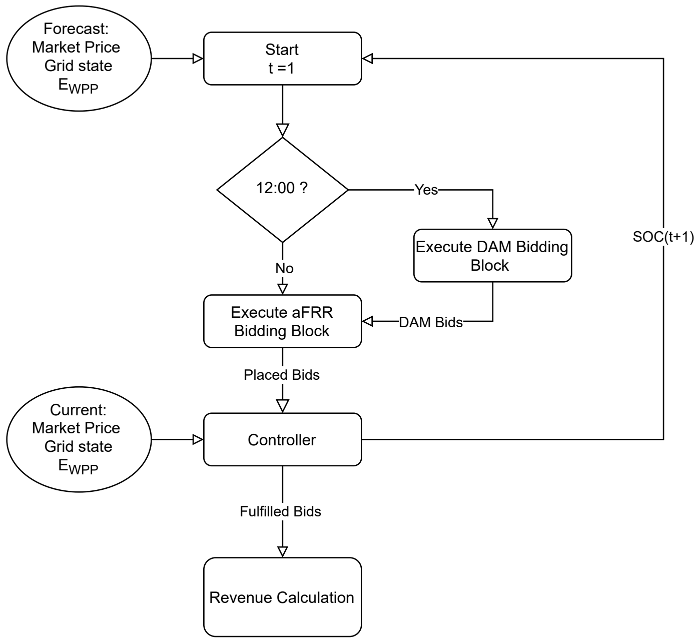

Figure 3.4: Flowchart of model execution when combining DAM arbitrage and free-bid aFRR

Scenarios that operate with imperfect market forecasts face a similar problem. The SOC that was expected by the bidding block is not the SOC that will occur at the end of the period. In this example, this is not caused by the bids from a second market altering the SOC but rather by errors in the market forecast. The bidding block places the bids for the upcoming period based on the forecast of what it thinks will happen in the market and grid regulation states. Then in real-time the controller takes the placed bids and compares them to the actual market and grid states to determine the flows of energy. The controller cannot exactly fulfil all the bids as placed by the bidding block due to market and regulation state forecast errors. The intervention by the real-time controller causes the SOC at the end of the period to differ from the SOC that the bidding block expected. Therefore the bidding block must be executed again before the start of a new period with the actual achieved SOC value at the end of the previous period serving as the starting value of the new period. In short, the bidding block requires updated starting variables before being executed again.

The above will be referred to as the forecast horizon approach. This name stems from the fact that the bidding block will only optimize the bids up to a certain simulation length. Executing the bidding block with a simulation length of one year, or the remainder of the year, at the start of each new bidding period is computationally expensive and the market and weather data inputs are impossible to forecast with any degree of accuracy for the entire year. Therefore, the bidding block is executed with a forecast horizon. The length of the forecast horizon depends on the market.

Figure 3.5 shows a visualization of the forecast horizon approach for contracted and free-bid aFRR. For the contracted bid case the forecast horizon is set to 2.5 days. The bids for day D+1 have to be placed at 12:00 on day D, 12 hours before the delivery of the first bids. The bidding block for day D+1 is executed in timestep 48 in the simulation which corresponds to this deadline. The optimization or simulation length of the bidding block, therefore, stretches from timestep 48 up to timestep 288. In the first 48 timesteps of the optimization, the bids from the previously executed bidding block are still active which cannot be altered. For timestep 96 up till 288, the new bids are optimized. However, only the bids from timestep 96 to 192 are actually sent to the controller. Bids from timestep 193 to 288 are discarded. These last 96 timesteps are still simulated so that when optimizing the bids placed for D+1 the bidding block also takes into account what will happen on D+2. This will lead to better results. For example, if the bids were only optimized for D+1 then the optimizer will likely discharge the battery during the final timesteps of the day to squeeze out the last potential revenues during the simulation length. However, if the market price on D+2 just after midnight is much higher than at D+1 just before midnight then this is not an optimal outcome. Instead, the battery should have not discharged at the end of D+1 but saved the stored energy up until the higher prices at the start of D+2. Using a simulation length, or forecast horizon, that is longer than the bidding period allows these bidding blocks to make more optimal decisions. Figure 3.5 also shows the forecast horizon for free-bid aFRR where the bidding block is executed every ISP for the ISP + 2 with a forecast horizon of 12 hours.

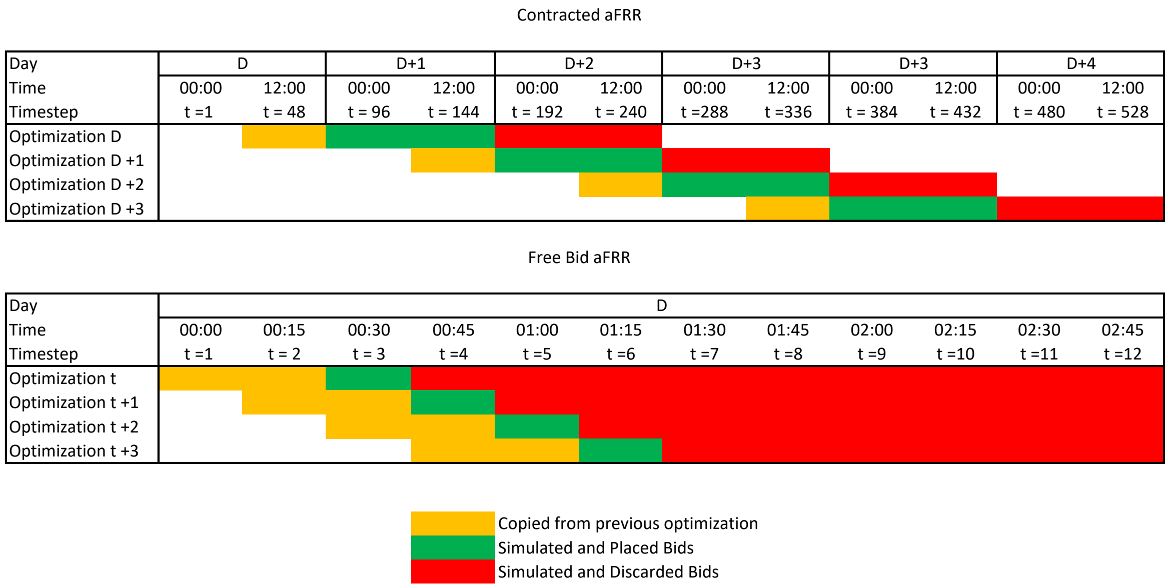

Figure 3.5: Visualization of forecast horizon approach for contracted and free bid aFRR

3.2. Case Descriptions

In the introduction, the objective for this studywas defined. To achieve these objectives three cases have been defined. These cases will be introduced in this section. Within one case, multiple scenarios can exist. The first case is set up to explore DAM arbitrage. In the first scenario of this case, the assumption is made that the model has perfect forecasting capabilities for both wind production and market prices. Consequently, during this assumption, there is no activity on the imbalance market as the BRP makes a perfect prediction day ahead. For the second scenario of this case, the assumption of perfect knowledge of wind production is let go and replaced with an imperfect forecast. This introduces the imbalance market into the model as now the BRP will make an imperfect prediction day-ahead leading to deviations between scheduled production and actual production for which it will have to compensate for in the imbalance market. These deviations from the schedule are called the Imbalance Volume. The model retains a perfect market price forecasting capability. The effect of errors in the market forecast is part of the sensitivity analyses.

The second case is set up to explore providing frequency support in the form of aFRR to the grid. The balancing energy will be provided by the storage system while the WPP bids the forecasted production in the DAM. This case is divided into four scenarios. aFRR can be sold by the system through contracted bids or free bids. For both aFRR approaches, a scenario with and without imbalance volumes is simulated.

The third case will explore strategies to combine DAM arbitrage and providing frequency support. This case consists of three scenarios that are differentiated by the order in which the different markets are prioritized by the bidding block. The following sections provide an overview of the defined cases and their constraints.

3.2.1. Day Ahead Market Arbitrage

The first case that will be introduced uses the battery for energy arbitrage in the DAM. This case corresponds with the first sub-objective as defined in section 1.3. Within this case, two scenarios are defined. In the first scenario, the assumption is made that the BRP places perfectly forecasted bids in the DAM.

Consequently, there are no imbalances that have to be settled in the imbalance market. In Figure 3.6 this scenario is schematically shown. It is shown that the wind power can either flow directly to the DAM to fulfil a placed bid or to the battery to be stored. Energy stored in the battery is traded in the DAM and can flow alongside the wind turbine energy. The real-time controller doesn't intervene in this scenario because there is no imbalance. This scenario can be interpreted as the maximum upper limit of the potential that DAM arbitrage holds. This scenario has a perfect forecast, therefore to speed up the run time of the simulation the optimization is run for the entire simulation length instead of using the forecast horizon approach.

Figure 3.6: DAM arbitrage scenario

The objective function for this scenario is shown in (3.4) and the additional constraints are given by (3.5). Here $E_{WPP\ sell}(t)$, $E_{WPP\ store}(t)$,$E_{BESS\ buy}(t)$ and $E_{BESS\ sell}(t)$ are the optimization variables and respectively pertain to the wind energy sold directly, the wind energy stored, the energy charged from the grid and the storage system contribution to the DAM bid. $E_{WPP\ sell}(t)$ and $E_{WPP\ store}(t)$ are coupled as the sum of these optimization variables must be equal to the total turbine production $E_{WPP}(t)$. $E_{WPP}(t)$ and $P_{DAM}(t)$ are the known wind production and DAM price and η is one-way efficiency of the storage system.

$$f(E) = \sum_{t=1}^{t=simlength} P_{DAM}(t) * (E_{WPP\ sell}(t) + E_{BESS\ sell}(t) - E_{BESS\ buy}(t)) \tag{3.4}$$

$$\begin{aligned} \max_{E} \quad & f(E) \\ \text{s.t.} \quad & E_{WPP}(t) = E_{WPP\ sell}(t) + E_{WPP\ store}(t) \\ & E_{charge}(t) = \eta * (E_{WPP\ store}(t) + E_{BESS\ buy}(t)) \\ & E_{discharge}(t) = \frac{E_{BESS\ sell}(t)}{\eta} \end{aligned} \tag{3.5}$$

In the second scenario, the assumption of no imbalance volume is abondoned and the BRP places bids based on an imperfect forecast of the turbine's production. Consequently, this leads to imbalances that need to be settled in the imbalance market. The battery is used in two ways in this scenario. Energy from the wind turbine can be stored in the battery and used for arbitrage in the DAM and, alternatively, energy can flow in and out of the battery to reduce the imbalance volume. In this scenario, the controller can intervene to mitigate imbalance where possible.

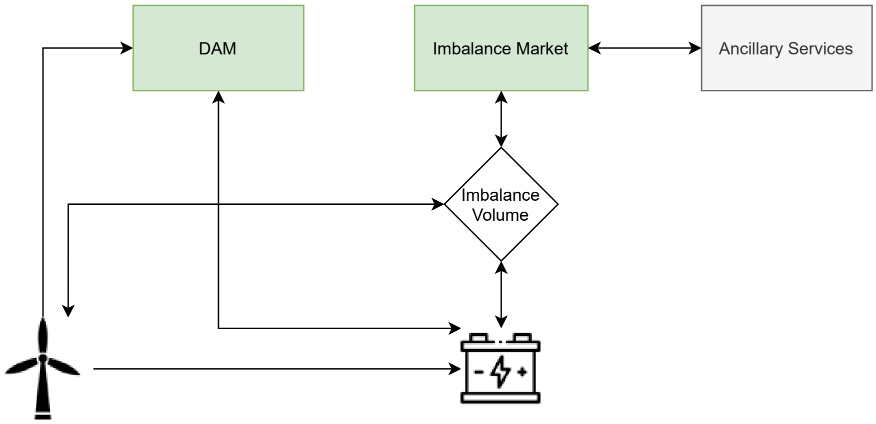

Figure 3.7: DAM arbitrage and imbalance reduction scenario

In this scenario, the DAM arbitrage optimization described in the paragraph above is executed first with $E_{WPP}(t)$ being the forecasted produced wind energy instead of the actually produced wind energy. The controller that attempts to mitigate the imbalance has a perfect forecast of future system imbalance volumes and imbalance prices. The mitigation effort by the controller is given by the optimization setup with objective function (3.6) and additional constraints (3.7). $E_{BESS\ sell}(t)$ and $E_{WPP\ store}(t)$ are the decision variables that respectively pertain to the discharging and charging operation of the battery. Here $E_{WPP}(t)$ is the actually produced wind energy. $E_{DAM\ bid}(t)$ is the bid that was placed by the DAM arbitrage optimizer based on the imperfect wind forecast. $E_{imbalance}(t)$ is the imbalance volume that will be settled in the imbalance market. $E_{imbalance}(t)$ is also the only variable that can be negative. All other variables are constrained to be positive numbers. In this scenario, the system is not allowed to trade more energy in the imbalance market than its own current imbalance volume which is given by the forecast error in the wind production. Therefore, $E_{imbalance}(t)$ is constrained to be smaller than the wind production forecast error.

$$f(E) = \sum_{t=1}^{t=simlength} P_{imbalance}(t) * E_{imbalance}(t)) \tag{3.6}$$

$$\begin{aligned} \max_{E} \quad & f(E) \\ \text{s.t.} \quad & E_{imbalance}(t) = E_{WPP}(t) + E_{BESS\ sell}(t) - E_{WPP\ store}(t) - E_{DAM\ bid}(t) \\ & \|E_{imbalance}(t)\| \leq \|E_{WPP\ FC\ delta}\| \\ & E_{charge}(t) = \eta * E_{WPP\ store}(t) \\ & E_{discharge}(t) = \frac{E_{BESS\ sell}(t)}{\eta} \end{aligned} \tag{3.7}$$

3.2.2. Ancillary Services

In the second case, the battery is used to provide ancillary services to the grid. This case corresponds to the second sub-objective defined in section 1.3. Consistent with case 1, two scenarios are defined. In the first scenario, no imbalance volume is assumed. Power from the wind turbine flows either directly to the DAM or to the battery. Energy in the battery is used to place balancing energy bids in the ancillary services market. In contrast to the first case, the battery cannot store energy to be used for DAM arbitrage.

Providing aFRR can be done either through contracted bids or through free bids. In the case of a contracted bid, the bid is placed and the bid size has to be the same for every ISP off the day.

Figure 3.8: DAM and Ancillary services scenario

The optimization setup for the contracted bid scenario is given by objective equation (3.8) and additional constraints of equation (3.9). $E_{aFRR\ up}$ and $E_{aFRR\ down}$ are the activated aFRR volumes. Reg_{down} and Reg_{up} are binary variables that are equal to one when the regulation state is down or up respectively and are 0 when otherwise. Cap_{up} and Cap_{down} are the optimization variables that contain the bid size, or capacity, in both directions for each day of the year D. The $Cap_{up} * Reg_{up}$ term governs the activation of the bids and the corresponding energy flow from the storage system, $E_{aFRR\ up}$. For instance, upregulation bids are placed for every ISP in the day but are only activated when the regulation state in an ISP is indeed up, which is given by $Reg_{up} = 1$.

$$f(E) = \sum_{t=1}^{t=simlength} P_{aFRR\ up}(t) * E_{aFRR\ up}(t) - P_{aFRR\ down}(t) * E_{aFRR\ down} \tag{3.8}$$

$$\begin{aligned} \max_{E} \quad & f(E) \\ \text{s.t.} \quad & for\ D[1 \rightarrow 365] \\ & E_{aFRRdown}(t = D*96 \rightarrow D*96+95) = Cap_{down}(D) * Reg_{down}(t = D*95 \rightarrow D*96+95) \\ & E_{aFRRup}(t = D*96 \rightarrow D*96+95) = Cap_{up}(D) * Reg_{up}(t = D*96 \rightarrow D*96+95) \\ & E_{charge}(t) = \eta * E_{aFRR\ down}(t) \\ & E_{discharge}(t) = \frac{E_{aFRR\ up}(t)}{\eta} \end{aligned} \tag{3.9}$$

The optimization setup for the free bid aFRR is given by the objective equation 3.10 and additional constraints in equation 3.11. The optimizer can choose in which ISPs it wants to place bids instead of having to place bids for every ISP. Furthermore, the size of the bid can vary for every ISP. The first two additional constraints limit the optimizer to only place bids in the ISPs for which the corresponding regulation state will occur. In other words, due to the perfect forecast of regulation states, all placed bids will be activated.

$$f(E) = \sum_{t=1}^{t=simlength} P_{aFRR\ up}(t) * E_{aFRR\ up}(t) - P_{aFRR\ down}(t) * E_{aFRR\ down}(t) \tag{3.10}$$

$$\begin{aligned} \max_{E} \quad & f(E) \\ \text{s.t.} \quad & \\ & if:\ Reg_{up}(t) = 0 \rightarrow E_{aFRR\ up}(t) = 0 \\ & if:\ Reg_{down}(t) = 0 \rightarrow E_{aFRR\ down}(t) = 0 \\ & E_{charge}(t) = \eta * E_{aFRR\ down}(t) \\ & E_{discharge}(t) = \frac{E_{aFRR\ up}(t)}{\eta} \end{aligned} \tag{3.11}$$

In the second scenario, the assumption of no imbalance volume is abandoned and the BRP places bids based on an imperfect forecast of the wind turbines production. Consequently, this leads to imbalances that need to be settled in the imbalance market. The battery is used in two different ways in this scenario. Energy from the wind turbine can be stored in the battery to be used for placing balancing bids in the ancillary services market or, alternatively, the energy in the battery can be used to reduce the imbalance volume.

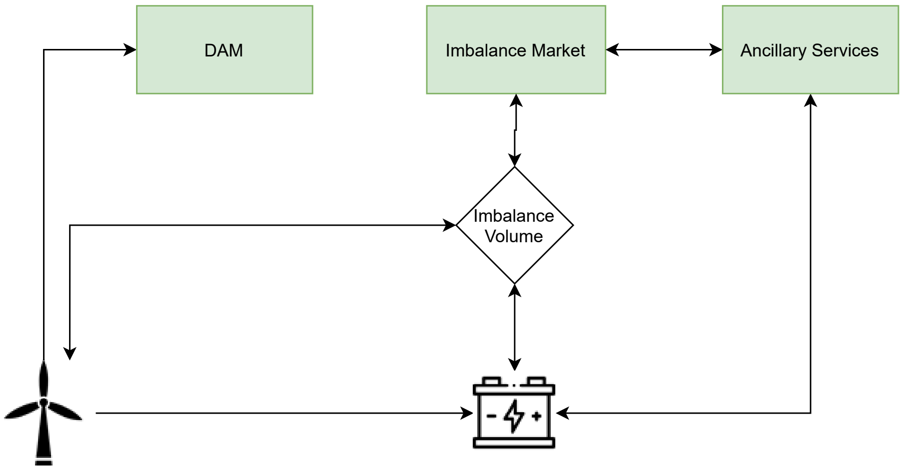

Figure 3.9: DAM, Imbalance and Ancillary Services scenario

The aFRR bidding is prioritized above the imbalance mitigation effort. Therefore, the aFRR optimizers described above are executed first giving the $E_{aFRR\ up}(t)$ and $E_{aFRR\ down}(t)$ values. The action from the imbalance optimizer is not allowed to disturb the placed aFRR bids. Therefore, $E_{aFRR\ up}(t)$ and $E_{aFRR\ down}(t)$ are given variables in the optimization setup for the imbalance mitigation given by objective equation (3.12) and additional constraints (3.13).

$$f(E) = \sum_{t=1}^{t=simlength} P_{imbalance}(t) * E_{imbalance}(t)) \tag{3.12}$$

$$\begin{aligned}
\max_{E} \quad & f(E) \\
\text{s.t.} \quad & E_{imbalance}(t) = E_{WPP\ FC\ delta}(t) + E_{Imbalance\ sell}(t) - E_{Imbalance\ charge}(t) \\
& E_{Imbalance\ sell}(t) \leq \|E_{WPP\ FC\ delta}(t)\| \\
& E_{Imbalance\ charge}(t) \leq \|E_{WPP\ FC\ delta}(t)\| \\
& E_{charge}(t) = \eta * (E_{Imbalance\ charge}(t) + E_{aFRR\ down}(t)) \\
& E_{discharge}(t) = \frac{E_{Imbalance\ sell}(t) + E_{aFRR\ up}(t)}{\eta}
\end{aligned} \tag{3.13}$$

3.2.3. Stacked Operation

In the third case, the battery has the ability to simultaneously use stored energy from the wind turbine for arbitrage in the DAM and to place balancing energy bids in the ancillary services market. This case corresponds to the third sub-objective in section 1.3. For this case to work, the different markets need to be prioritized by optimization order. Optimization order determines which mechanism gets stacked on top of the other. In other words, if DAM arbitrage is prioritized over aFRR, then that optimization is executed first and then followed by the aFRR optimizer. The optimizer that is second in line has to respect the bids made by the previous optimizer and can therefore only use the battery capacity that is left following the first optimizer.
The optimization setups for this case use the optimization equations as described in the sections above,

with the addition that the optimization that is second has to respect the bids made by the first. Additionally, the optimizations are not run for the entire year at once but instead use the forecasting horizon approach. The forecast horizon length is set to 2.5 days, as longer forecast horizons were not giving other results.

Three scenarios will be examined for this case. The first scenario will prioritize DAM arbitrage followed by free bid aFRR. The second and third scenarios will respectively prioritize free bid and contracted aFRR followed by DAM arbitrage. For all three scenarios, the imbalance mitigation attempt is executed last.

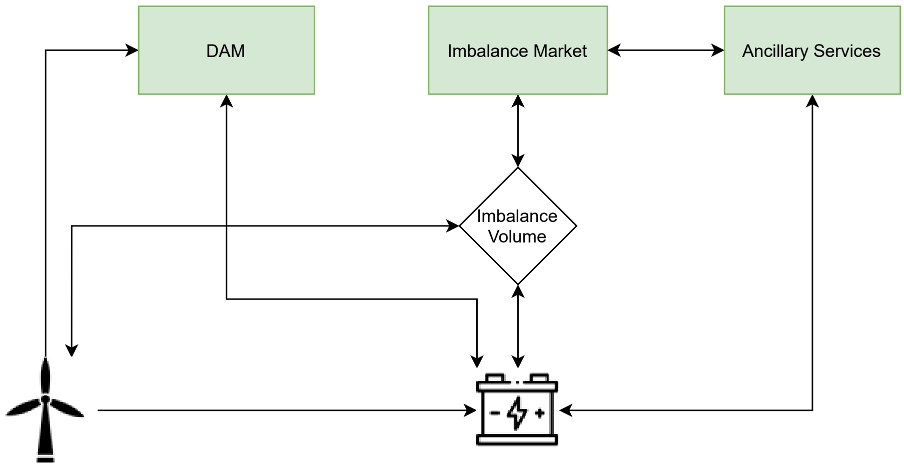

Figure 3.10: DAM arbitrage, Imbalance and Ancillary Services Scenario

3.3. Sensitivity Analyses

The case descriptions above operate under the assumption of perfect market forecasts. Furthermore, the current investment cost of Li-ion BESS is assumed without regarding storage degradation or replacement costs. The market forecast assumption is made to find the upper limit of the potential of each value-adding mechanism under ideal circumstances. Perfect market forecasting allows the model to operate at the maximum potential. To gain further insight into the various strategies it is deemed valuable to research how significant the negative effect on the results is when the model operates with imperfect market forecasts. The goal of this sensitivity analysis is not to exactly quantify this negative effect. Rather, this analysis is used to gain insight into which stategies are more sensitive than others.

Section 3.1.1 showed that the model is indifferent to the exact type of storage technology used. The only parameters used are ramp rate, volume and cost. To compare the different strategies against one another a starting point for these parameters is required. Subsequently, it was chosen to use Li-ion BESS as the example technology for storage when defining the cases. To gain further insight into the various strategies, an analysis will be made of the generic storage costs at which co-location causes no loss or gain of IRR compared to having no co-located storage. This result can be used in further research to identify storage technologies that meet these cost requirements.

In the definition of the cases, it was assumed that the storage systems lasted the entire lifetime of the project. Various storage technologies are prone to degradation during their lifetime. This degradation often correlates with the amount of charge and discharge cycles that are made by the storage system in a certain time span. After a certain cumulative amount of cycles, the storage system needs to be replaced. The different bidding strategies give rise to a differentiation between the strategies based on the number of cycles they take the storage system through in a certain time span. Strategies with higher cycle counts per year will be more prone to degradation costs. However, strategies with higher cycle counts also trade more energy in one year and therefore can reasonably be assumed to also make more revenue. To gain insight into this trade-off, an analysis is made of the sensitivity of the various strategies to replacement costs. The result of this analysis will consist of the minimal required cycle lifetime that the storage system must have to retain a positive IRR for co-location compared to having no co-location.

3.3.1. Market Forecasting Errors

Perfect market forecasting capability was assumed in the case descriptions in the section above. This is done to gain insight into the theoretical upper limits of the potential that these markets can harbour for co-location. Naturally, perfect market forecasting is not realistic for any real-world operator of co-located storage. The objectives of this studyare to gain insights into and compare the different value-adding strategies for co-location. To make these insights more valuable for real-world operators, an analysis comparing the sensitivities of the different strategies to imperfect market forecasting will be made.

Market forecasting can be subdivided into three parameters that are relevant for the modelling setup of this project. The model uses the DAM price and imbalance price in the objective functions of the various cases and, alternatively, the grid regulation state is used in various constraint functions. The regulation state and imbalance price are correlated. In general, up-regulation correlates with higher imbalance prices and down-regulation with lower imbalance prices.

Market price forecasts are hard to come by as they are competitively sensitive to companies that deal in these forecasts. Alternatively, there are methods to forecast market prices in the literature. Methods to forecast future energy prices and to value stored energy have been proposed for general RES systems (Carriere & Kariniotakis, 2019) (Munoz et al., 2020) and for intra-day trading of wind energy in Denmark (Skajaa et al., 2015).

In summary, obtaining commercial forecasts or recreating forecasting methods from literature is challenging or time-consuming. Therefore, pursuing this is out of scope for this study. Luckily, real-world forecasts are not necessary for the objectives of this study. The objectives are to gain insights into the different strategies and not to exactly quantify potential profits. These objectives translate to this sensitivity analysis in the sense that no real forecast method is needed to be able to gain insights into which strategies are more susceptible to forecasting errors. By feeding the model any inaccurate forecast an indication of this susceptibility can be obtained. These results can be useful to further understand the dynamics and behaviour of the different strategies.

In the this paragraph, the chosen methodology of producing a forecast will be explained and motivated. To reiterate, the chosen method in no way resembles the current state of the art of forecasting methods and is merely chosen as a satisfactory alternative for the scope of this study. For the sensitivity analyses of the market prices, a moving average filter will be used on the historic data. The resulting forecast is capable of following general trends but will miss outliers and erratic price behaviour. These price spikes are often caused by events that are unpredictable in nature such as unforeseen outages or weather forecast errors. In figure 3.11 the results are shown when a 4-hour moving average is applied to the price data.

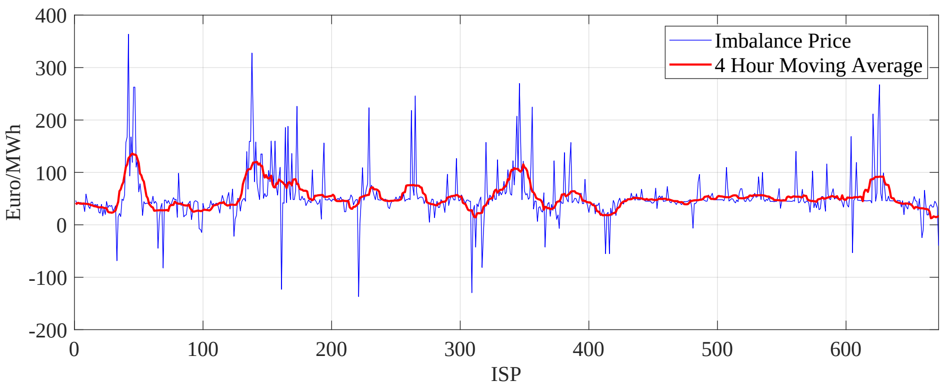

Figure 3.11: Actual Imbalance Price and 4-hour moving Average

The error distribution when using this method is shown in figure 3.12 alongside a fitted normal distribution. The parameters for the fitted normal distribution are a mean of -0.04 and a standard deviation of 36.4. The Mean Absolute Error (MAE) is 22.4 €/MWh and the Root Mean Square Error (RMSE) is 42.9 €/MWh. Attempts at predicting imbalance prices in the Netherlands using neural networks have achieved results with MAEs ranging from 26.85 to 41.23 €/MWh and RMSEs of 54.38 to 57.54 €/MWh (Terpstra, 2020). Therefore, the accuracy of the forecast constructed with the moving average is verified to be in the same order of magnitude as the state of the art of imbalance price prediction methods.

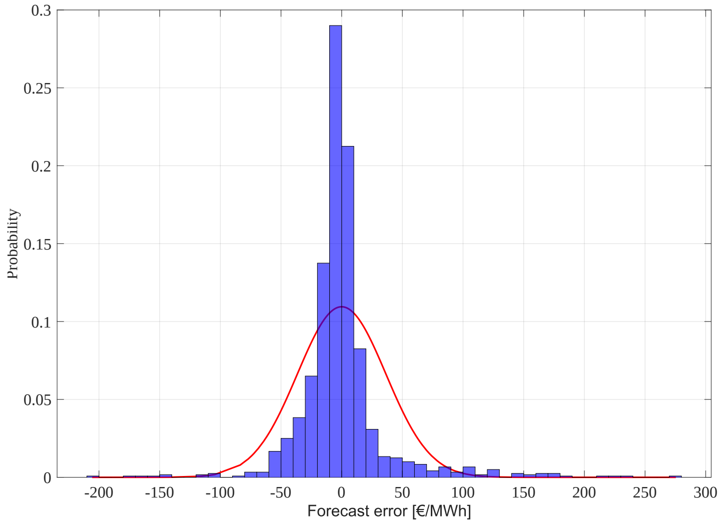

Figure 3.12: Errors of the Forecast of Imbalance Prices based on the Moving Average

For the aFRR scenarios, the bidding blocks require a regulation-state forecast. Not much literature can be found on regulation-state forecast. To construct a forecast the insight used is that, in general, the imbalance prices tend to be higher than the DAM price when the grid is in an up-regulation state and vice versa. Using this logic the regulation state is constructed from the imbalance price forecast and the DAM price. This only allows for the up and down regulation states in the forecast and excludes the 0 and 2 regulation states. The bidding blocks are constrained from bidding during these regulation states. Therefore, these values are substituted into the regulations state forecast for the ISPs wherein they occur. This approach leads to a regulation state forecast that is correct in 76% of ISPs.

3.3.2. Storage Costs

Storage costs can be subdivided into initial investment costs (CAPEX) and potential battery replacement or degradation costs (OPEX). In this section, the chosen approach for the sensitivity analysis of the initial investment costs will be explained.

The goal of this study is not to determine the exact business case for using Li-ion batteries, or any specific type of storage, for co-location. Instead, Li-ion is used as an example of a realistic storage technology and the associated costs are assumed for the case studies. The goal of the sensitivity analysis of the investment costs is to estimate the investment cost at which the projected IRR curves are around the break-even point compared to having no storage. For cases that show potential for profitable co-location of storage, this entails identifying the maximum allowable increase in investment cost and for cases that don't show potential, this entails identifying the needed decrease in investment costs. Because this process represents a high-level approach with little details the results of this sensitivity analysis can only be interpreted as a rough estimate.

3.3.3. Battery Degradation

Alongside investment costs, the addition of storage can also bring operational costs. For many storage technologies, the operational costs depend on replacement costs. For the purpose of this study, the assumption is made that the replacement costs depend purely on the number of cycles made by the storage system. Furthermore, it is assumed that the performance of the storage system doesn't change or degrade over time until the cycle lifetime is reached and it is replaced. This is a simplification as in reality other factors such as depth of discharge, external conditions and capacity fading will have an effect. These factors, amongst others, should be taken into account when exactly quantifying degradation costs. Since the objective of this study is merely to compare different strategies against one another these effects are left out. The number of cycles made in one year is calculated with equation (3.14)

$$Yearly\ Cycles = \frac{\sum_{t=1}^{t=simlength} E_{charge}(t)}{Volume} \tag{3.14}$$

This result is then divided by the assumed cycle lifetime of the storage system to come to the lifetime of the storage system in years. To calculate the effect of the replacement costs on the IRR the cost of storage replacement is subtracted from the cash flow in the year of replacement. For example, if the storage system lifetime turns out to be 7 years then it will have to be replaced after year 7 and year 14 of the study. Therefore, the replacement costs are subtracted from the cash flow for years 7 and 14. The analysis is executed for the example storage technology. For Li-Ion storage systems that are cycled in 70% depth of discharge the cycle life is approximately 5000 cycles (Mallon et al., 2017). Furthermore, the maximum amount of replacements that can be made before the normalized IRR drops below 1 is calculated. This number combined with the cycles per year and the 20-year lifespan of the study gives the required cycle life that a storage system would need to retain value addition.

4

Results Day Ahead Market Arbitrage

In this section, the results of the first proposed use case will be discussed. As explained in section 3.2.1, two scenarios are run for this case. In the first scenario, the battery will only be used to perform DAM arbitrage where perfect forecasting of wind power is assumed. In the second scenario, a wind forecasting error is introduced, which leads to an imbalance for the HWSS. The battery is used to perform DAM arbitrage as well as to mitigate imbalances. Firstly, the operation of the algorithm will be examined for both scenarios on a short timeframe, followed by an economic analysis of this strategy, and lastly, the main findings and sensitivity of this case is discussed.

4.1. Operational Strategy

In this section, the operation of the model will be analyzed in a short time frame of one week. The aim is to verify that the model is making optimal choices and to show what this optimal operation looks like. Both scenarios will be evaluated, starting with the arbitrage scenario with a perfect wind forecast.

In figure 4.1, the results of selected operational parameters of the system are shown. The top plot shows the incoming wind energy and DAM bids per ISP. The blue bars depict the turbine's contribution and the black bars depict the batteries contribution to the total DAM sell bid. Stacked, the blue and black bars represent the total DAM sell bid. The negative red bars represent DAM buy bids. These buy bids are placed whenever the turbine doesn't produce enough energy to fulfil the amount of energy the storage systems wants to charge. The magenta line shows the volume of incoming wind energy per ISP. In the second plot, the battery energy flows are shown. The blue bars depict the energy that is charged to the battery from the turbine. These bars coincide with the gaps under the magenta line from the first plot. The red bars depict energy charged to the battery from the grid. The black bars depict the discharging of the battery and coincide with the black bars in the first plot that depict the batteries contribution to the DAM sell bid. The charging and discharging of the battery leads to changes in the batteries SOC which is shown in the third plot. Lastly, the DAM prices are shown.

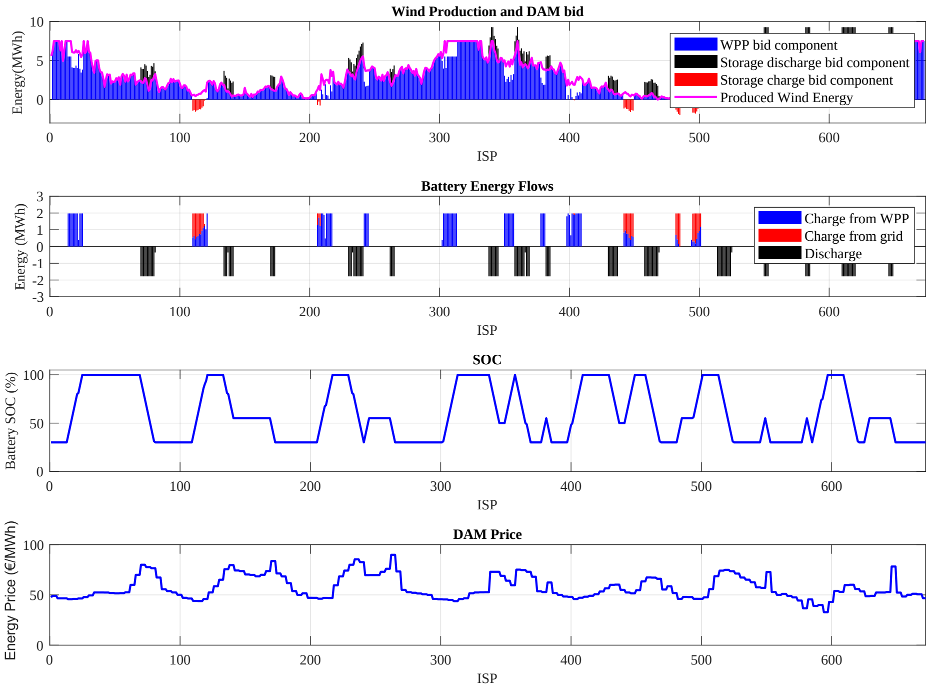

Figure 4.1: Selected Parameters from DAM Arbitrage Only scenario using input data from 1-1-2019 up to 8-1-2019 for a 4-hour 30 MWh battery.

The objective of the model is to generate as much revenue as possible. For this scenario, the optimal operation is still intuitively simple. Charging the battery from the turbine when prices are low and discharging the battery when prices are high will lead to higher revenues. From figure 4.1 it can be verified that the model operates in this way. For example, at the start of the week, prices are average and the battery is empty. The price drops slightly in the next ISPs and the battery is charged from the turbine around ISP 25. The energy is stored in the battery for approximately 55 ISPs until prices start rising around ISP 75 and the battery is discharged, resulting in the addition of a battery component in the DAM bid. This process continues throughout the week.

In the next scenario, the imbalance market is introduced, according to the explanation in section 3.2.1. In figure 4.2, the results of selected operational parameters of the system are shown. In real-time, the controller registers the imbalance between the forecasted and produced wind power, represented by the black line in the first plot. The controller can choose to (partially) mitigate the imbalance if it is economically beneficial. These mitigation actions are shown by the red and blue bars in the first plot. These bars only show extra charge or discharge actions by the storage systems. Imbalance can also be mitigated by retracting planned charge or discharge actions. For instance, if a discharge bid is active and more wind energy is being produced than forecasted, then less energy from the storage system needs to be discharged to fulfil the bid. These retracted operations are not shown in the figure. In the second plot, the planned SOC of the battery as scheduled by the DAM optimizer day ahead is shown in blue along with the actually achieved SOC after the mitigation actions of the real-time controller. Finally, the imbalance prices and DAM prices are shown.

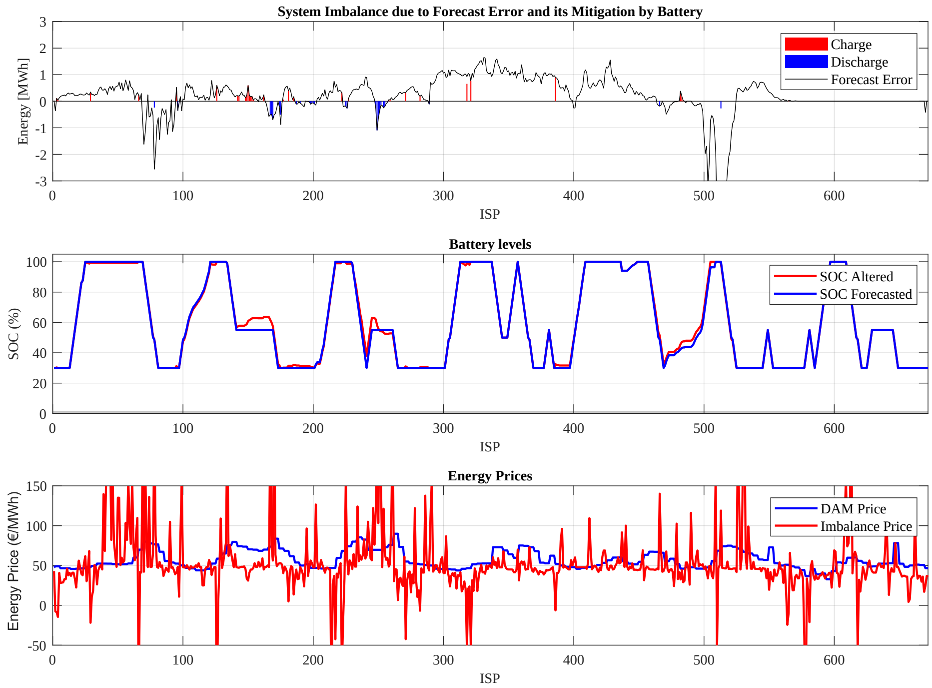

Figure 4.2: Selected Parameters from DAM Arbitrage and Imbalance Mitigation scenario during first week of 2019 for a 4-hour 30 MWh battery.

From figure 4.2 it can be seen that, in this setup, the real-time controller doesn't choose to mitigate the imbalance very often. Only slight interventions from the planned schedule can be observed and the planned SOC and achieved SOC are very similar. There are multiple explanations for this. Firstly, the constraints set in section 3.2.1 are strict. The controller cannot intervene more than the imbalance volume of the system. It can be argued that is sub-optimal. For example at ISP 250 the system has a negative imbalance volume, more energy has been bid in the DAM than is produced. This deviation from the submitted DAM bid is mitigated exactly by the real-time controller as can be seen in the first plot. The real-time controller chooses to do so because the imbalance price is very high so the non-mitigated negative imbalance volume would have been costly. However, during this ISP the system could have made even more revenue if the battery would have been discharged even further than necessary just to mitigate the imbalance volume. Increasing the energy output above the DAM bid would have resulted in the generator earning the additional volume times the imbalance price as additional revenue. Because the imbalance price is very high at this ISP this would lead to higher revenue than the operation as scheduled by the controller.

The operation as suggested above is a mechanism through which a BRP can actively help the TSO with reducing the imbalance volume on the grid. When the imbalance price is high the grid is most likely in a deficit and therefore BRPs delivering more energy than was bid in DAM help the TSO in maintaining balance on the grid without having to activate increasingly expensive balancing reserves. Removing the constraint that the controller cannot intervene more than the imbalance of the system would allow the system to participate in this grid balancing effort.

This concept that both BRPs and BSPs can support the balancing effort on the grid has been discussed in section 2. To recap briefly, from a generator standpoint the main difference between the two is the difference in regulations and bidding rules. Providing frequency support as BSP means bids have to be placed half an hour, in the case of free bids, before the intended ISP whereas BRP's don't have to submit separate frequency support bids. They can offer frequency support by being in a deficit or surplus compared to their DAM bid. This study does not look into providing frequency support as a BRP because the economic result of this scenario is expected to be very similar to providing free-bid aFRR as a BSP, which is discussed in chapter 5.

4.2. Economics

In this section the economics of the above bidding strategy will be evaluated. The goal of this project was not to exactly quantify the different scenarios, but rather compare bidding strategies against one another and against the case of having no co-location of wind and storage. Furthermore, there are many assumptions in the methodology as explained in section 3. Therefore, in this section the results will not be presented in exact numbers but rather normalised with respect to the wind only scenario. Consequently, the IRR values don't represent the actual business case but merely compare the case with respect to having no storage at all as given by the 0 MWh battery data point.

In figure 4.3 the normalised revenue for the Arbitrage case is shown. The co-location clearly increases revenue compared to having no storage. It can also be seen that a larger battery and higher power output give higher additional revenue. However, larger batteries and high power outputs are also expensive. In figure 4.4 the consequences of these high costs can be seen. None of the battery configurations has a higher IRR compared to having no storage.

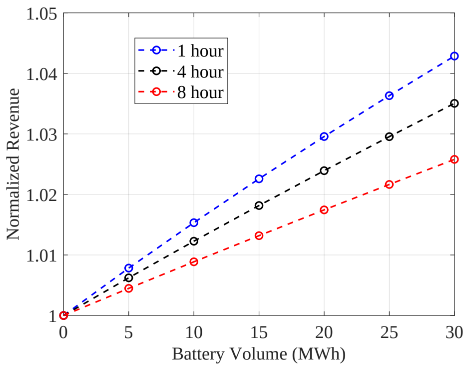

Figure 4.3: Normalized Revenue for Arbitrage Scenario

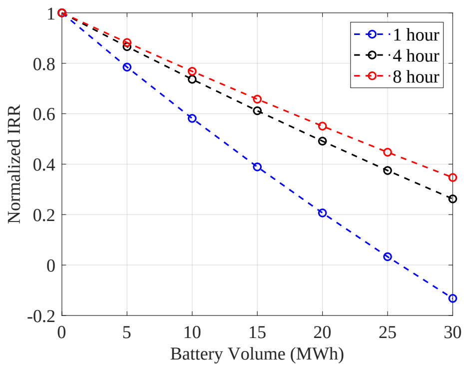

Figure 4.4: Normalized IRR for Arbitrage Scenario

In figure 4.5 and 4.6 the results for the arbitrage and imbalance reduction scenario are shown. Similarly, as with the Arbitrage scenario, the co-location of storage adds revenue but doesn't present a more attractive IRR compared to adding no storage. The figures also show the effect of the impact of the imbalance mitigation effort. The dashed lines show the results when the controller attempts to partially mitigate the imbalance whereas the solid lines show the results when the controller does not intervene and the imbalance is settled with the TSO. Although it was shown in figure 4.2 that the controller fails to mitigate the imbalance during all timesteps, the addition of the mitigation effort by the controller has a beneficial effect on both the revenue and the IRR for all battery sizing configurations.

Interestingly, the 1-hour battery adds the most revenue but has the lowest IRR. This shows that the slightly higher revenue doesn't make up for the much higher costs of the 1-hour battery. A higher power battery can trade more energy, thus the relatively low revenue addition of the 1-hour battery compared to the 8-hour battery might be unexpected. From figure 4.1 an explanation for this low difference can be extracted. The frequency of charge cycles is relatively slow, meaning that the algorithm tends to only charge and discharge once a day. This is caused by the gradual changes and low volatility of the DAM price. This provides low incentives to charge and discharge more often because the energy loss due to charging inefficiencies is higher than the arbitrage revenue that can be made during these times of small DAM price changes. Therefore, the fast reaction times provided by a high power battery are not necessary to extract the arbitrage potential in the low volatility DAM. Following this logic, it can be expected that when the battery is used to operate in a more volatile market, such as when providing AS, the 1-hour battery might outperform the 8-hour battery in terms of IRR. This will be examined in section 5.

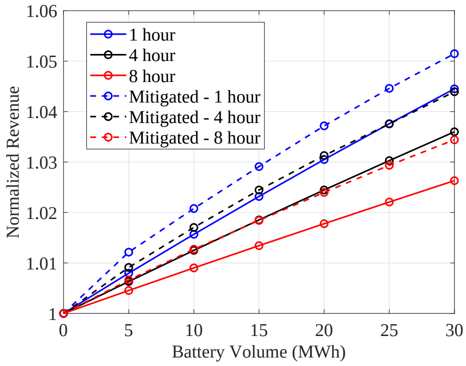

Figure 4.5: Normalized Revenue for Arbitrage and Imbalance Scenario

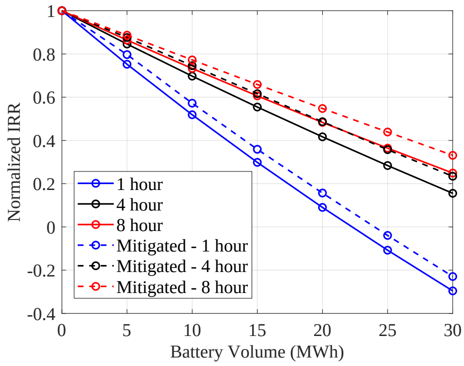

Figure 4.6: Normalized Revenue for Arbitrage and Imbalance Scenario

In the case above, a difference was made between scenarios with and without imbalance volumes caused by wind forecasting errors. In the scenarios with imbalance volumes, an attempt was made to mitigate the imbalance through the controller. However, the question remains what the actual cost of imbalance is and what the potential benefit of mitigating this imbalance could be. The cost of imbalance can be calculated by comparing the no-storage revenues from the scenario without imbalance and the scenario with imbalance. These revenue points lie in the origin of the normalized revenue plots above and are the revenues that the data points with added storage are normalized against. The cost of imbalance is the difference between the revenue made when bidding the correct volume versus the revenue made when bidding the forecasted volume in the DAM and thereafter being obligated to settle the resulting imbalance volumes. The result of this calculation is that the revenue made when bidding based on the forecast is 3% lower than when bidding the correct volume. It can be verified that this is not caused by a mean error in the wind forecast. When examining the wind forecast used in this project it can be noted that cumulative produced wind energy was in total 3% higher than forecasted for the used data set of one year. The imbalance settlement caused by the forecast error is therefore indeed negative, despite more energy being produced than forecasted. Nevertheless, the cost of imbalance is relatively low. This number gives reason to believe that employing a battery just to mitigate the imbalance of a RES system would not be profitable. Hence, this use case was not part of this project. Now the cost of imbalance is known the question remains how successful the controller is at mitigating this imbalance. To do this, the percentage of imbalance cost that is mitigated can be examined. The percentages are shown in table 4.1. The larger batteries can mitigate more of the imbalance. This is to be expected as the imbalance volume is independent of the battery size whereas the battery volume available for mitigating imbalance grows with the overall battery volume. This follows from the fact that the imbalance volume doesn't change in size but the leftover space in the battery does grow. 100% mitigation of imbalance could be possible in this setup but due to the low imbalance costs, this would not be profitable. Furthermore, the low cost of imbalance provides the insight that imbalance mitigation has less potential than arbitrage or providing frequency services as a value-adding strategy of co-location.

Table 4.1: Percentage of imbalance cost mitigated by the controller

Battery Size (MWh)	1 Hour	4 Hour	8 Hour
0	0%	0%	0%
5	26%	18%	13%
10	33%	29%	23%
15	38%	38%	32%
20	44%	44%	39%
25	46%	47%	46%
30	47%	52%	52%

4.3. Sensitivity

Arbitrage has proven out to be unrealistic at the current storage costs when using a BESS. The negative outcome of this case doesn't warrant a sensitivity analysis of storage replacement costs or imperfect market forecasts as these will only make the case more negative. The yearly cycles are shown in table 4.2. For an assumed cycle life of 5000 cycles, this would entail 1 replacement for the 20-year project lifespan for all three variants.

Table 4.2: Yearly number of cycles made by the storage system

Scenario	1 Hour	4 Hour	8 Hour
Arbitrage	420	365	290

Alternatively, the required drop in storage investment costs that are needed for DAM arbitrage to have a chance at becoming value-adding is estimated. The results per scenario are shown in table 4.3.

Table 4.3: Estimated required drop in investment costs for the normalized IRR become break-even compared to having no storage.

Scenario	1 Hour	4 Hour	8 Hour
No Imbalance	77%	72%	68%
Imbalance	80%	75%	70%
Imbalance - Mitigated	75%	70%	65%

4.4. Main Findings

Arbitrage is arguably the most well-known storage application but fails to live up to the expectations to date. The volatility, or price spreads, in the DAM market are too low to recoup the costs of installing co-located storage. Furthermore, it has been shown that the costs of imbalance from imperfect weather forecasts is relatively low at 3% of the total WPP revenue. Therefore, employing the co-located storage to mitigate imbalance also has low potential. A drop in storage costs ranging from 80 to 65 percent is needed to make DAM arbitrage plausible and this figure is without taking replacement cost and imperfect market forecasts into account.

Furthermore, it has been shown that DAM arbitrage doesn't require high power output storage methods. In the case of BESS the low power batteries outperform the high power batteries and will plausibly reach a profitable level sooner. This conclusion can be expanded by stating that DAM arbitrage will not require fast-reacting or high ramp rate storage technologies to capture the arbitrage potential. The DAM price shows a daily cycle in price levels. Therefore, a storage technology that has ramp rates in the order of the 8-hour BESS used in the case but that offers a lower price point can become profitable in DAM arbitrage. This estimate can be used in further research into the profitability of DAM arbitrage. Further examination of this result is outside the scope of this project.

Alternatively, DAM arbitrage can become plausible if the DAM becomes more volatile and price spreads increase. It can be argued that in the future the higher penetration of RES on the grid will lead to a more volatile market as the generation capacity will become more dependant on weather conditions (IEA, 2021).

The optimization of the imbalance mitigation contains a peculiar assumption. The imbalance originates from errors in the wind forecast. However, in the optimization set up it is assumed that the optimizer knows what this error is going to be for the entire simulation length. This information is used to optimize the imbalance mitigation effort. However, in real-life, knowing exactly how wrong your forecast will be is impossible. This problem can be resolved by employing more complicated optimization techniques that were out of scope for this project. However, it is expected that the conclusions in this report will not be affected as the potential for imbalance mitigation remains low.

In the scenario without the imbalance mitigation, the storage system was allowed to charge from both the turbine and the grid. This is beneficial during periods when the storage systems wants to charge but the turbine doesn't produce enough energy. Solely allowing the storage systems to charge from the turbine would result in an average 3% revenue loss for each storage configuration. The loss in revenue would result in an average 5% loss in the normalized IRR curves. Allowing the storage system to charge from the grid proved to be complicated to model for the scenarios with DAM arbitrage and imbalance mitigation. The effect of this option on the outcome of the scenario is low. Therefore, in the imbalance mitigation scenario, as well as in the stacked case, the storage system is only allowed to charge from the turbine when performing DAM arbitrage.

5 Results Ancillary Services

In this section, the results of the AS case as explained in section 3.2.2 will be reviewed. First, the contracted bids scenario with and without imbalance mitigation will be discussed, followed by the free-bids scenario with and without imbalance mitigation. To recap, the inclusion of imbalance mitigation means that a non-perfect wind forecast is used for the DAM bids leading to imbalances for the system which the controller will attempt to mitigate.

5.1. Operational Strategy

In this section, the operation of the model will be analyzed in a short time frame of one week. The aim is to verify that the model is making optimal choices and to study what this optimal operation looks like.

In figure 5.1 the operational parameters for the contracted bid scenario with no imbalance are shown. In the top plot, the activated bids are shown. This plot will be used that the model shows the correct bidding behaviour. To recap, in the contracted bids scenario the same bid is placed for every ISP in one day, per regulation direction. The up bids are activated whenever the regulation state is up and vice versa for down. From the top plot, it can be verified that the model indeed places the same size bids for every ISP in one day because the activated amount is constant during periods of 96 ISPs, varies after each period of 96 ISPs and remains constant again for the next 96 ISPs. Whenever an up-regulation bid is activated, shown as aFRR sold, it means that the regulation state of the grid was up during this ISP and vice versa for down. The regulation state is not shown in the figures but it has been verified that the model correctly interprets this constraint. The mechanism that makes revenue for this case is the fact that, in general, imbalance prices are lower during down-regulation than during up-regulation. Consequently, the battery is charged when imbalance prices are low and discharged when imbalance prices are high. This behaviour can be observed and verified by comparing the first and third plots.

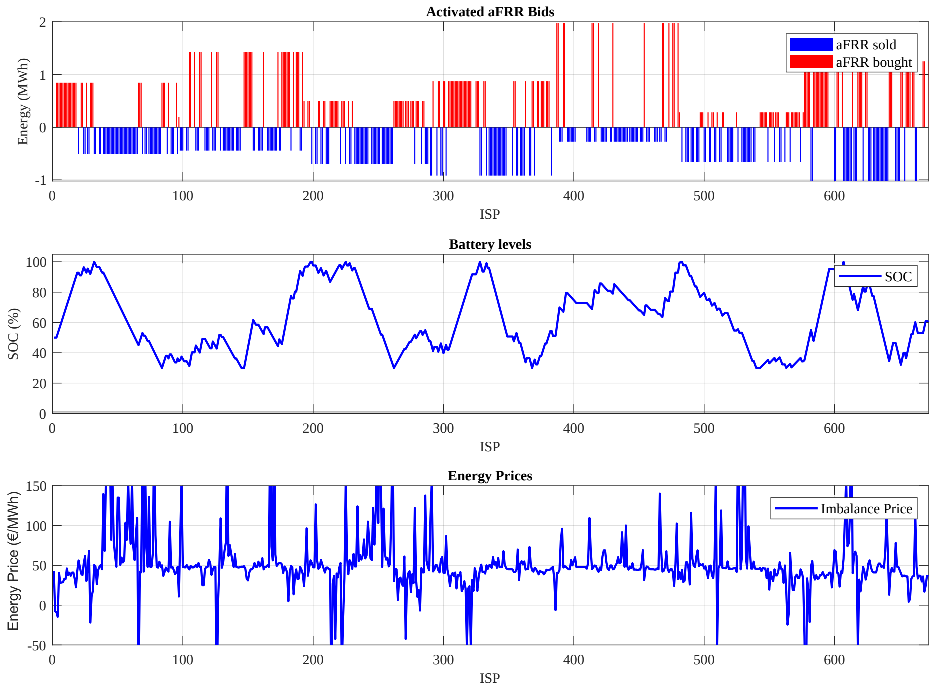

Figure 5.1: Selected Parameters from contracted aFRR scenario during the first week of 2019 for a 4-hour 30 MWh battery.

The size of the bids that are placed for one day is limited by the longest stretches of consecutive up or down-regulation states. A good example of this can be seen from ISP 231 up till ISP 262. At the start of this period, the battery is almost fully charged. During this period the regulation state is constantly down or zero. At the end of the period, the battery has reached its minimal SOC limit. The bid size for the down direction for this day is limited by this period of consecutive down-regulation ISPs divided by the amount of available discharge capacity in the battery at the start of the period. The same goes for periods of consecutive up-regulation bids and available space to charge the battery. Later on the same day, around ISP 280 the regulation state switches back and forth in a short period of time. This limiting behaviour governs the amount of energy that can be traded by the battery. In the free-bids scenario, the optimizer can choose in which ISPs it wants to place a bid instead of being contracted to place bids for every ISP. Consequently, it will probably place bids sized at the full battery energy ramp rate during the ISPs when the imbalance price is either very high or very low. Therefore, it can be expected that the free-bid scenario can trade more energy in a more aggressive trading strategy through which it can earn more energy remunerations than the contracted bids scenario. On the other hand, the contracted bid scenario also earns a capacity remuneration for all the placed bids. In the next section, it will be examined whether this capacity remuneration makes up for the smaller energy remuneration caused by the smaller bid size in the contracted bid scenario.

In figure 5.2 the operational parameters from the free-bid scenario with no imbalance are shown. Similarly to the previous figure, the top plot shows the activated bids, the middle plot shows the SOC and the final plot shows the imbalance price. As suggested in the paragraph above this trading strategy is more aggressive, which is exhibited by the larger amount of charge and discharge cycles during the same time period. The optimizer is free to choose in which ISPs it wants to place a bid. This leads to the optimizer bidding in fewer ISPs than the contracted bid scenario, but on the contrary, the bids that are placed are placed in the most lucrative ISPs and higher volumes are bid.

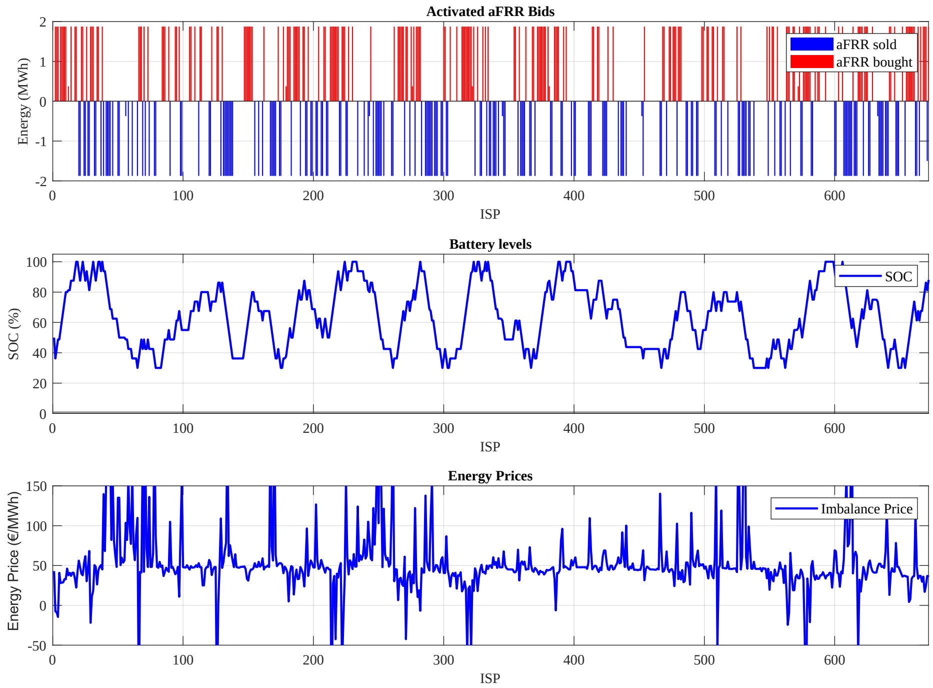

Figure 5.2: Selected Parameters from free-bid aFRR scenario during the first week of 2019 for a 4-hour 30 MWh battery.

In the past two scenarios, all energy coming in from the WPP was directly bid and sold in the DAM and therefore not shown in the figures. As a perfect wind power forecast is assumed, there is no imbalance volume. In the next two scenarios, this imbalance volume caused by the wind forecasting error is introduced for both the contracted and free-bid scenarios. As explained in section 3.2.2, the battery operation will first be optimized for providing AS. Second, the controller can use the battery capacity to partially mitigate the imbalance volume on the condition that this doesn't interfere with the bids placed by the optimizer for providing AS.

In figure 5.3 the operational parameters for the contracted bid and imbalance mitigation scenario are shown. In the top plot the addition of an imbalance volume is represented by the black line. This imbalance volume is caused by the difference between forecast and produced wind energy. Under the black line, the blue and red blocks represent the imbalance volume that the controller has mitigated. The effect of the mitigation action on the SOC is shown in the third plot. Here the blue line represents the SOC that would have occurred without the mitigation by the controller and the red line shows the resulting SOC after the controller's intervention.

At ISP 170 it can be seen that the controller successfully mitigated what would have been an expensive imbalance. The imbalance price is very high and the turbine is producing less than forecasted causing the system to be in a negative imbalance. This imbalance volume is mitigated by discharging the battery using energy that was charged to the battery from the turbine around ISP 150 when the system was in a surplus. Because the imbalance price was low around ISP 150, charging the surplus energy to mitigate the negative imbalance at ISP 170 was more beneficial than selling the surplus energy directly during ISP 150.

This strategy is successful in mitigating smaller imbalances but lacks the flexibility to tackle the larger ones. This can be observed in the period around ISP 500. The general trend in the AS bids is discharge of the battery from fully charged to the minimal SOC limit. Simultaneously, during this period the turbine produces much less than forecasted causing a relatively large negative imbalance volume. Additional discharging the battery to mitigate this negative imbalance volume would cause the battery to exceed its minimum SOC limit. Consequently, this imbalance is not mitigated and the system is charged imbalance penalties in the amount of the product of the imbalance volume and the imbalance price.

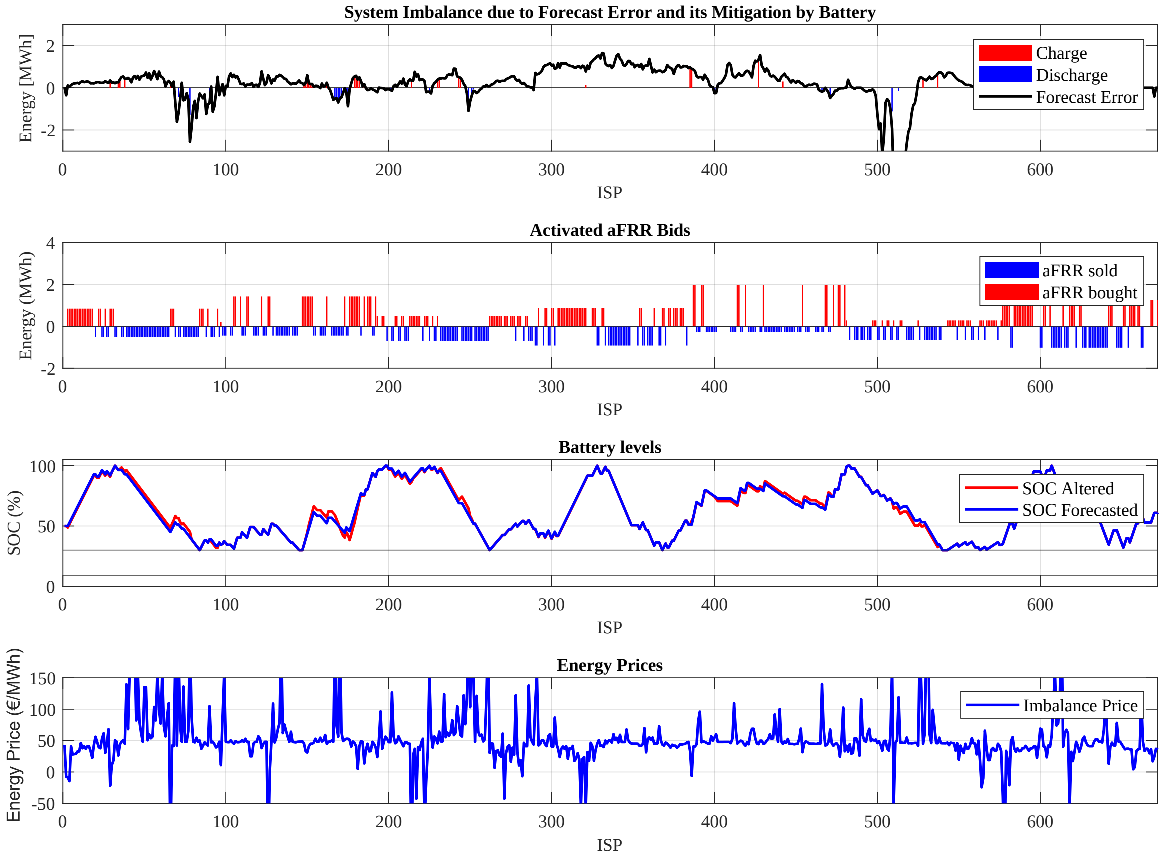

Figure 5.3: Selected Parameters from contracted bid aFRR and imbalance mitigation scenario during the first week of 2019 for a 4-hour 30 MWh battery.

In figure 5.4 the operational parameters for the free-bids and imbalance mitigation scenario are shown in the same order as the previous scenario. In this scenario, it can be observed that the controller is successful in mitigating the imbalance volume during periods when the storage is not operated at the extremes of the SOC. In the middle of the week the forecasted SOC rapidly cycles between the minimum and maximum and therefore almost no room is left for additional imbalance mitigation. However, before and around ISP 500 the forecasted SOC remains around 50% for approximatly one day. During this period it can be seen that the real time controller manages to mititate more of the imbalance volume. Still, the altered and forecasted SOC lines are nearly identical. The explanation for this behaviour is that the AS optimizer operates the battery in a more aggressive manner than in the contracted bid scenario. Consequently, during ISPs when it would be lucrative to use the battery to mitigate the imbalance it is not possible to do so because the full ramp rate of the battery is already used to fulfil the activated AS bid.

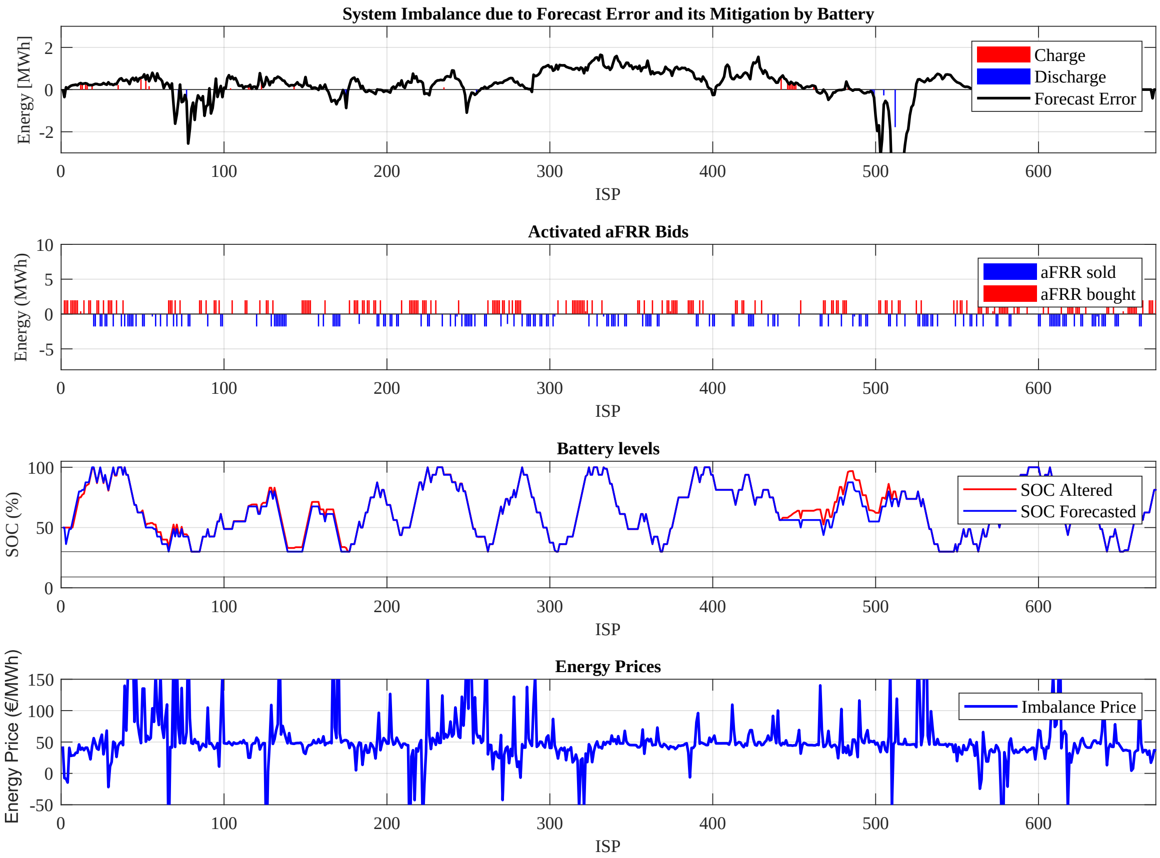

Figure 5.4: Selected Parameters from free-bid aFRR and imbalance mitigation scenario during the first week of 2019 for a 4-hour 30 MWh battery.

5.2. Economics

In this section, the economics of the AS case will be evaluated. The goal of this project was not to exactly quantify the different scenarios, but rather compare bidding strategies against one another and against the case of having no co-location of wind and storage. Furthermore, there are many assumptions in the methodology as explained in 3. Therefore, in this section, the results will not be presented in exact numbers but rather as normalized with respect to the wind only scenario. Consequently, the IRR values don't represent the actual business case but merely compare the case with respect to having no storage at all as given by the 0 MWh battery data point.

In figures 5.5 and 5.6 the normalized revenue and the normalized IRR are shown for the contracted bids scenario without imbalance. The 1 and 4-hour batteries provide similar additional revenue but due to the high cost of the 1-hour battery, the 4-hour battery performs better in the normalized IRR figure. This is similar to the DAM arbitrage case from section 4 where it was concluded that in scenarios where the cycle frequency of charge and discharge is low a high power battery is not needed to extract the potential from the market and is therefore too expensive compared to a low power battery. Just as with the DAM arbitrage case, the contracted bids scenario shows this relatively slow cycle frequency but slightly faster than in the DAM arbitrage case. Consequently, in this contracted bids scenario the middle road of the 4-hour battery performs best.

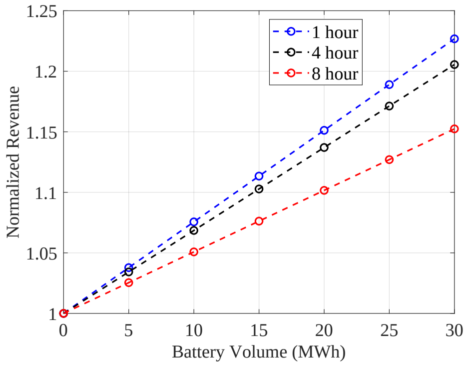

Figure 5.5: Normalized Revenue for contracted AS scenario

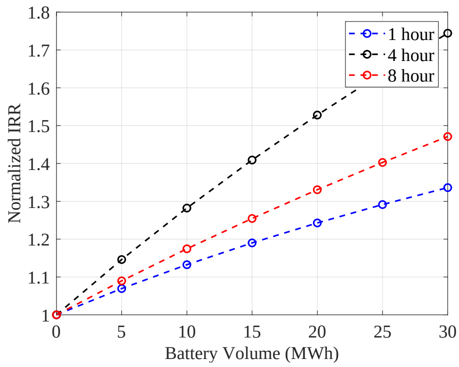

Figure 5.6: Normalized IRR for contracted AS scenario

Contrary to the contracted bids scenario, the free-bids scenario showed a volatile and aggressive battery operation with a high cycle frequency in figure 5.2. In line with the theory that low cycle frequency cases don't need high power batteries, it can be expected that the contrary is true for cases with high cycle frequencies. Markets with volatile prices have more potential for revenue addition through trading large amounts of energy fast.

In figures 5.7 and 5.8 the normalized revenue and the normalized IRR are shown for the free-bids scenario without imbalance. As expected, the 1-hour battery provides significantly more revenue than the low power batteries. In this case, the added revenue is enough to make up for the extra cost of the high power battery. This is shown by the 1-hour battery performing the best in the normalized IRR curve. This validates the idea that a volatile market has more potential for high power batteries. In a sense, the contracted bids scenario operates in the same volatile market as the free-bids scenario. However, due to the bidding constraints, the battery operation is not as volatile as in the free-bids scenario.

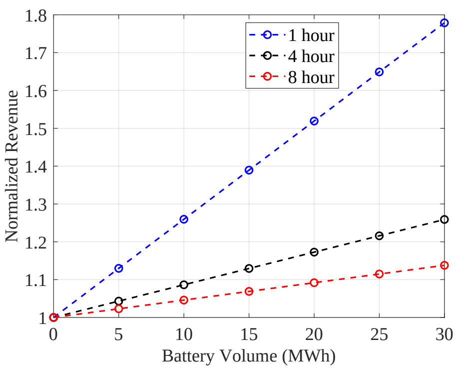

Figure 5.7: Normalized Revenue for free-bid AS scenario

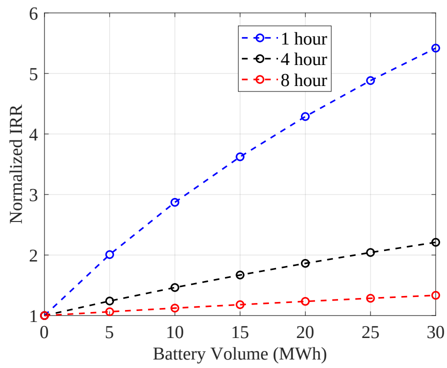

Figure 5.8: Normalized IRR for free-bid AS scenario

In figures 5.9 and 5.10 the normalized revenue and the normalized IRR are shown for the contracted bids scenario with imbalance. The main findings from the contracted bids without imbalance scenario are also valid for the contracted bids with imbalance scenario. The 4-hour battery still performs best in the IRR figures but the 1 and 8-hour batteries partly show a shift in performance. In both the revenue and IRR curves the difference between accepting the imbalance, (solid lines) and partially mitigating the imbalance (dashed lines) is largest for the 1-hour battery. Therefore, the positive effect of imbalance mitigation by the controller is most significant for the 1-hour battery. In fact, the 1-hour battery outperforms the 8-hour battery for the smaller battery sizes. While the high power battery is not needed to grasp the maximum potential of the contracted bids, it does come into its own when performing imbalance mitigation alongside delivering the contracted bids. This can be explained when looking at the SOC curves of figure 5.3. The altered SOC curve tends to stay close to the forecasted SOC curve as it’s constrained by the obligation to fulfil the contracted bids. However, having a higher power battery allows it to deviate further from the forecasted SOC whilst not failing to deliver the contracted bids, hereby mitigating more imbalance volume than a low power battery. To summarize, the 1-hour battery performs better in the scenario with imbalance than without imbalance but still not better than the 4-hour battery, which remains the battery with the most optimal balance between costs and a high enough power output to capture the potential value in these scenarios.

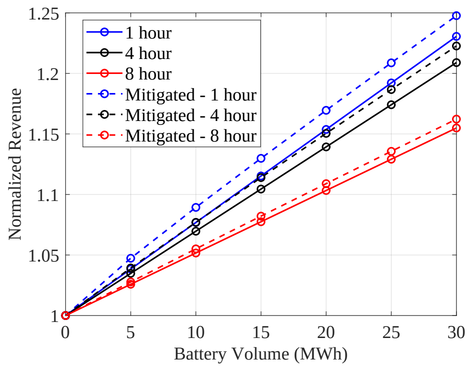

Figure 5.9: Normalized Revenue for the Contracted Bids and Imbalance Mitigation Scenario

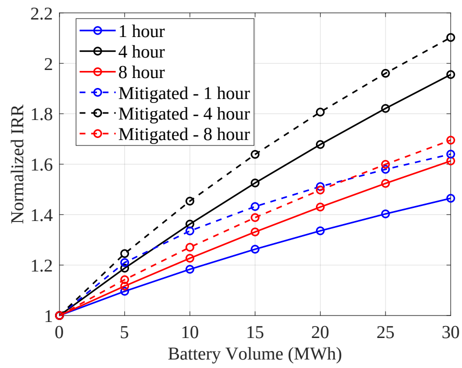

Figure 5.10: Normalized IRR for the Contracted Bids and Imbalance Mitigation Scenario

In figures 5.11 and 5.12 the normalized revenue and the normalized IRR are shown for the free-bids scenario with imbalance. Looking at these figures the difference between dashed and solid lines can almost not be seen. In figure 5.4 it was observed that in this scenario the controller had almost no options to mitigate the imbalance. With almost no imbalance volume mitigated it is logical that the lines are close together.

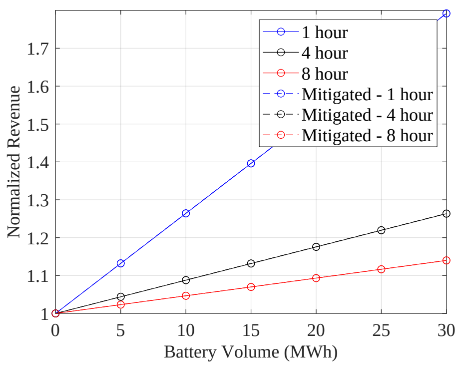

Figure 5.11: Normalized Revenue for the free-bids and Imbalance Mitigation Scenario

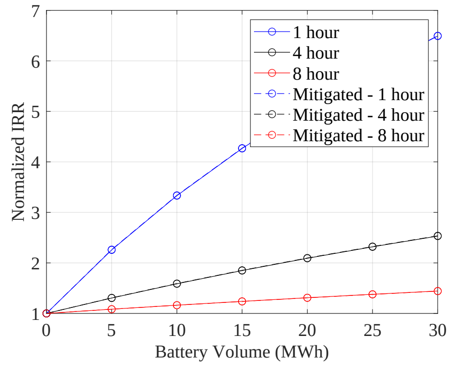

Figure 5.12: Normalized IRR for the free-bids and Imbalance Mitigation Scenario

5.3. Sensitivity

Providing aFRR with co-located storage clearly shows value-adding potential. In this section, it will be examined how sensitive this result is to imperfect market forecasting, storage investment costs and storage degradation costs. The methods used for these analyses have been explained in section 3.3.

Figure 5.13 shows the SOC and bids for the free-bid scenario with an imperfect market forecast. The imperfect forecast can lead to two types of non-optimal situations. The errors in the regulation state forecasting can cause the optimizer to place an up-regulation bid for an ISP that will turn out to be in a state of down-regulation, causing the bid to not be activated and therefore the system missing out on revenue. Alternatively, if the regulation state is forecasted wrongly over multiple ISPs the system might not be able to fulfil its activated bids because the SOC is at the limit state. This can be illustrated with an example. If alternating up and down-regulation states are predicted then alternating up and down bids will probably be placed by the optimizer. If the actual regulation state turns out to be only up during these ISPs, then only the placed up-regulation bids will be activated and the down-regulation bids will not. This will cause the SOC to quickly reach the lower SOC whereas the forecasted SOC would have remained stable. If the SOC is at the lower limit and an up-regulation bid is activated then the system will be unable to fulfil the bid. These non-optimal situations can be observed in figure 5.13.

The black SOC FC (Forecast) line shows the SOC that the optimizer has planned and that would have resulted if all placed bids are activated. This is not the SOC that will actually occur because not all placed bids will be activated due to the errors in forecasting. The red SOC BC (Before Correction) shows the resulting SOC after the activation of the placed bids, including when the activated bids would have taken the SOC out of the limits. The blue SOC line shows the achieved SOC following corrections when bids are not activated if they would have brought the SOC out of the limits. In the second plot, the placed and activated bids are shown. The blue bars are the placed bids that have been activated whereas the red bars are the placed bids that weren't activated because the regulation state was not as forecasted.

The red bars pertain to the first of the non-optimal situations as described in the paragraphs above. The second non-optimal situation is shown by the SOC BC correction line violating the limits. The imperfect market forecast causes the battery to not be able to fulfil activated bids a total of 11 times during one week.

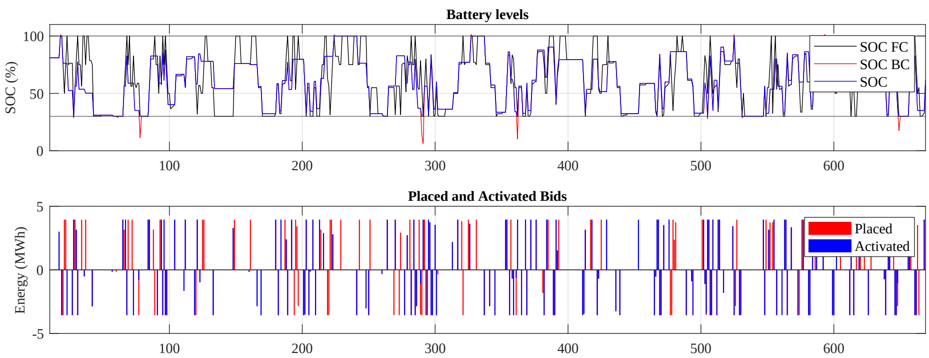

Figure 5.13: Selected Parameters from free-bid aFRR scenario with imperfect market forecasting during the first week of 2019 for a 1-hour 15 MWh battery.

Figure 5.14 shows the SOC trajectories and bids for the contracted aFRR scenario. The main difference between the two scenarios is that the contracted bidding block is executed once a day and the free-bidding block is executed every ISP. This means that the free-bid optimizer is updated after every ISP if its bids were activated and if the SOC is near the limits and it can place future bids accordingly. The bidding block for the contracted bids is only updated once a day. This causes the contracted bids case to be more prone to not being able to fulfil placed bids because the battery is at its limit. This can be seen between ISP 300 and 400. The blue SOC goes to the minimal limit much faster than the forecasted black SOC line. As a consequence, the battery cannot fulfil the placed bids that are activated by the TSO. This is shown by the red SOC Before Correction line crossing the limit. In the contracted bids scenario the bids have to be placed in every ISP of the day. The errors in the regulation state forecast are the main driver behind the difference between the forecasted and achieved SOC trajectory as they control when bids are activated. The bids that are activated but cannot be fulfilled are shown magenta in the bids plot. Bids that were expected to be activated but were not are shown in red and their counterpart are the black unforecasted activated bids. Finally, in blue the forecasted and activated bids are shown.

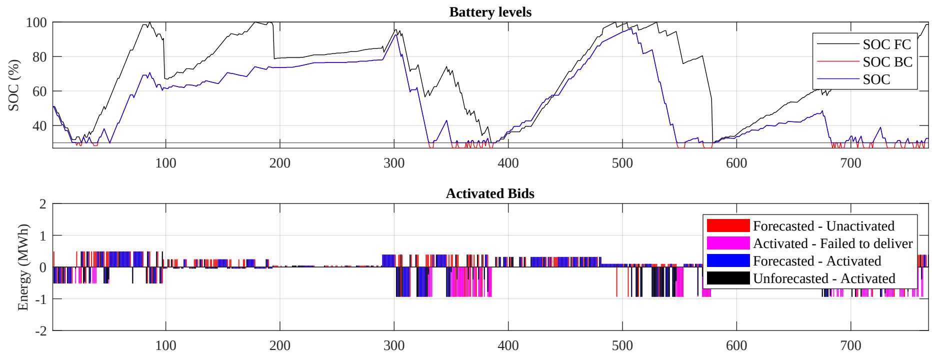

Figure 5.14: Selected Parameters from contracted aFRR scenario with imperfect market forecasting during the first week of 2019 for a 8-hour 30 MWh battery.

In figure 5.15 and figure 5.16 the economics of the contracted and free-bid scenarios with imperfect market forecasting are shown. The contracted bids scenario loses its value-adding potential under these circumstances. The co-location of storage for free-bid aFRR still shows value-adding potential despite a normalized IRR loss of 50% caused by the imperfect market forecast.

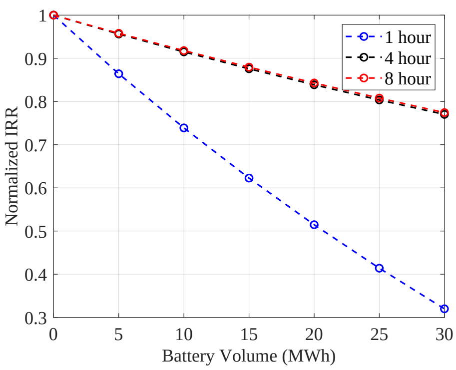

Figure 5.15: Normalized IRR for the Contracted Bids Scenario with Imperfect Market Forecast

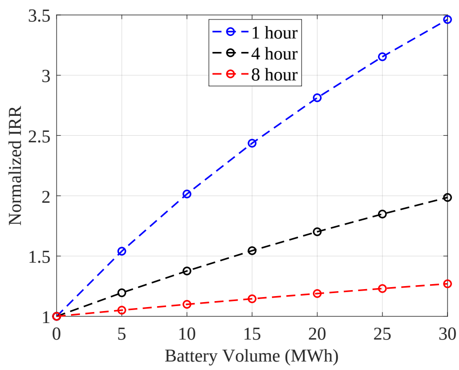

Figure 5.16: Normalized IRR for the free-bids Scenario with Imperfect Market Forecast

In the previous section, it was shown that the cycle frequency of the storage system was higher for the free-bids scenario than that of the DAM arbitrage or contracted aFRR scenarios. The promising potential of the free-bid scenario partly comes from these large amounts of energy that are traded by the storage system. The downside of the high cycle frequency is that the storage system will degrade at a faster rate and will need to be replaced more often in the project lifetime. Table 5.1 confirms the higher cycle frequency of the free-bid scenario compared to the contracted bid scenario.

Table 5.1: Yearly number of cycles made by the storage system

Scenario	1 Hour	4 Hour	8 Hour
free-bid	1500	560	315
Contracted Bid	400	370	270

For the sensitivity towards replacement costs, the BESS is used as an example. Currently, 5000 cycles is the state of the art for a BESS. When the storage system reaches its cycle lifetime it must be replaced. The replacement costs are subtracted from the cash flow in the replacement year(s). Table 5.2 shows the system lifetime when assuming a 5000 cycle lifetime. The system lifetime translates into the number of times the storage system needs to be replaced during the 20 year project lifetime.

Table 5.2: Storage system lifetime and number of replacements during project lifetime for an assumed cycle life of 5000 cycles.

Scenario		1 Hour	4 Hour	8 Hour
Free-Bid	Lifetime (years)	3	9	16
	Replaced (times)	6	2	1
Contracted Bid	Lifetime (years)	12	14	18
	Replaced (times)	1	1	1

Figures 5.17 and 5.18 show the resulting normalized IRR curves when the storage replacement costs are taken into account. The IRR curves all drop below 1 for this assumed cycle lifetime. This raises the question of what cycle life is needed to retain an IRR of 1. This comes down to how many replacements can occur during the project lifetime.

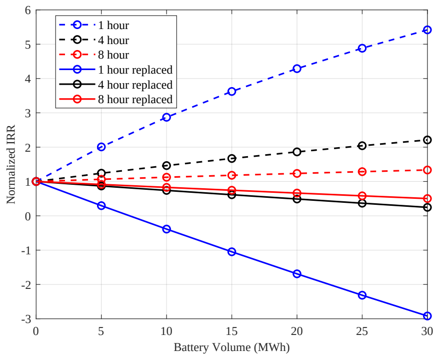

Figure 5.17: Normalized IRR for free-bid aFRR with and without storage replacement costs.

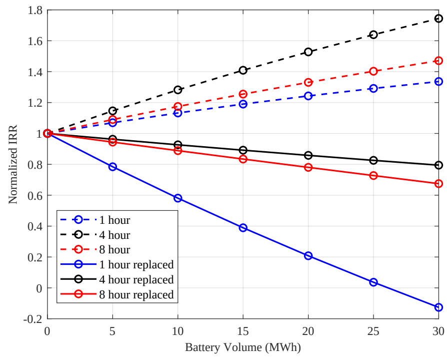

Figure 5.18: Normalized IRR for Contracted aFRR with and without storage replacement costs.

The required lifetime, number of replacements and resulting cycle lifetime are given for both scenarios in table 5.3. The contracted bids cases are closer to the current state of the art of BESS with regards to cycle lifetime. The replacement costs of BESS were used in this analysis as BESS is the chosen example storage technology in this project. These results can be translated to any other storage technology by changing the replacement costs

Table 5.3: Required storage system lifetime, the maximum number of replacements and resulting required cycle life to retain a normalized IRR of 1 for co-located storage

Scenario		1 Hour	4 Hour	8 Hour
Free-Bid	Life time	6	11	20
	Replacements	3	1	0
	Cycle Life	9000	6000	6500
Contracted Bid	Life time	20	20	20
	Replacements	0	0	0
	Cycle Life	8000	7400	5400

Table 5.4 shows the maximum allowable rise in initial investment cost for the scenarios to retain a normalized IRR of 1 compared to having no co-located storage. This estimation can be used to identify storage technologies that are more expensive than current Li-ion price levels but have advantages over Li-on other than cost. Storage system replacement costs are not factored into this estimation.

Table 5.4: Rise in investment cost that would cause the normalized IRR's to drop to 1 when adding co-located storage

Scenario	1 Hour	4 Hour	8 Hour
Free-Bid	315%	110%	35%
Contracted Bid	25%	70%	50%

5.4. Main Findings

Co-located storage shows significant value-adding potential when employed to provide aFRR services to the grid. The potential is particularly high for the free-bid scenarios with up to a 6 fold increase in IRR compared to having no co-located storage. It has been shown that high power storage systems are worth the extra investment when providing free-bid aFRR. For contracted aFRR, medium to low power storage systems outperform the high power systems. These results can be interpreted as the upper limit of the potential in these markets as no market forecasting errors or replacement costs are taken into account.

To provide aFRR a storage system doesn't necessarily need to be co-located with a RES. A standalone storage system can also provide aFRR. In the Introduction, it was theorized that a benefit of co-locating storage is the possibility to use the storage to mitigate the imbalances from the RES alongside providing aFRR. It has been shown that this is not valid for the free-bids case. The aggressive trading of the free-bid case allows for little additional room to appropriate the storage system for imbalance mitigation. The contracted aFRR case allows for more room to mitigate the system imbalances and makes a more compelling case for co-location.

The free-bid scenario remains positive in the sensitivity analysis for imperfect market forecasting. Contracted aFRR suffers a less severe normalized IRR loss than free-bid aFRR. However, the normalized IRR of contracted aFRR was lower in the perfect forecast scenario. Thus, even though contracted aFRR is affected less by the imperfect market forecast, the normalized IRR becomes lower than 1 for contracted aFRR.

With the free-bids scenario requiring cycle lifetimes in the range of 6000 to 9000 cycles and the contracted bids scenario requiring a smaller 5400 to 8000 cycles, the sensitivity towards replacement costs has shown that the contracted scenario requires lower cycle lifetimes to retain a positive outcome. The 4-hour free-bid and 8-hour contracted bid configurations are already close to the current cycle lifetime assumption for Li-ion BESS. No literature on regulation state forecasting could be found. Therefore, the method used to construct a regulation state forecast is not verified to resemble any state of the art forecasting method.

In the model, the assumption is made that no bids are placed or activated during regulation state 2. This was complicated to model as both up and down bids are activated by the TSO during regulation state 2. The imbalance price that the BSP receives during regulation state 2 is not equal to the imbalance price. Instead, a differentiation is made between the aFRR up and down prices. The aFRR up price that the BSP receives is equal to the price of the highest activated up bid and vice versa for down bids. Therefore, the assumption of no activation during regulation state 2 influences the results negatively.

The IRR was chosen as the parameter of interest for the economic analyses. For the scenarios with positive outcomes it can be seen that the IRR seemingly tends to keep rising with increasing storage size. This begs the question whether an optimum exists or whether bigger is always better. The costs and cashflows in the IRR equation 3.1 consist of a turbine part and a storage part. When the storage size increases, the storage system's costs and cashflow contribution increase but the turbine's costs and cashflow contribution remain unchanged. Therefore, with higher storage volumes, the impact of the storage system on the combined system's IRR grows. Eventually, the storage system's contribution to the costs and cashflows becomes dominant and the total system's IRR is almost equal to that of a stand-alone storage system's IRR. The IRR of the stand alone system was found to be independent of its size. The IRR curve of the stand-alone storage system would be a flat line. Therefore, no optimum exists in the IRR curves. The curves show an asymptotic behaviour due to the increasing dominance of the storage system's contribution to the system's IRR.

Whilst no optimum exists in the curves of this study, in real-life an optimum probably exists. This study made the simplification of not respecting the 1 MW minimum bidding size in the aFRR market. If this constraint was added the smaller storage systems would either not be able to participate at all or their performance would be effected. The costs for the storage system are assumed to only depend on the storage system's size. When going to large storage system sizes, other costs, such as land ownership costs, may come into play that would make the larger sized storage systems impractical.

6 Results Stacked Operation

In this section, the potential benefits of stacking Arbitrage and Frequency Services operations will be reviewed. The results from this case, explained in 3.2.3, will work towards reaching the third sub-objective as defined in 1.3. Three scenarios were defined for this case distinguished by the order in which the different markets were prioritized in the optimization algorithm. Similar to the previous sections the operational parameters will first be discussed, followed by the economics, sensitivity analyses and main findings.

6.1. Operational Strategy

In figure 6.1 selected operational parameters are shown for the scenario that prioritizes contracted aFRR bidding followed by DAM arbitrage and imbalance mitigation. The placed contracted aFRR bids are depicted by the black bars in the third plot. After the aFRR bids have been placed, the remaining space in the battery is used for DAM arbitrage. The placed DAM bids and planned charging operation can be seen in the first plot. The blue bars depict the wind turbines contribution and the black bars depict the batteries contribution to the DAM sell bid. The red bars depict the wind energy that the DAM arbitrage optimizer has planned to charge to the battery. The red and black bars from the first plot correspond with the blue bars in the third plot. The planned arbitrage operation depicted by these black and red bars can be altered by the real time controller that attempts to mitigate the imbalance volume. The magenta line in the first plot shows the actual produced wind energy. It can be seen that the DAM bid and planned charging volumes don't match the actual produced wind energy. This is caused by the wind energy forecast error which gives rise to the imbalance volume. This imbalance with the DAM bids is shown in the second plot along with the mitigation action from the controller.

The combined battery energy flows resulting from the aFRR bids, DAM arbitrage and imbalance mitigation are shown in the third plot. The imbalance mitigation effort is shown by green bars, depicting extra battery (dis)charge, or red bars, depicting retracted (dis)charge operation. The resulting SOCs following each operation are shown in the fourth plot. The black SOC aFRR line should be interpreted as the SOC trajectory that would have occurred if only the aFRR bids were activated. The blue SOC arbitrage line should be interpreted as the SOC trajectory if the aFRR bids and the arbitrage bids were executed. Finally, the red SOC line should be interpreted as the SOC trajectory that has actually occurred following activation of the aFRR, arbitrage and imbalance mitigation actions.

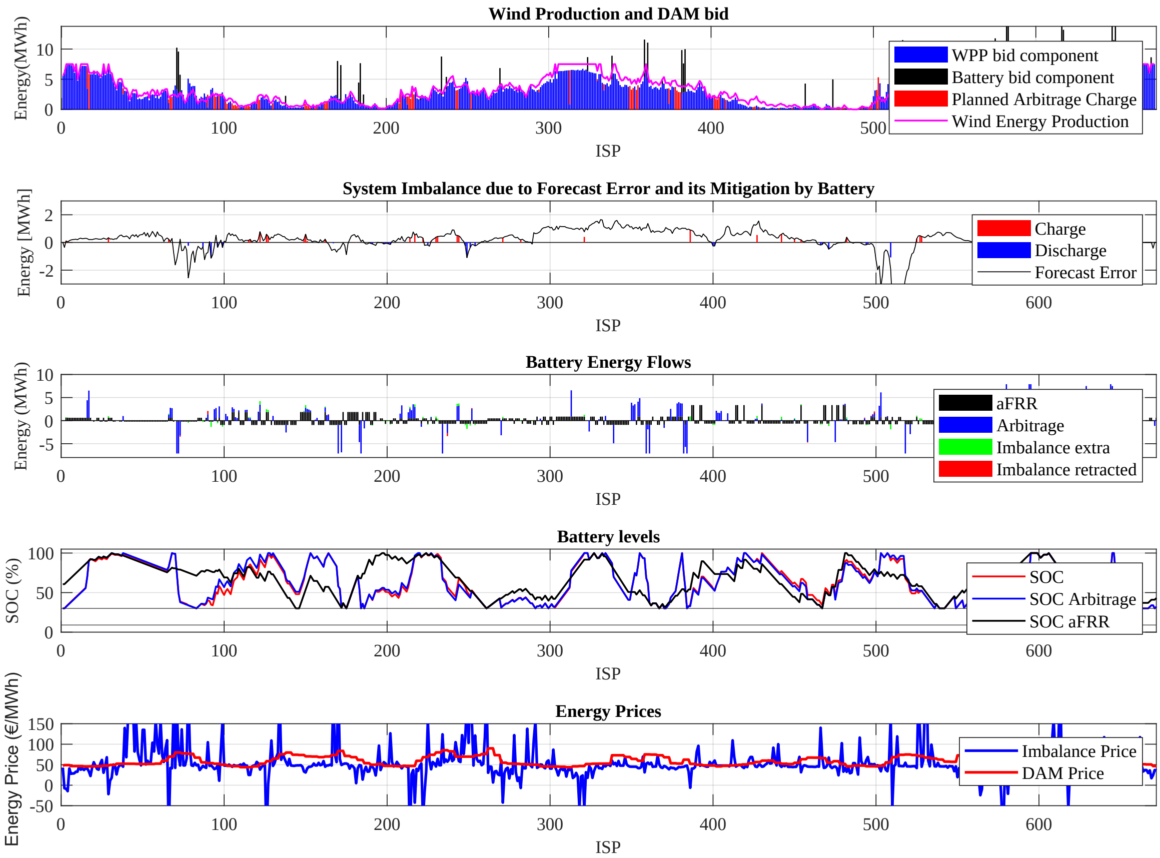

Figure 6.1: Selected Parameters from the stacked case with contracted aFRR followed by arbitrage and imbalance mitigation during the first week of 2019 for a 4-hour 30 MWh battery.

An example of this retracted discharge operation can be seen at ISP 237. In this ISP, the DAM bid contains a battery discharge component shown by a blue bar in the fourth plot and a black bar in the first plot. The size of this battery contribution to the DAM bid is equal to the stacked amount of the blue and red bar from the fourth plot. During this timestep, the wind turbine produced more energy than forecasted. Therefore, the battery doesn't need to discharge the full planned amount to fulfil the DAM bid as the extra energy from the wind turbine is used to this end. The red bar stacked on top of the blue bar depicts this amount of energy that doesn't need to be discharged thanks to the extra energy from the turbine.

An example of extra battery (dis)charge operation can be seen at ISP 243 where firstly during two ISPs the charge to the battery is increased because there is a positive imbalance from the turbine. This extra charge energy is used 5 to 9 ISPs later to discharge extra energy from the battery because there is a negative imbalance from the turbine during these four ISPs.

Comparing the aFRR SOC and arbitrage SOC trajectories shows that the conservative battery operation from the aFRR bids allows for enough space in the battery to perform a sizeable amount of DAM arbitrage. This is shown by the significant deviation of the arbitrage trajectory from the aFRR trajectory. Comparing the arbitrage trajectory with the achieved trajectory after imbalance mitigation shows that there is less space remaining in the battery to perform a large amount of imbalance mitigation.

In figure 6.2, the same operational parameters as above are shown for the scenario where, instead of contracted bids, free bids are placed for the aFRR market. In the SOC plot, the aggressive battery operation resulting from the free bids that was noted in section 5 can once again be observed. Because the free bids often take the SOC to the limits there is limited room for performing arbitrage and almost no room for imbalance mitigation. The energy prices are identical to those in figure 6.1.

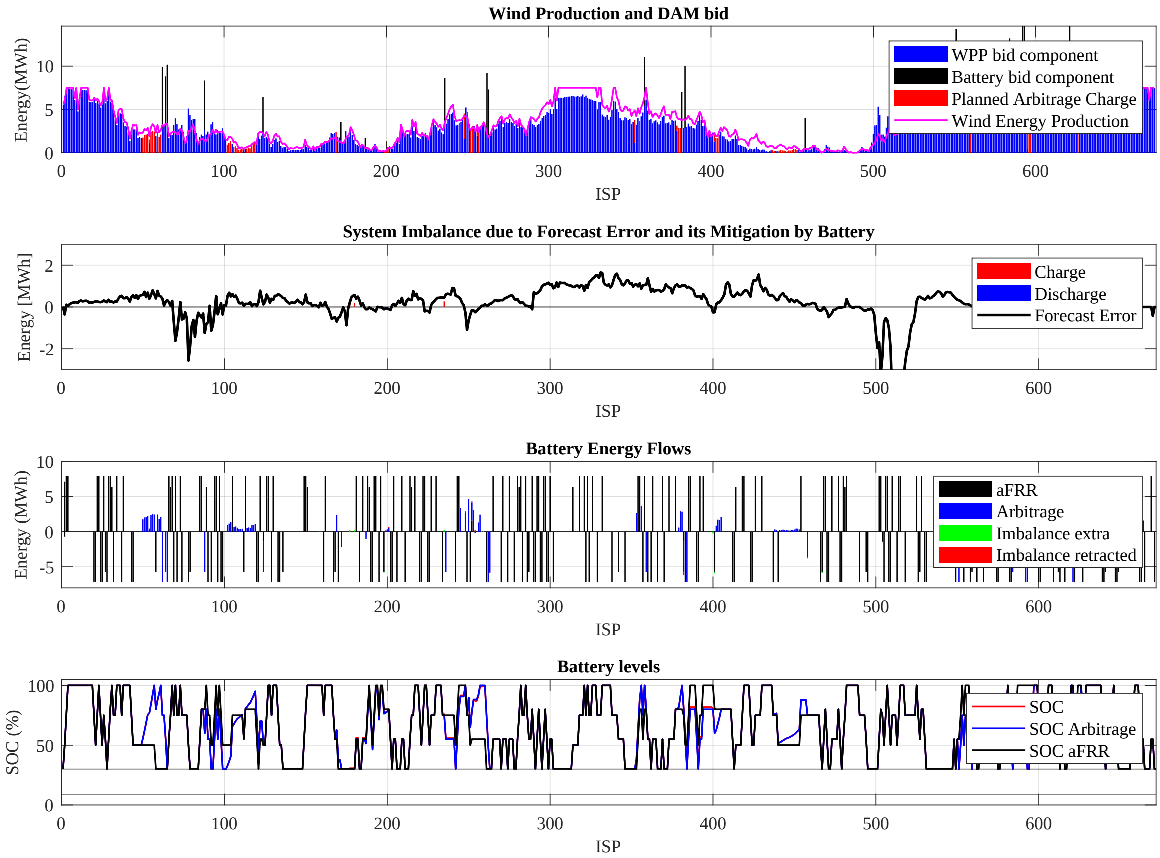

Figure 6.2: Selected parameters from stacked case prioritizing free bid aFRR, followed by arbitrage and imbalance mitigation, during the first week of 2019 for a 4-hour 30 MWh battery.

In figure 6.3 the operational parameters are shown for the scenario where the battery operation is first optimized for DAM arbitrage and the remaining space is used to place free bids in the aFRR market. In section 4 it was noted that the battery operation for DAM arbitrage has a low cycle frequency. This behaviour leaves room to placing aFRR bids alongside the arbitrage bids. This is shown by the frequent deviation of the blue aFRR SOC trajectory from the black arbitrage SOC trajectory. The combined aFRR and arbitrage bids leave little room for imbalance mitigation as can be seen in the second plot and the fact that the achieved SOC trajectory in red doesn't deviate often from the blue trajectory. The energy prices are identical to those in figure 6.1.

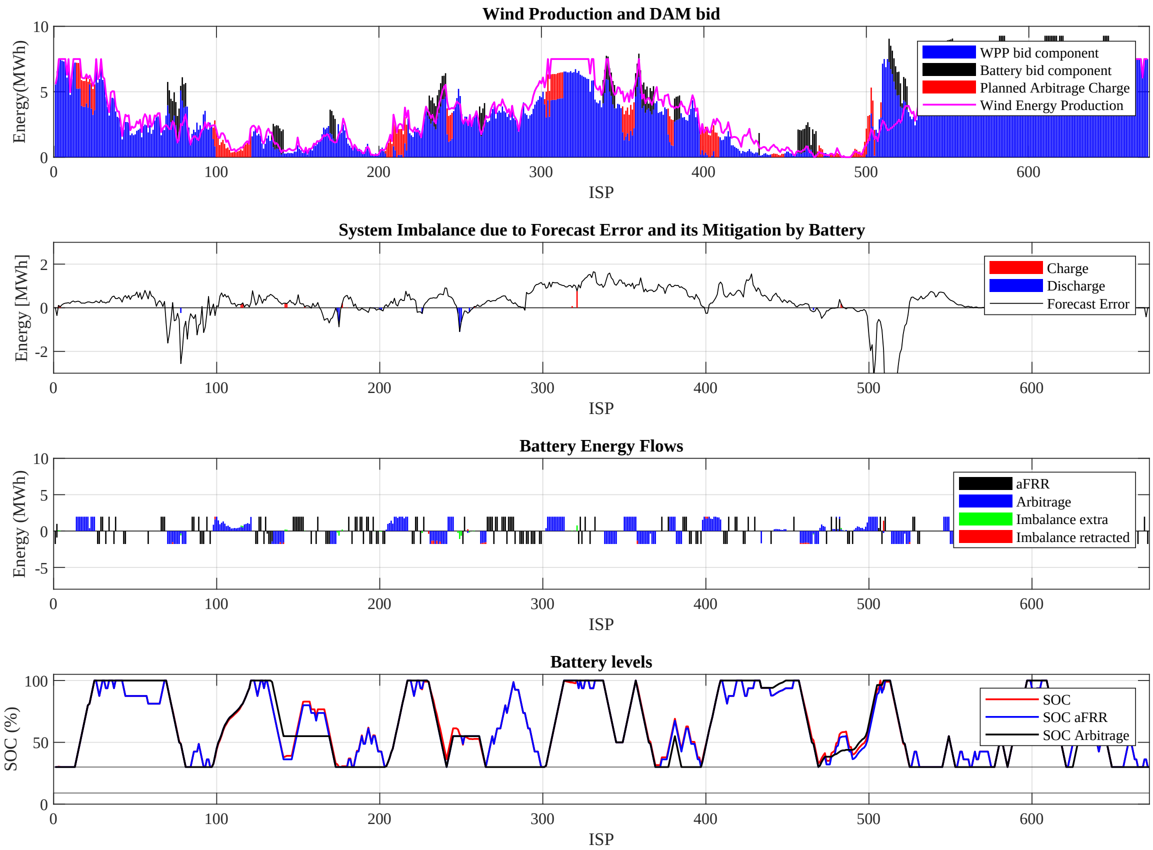

Figure 6.3: Selected Parameters from stacked case prioritizing DAM arbitrage, followed by free bid aFRR and imbalance mitigation, during the first week of 2019 for a 4-hour 30 MWh battery.

6.2. Economics

In figures 6.4 and 6.5 the normalized revenues and IRR curves are shown for the stacked case that prioritizes DAM arbitrage followed by free bid aFRR and imbalance mitigation. To recap, in section 4 it was shown that employing storage for arbitrage alone did not lead to higher IRRs compared to the no-storage case. In these figures, it can be seen that the addition of stacking arbitrage with free bid aFRR pushes the IRR curves of the 1 and 4-hour batteries into the value-adding region. Additionally, in the arbitrage only case, it was observed that, whilst all battery configurations were ultimately unprofitable, the 8-hour battery performed best and the 1-hour battery performed worst. In this stacking scenario, the 1 and 8-hour batteries have flipped these positions as now the 1-hour battery performs best. The explanation for this comes from section 5 where it was observed that high power batteries are more profitable than low power batteries when providing free bid aFRR. This observation still seems to be valid when providing aFRR on top of arbitrage.

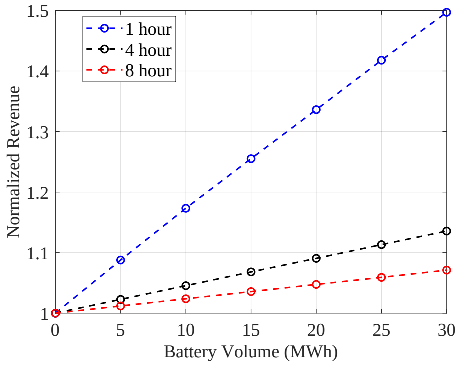

Figure 6.4: Normalized Revenue for Arbitrage followed by aFRR Scenario

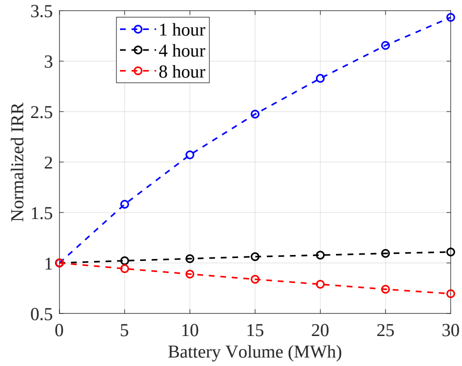

Figure 6.5: Normalized IRR for Arbitrage followed by aFRR Scenario

The benefit of this stacked behaviour becomes clear when the revenue is broken down by source as shown in table 6.1. In this table the added revenue compared to the wind only revenue is shown in percentages. For the 1-hour battery, the aFRR provides a significant addition to the total revenue.

Table 6.1: Added revenue break down from the stacked scenario prioritizing arbitrage for a 15 MWh battery

Revenue Source	1 Hour	4 Hour	8 Hour
Arbitrage	2%	2%	1%
aFRR	22%	4%	1%
Imbalance	1%	1%	1%

In figures 6.6 and 6.7 the normalized revenue and IRR curves are shown for the scenario that prioritizes contracted aFRR bidding followed by DAM arbitrage and imbalance mitigation. The IRR curve is similar to the non-stacked contracted bids case from section 5. In this case, stacking doesn't provide significant additional revenue. This is arguably contradictory to what could have been expected from the examination of the operational parameters for this case in figure 6.1. The operational parameters showed that this approach allowed for the trading of significant arbitrage volumes on top of providing contracted aFRR. However, the added revenue of arbitrage is relatively low as concluded in section 4. Therefore, even though significant arbitrage trading volume is present, the stacking of arbitrage doesn't provide significant revenue addition compared to the contracted aFRR case from section 5. The low potential of arbitrage can be confirmed by the added revenue breakdown in table 6.2.

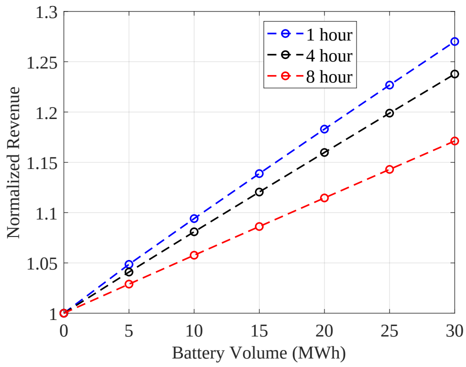

Figure 6.6: Normalized Revenue for Contracted aFRR followed by Arbitrage Scenario

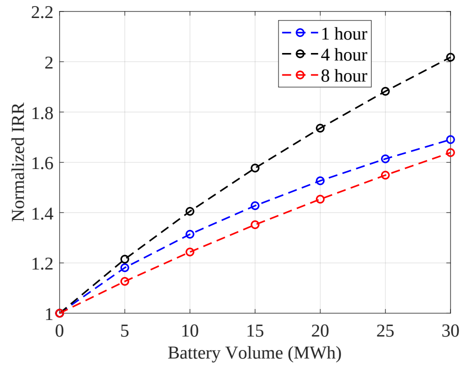

Figure 6.7: Normalized IRR for Contracted aFRR followed by Arbitrage Scenario

Table 6.2: Added Revenue Breakdown from the Stacking Case Scenario Prioritizing Contracted aFRR for a 15 MWh Battery

Revenue Source	1 Hour	4 Hour	8 Hour
Arbitrage	1%	1%	0%
aFRR - Energy	6%	6%	5%
aFRR - Capacity	6%	5%	3%
Imbalance	1%	1%	0%

Similar to contracted aFRR, the free bid aFRR normalized revenue and IRR curves in figures 6.8 and 6.9 show little improvement compared to their non-stacked case in chapter 5. Contrary to contracted aFRR, this behaviour could have been expected from the operational parameters in figure 6.2. Little room for stacked trading of significant arbitrage volume is left due to the aggressive nature of the free bid aFRR trading. Nevertheless, even if more arbitrage volume could have been traded it would still add relatively little revenue due to its previously concluded low potential. Table 6.3 confirms once again that stacking of arbitrage on aFRR provides relatively little revenue gains compared against the substantial added revenue that aFRR brings.

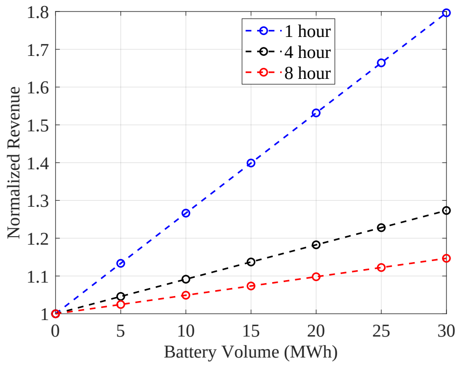

Figure 6.8: Normalized Revenue for Free Bid followed by Arbitrage Scenario

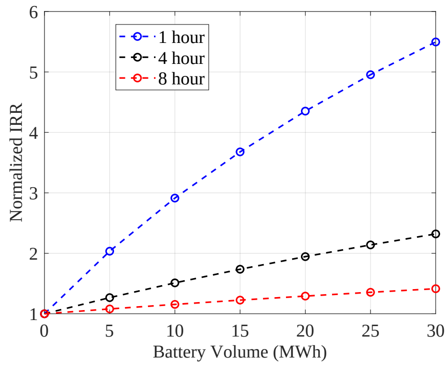

Figure 6.9: Normalized IRR for Free Bid followed by Arbitrage Scenario

Table 6.3: Added revenue breakdown as a percentage of WPP DAM revenue from the stacking case Scenario prioritizing Free Bid aFRR for a 15 MWh Battery

Revenue Source	1 Hour	4 Hour	8 Hour
Arbitrage	1%	1%	0%
aFRR - Energy	39%	13%	7%
Imbalance	0%	0%	0%

6.3. Sensitivity

The high percentage of aFRR revenue over DAM arbitrage revenue entails that the sensitivity of the aFRR bidding block to market forecasts, replacement costs and investment costs will dominate the sensitivities of the stacked cases. These analyses have been made in section 5. Rather than repeating these analyses for slightly different values, the question is asked if a case is possible without having any imbalance price forecast. In section 2.4 it was explained that a BRP receives a signal from Tennet with the imbalance price in the current ISP. Based on this signal an alternative strategy can be proposed. Whenever the current imbalance price is higher than the DAM price the storage system is discharged and vice versa. In this way, the system provides frequency services as a BRP instead of as a BSP.

This no-forecast scenario doesn't allow for stacking of the proposed value-adding mechanisms. Instead it should be seen as another type of stacking case. As mentioned in section 1.2, WPPs are sometimes required to have storage capacity on site. More use can be made of this pre-existing storage capacity by employing it to perform this no-forecast scenario.

The imbalance price is determined at the end of each ISP based on the highest or lowest priced activated bid. Whenever the grid state during an ISP was 2 it means that both up and down bids were activated. This also means that the imbalance price will have fluctuated severely during the ISP. The model only works with the final prices per ISP and would therefore benefit more than realistic during ISPs with regulation state 2. Therefore, in post-processing, the revenues made during ISPs with regulation state 2 are all set to be zero. The resulting normalized IRR for this scenario is shown in figure 6.10.

The high power batteries show potential in this scenario. However, this is once again a strategy with a high cycle frequency. This can be seen in table 6.4. The resulting replacement costs and their effect on the normalized IRR are shown in figure 6.11

Table 6.4: Yearly number of cycles made by the storage system

Scenario	1 Hour	4 Hour	8 Hour
No Forecast	1400	490	265

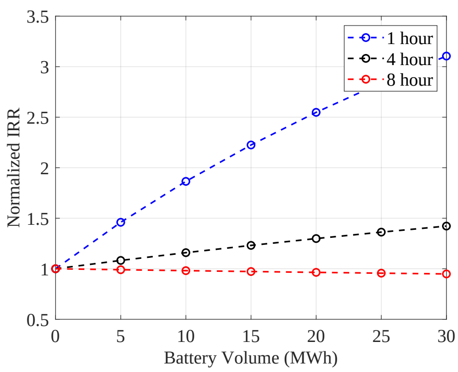

Figure 6.10: Normalized IRR for the no-forecast scenario

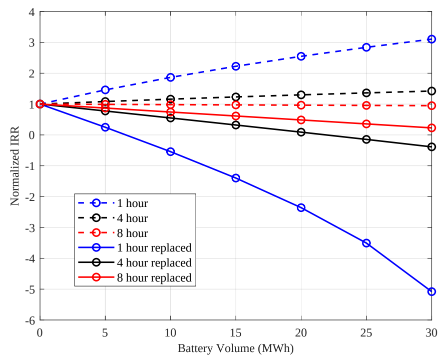

Figure 6.11: Normalized IRR for the no-forecast scenario with and without storage replacement costs

6.4. Main Findings

The potential of DAM arbitrage pales in comparison with the potential of aFRR. The main conclusion is then that aFRR is a valuable addition to stack on top of DAM arbitrage. DAM arbitrage offers marginal improvements when stacked the other way around. The aFRR revenues dominate in the stacking case. Therefore, the sensitivities of these scenarios are expected to be similar to those from the AS case.

The volatility of the DAM price is expected to rise in the future (CE Delft, 2020). This will increase the potential for DAM arbitrage. If the potential for DAM arbitrage increases to a point that it is significant compared to the potential of providing AS, then stacked operation can become an interesting topic for future research.

An attempt was made to perform simultaneous optimization in all markets. A working result was not achieved as the model would trade energy between DAM and aFRR without any energy flowing. For instance, it would place a down bid in aFRR and a DAM bid of the same size. Then it would deliver on the aFRR bid by not delivering on the DAM bid. Through this mechanism, the model would receive the price delta between the DAM price and imbalance price without actually having traded any energy. This problematic behaviour could be resolved by implementing several nonlinear constraints and consequently using a nonlinear solver. The simultaneous optimization of two markets will occur in reality only when providing contracted aFRR and DAM arbitrage because both bids need to be submitted at 12:00 D-1. For this reason, and the fact that stacking optimizations instead of performing one simultaneous optimization already gave relevant insights, this addition was deemed to be too time-consuming to include in the project and is, therefore, out of scope.

7 Conclusions

Energy systems are facing the challenges posed by the energy transition. The intermittent nature of RES will call for increased volumes of balancing energy to be available to guarantee grid stability. These developments have TSOs researching innovative approaches where balancing energy is provided by aggregated storage and RES systems. Storage is widely regarded as an answer to these technical challenges. The lack of economic incentives for utility-scale storage is the missing link between the technical benefits and mass implementation. This study was aimed at exploring the existence of these economic benefits. Three cases were defined and simulated for the example storage technology i.e. Li-ion BESS.

The potential for DAM arbitrage was found to be too low at current Li-ion investment costs. Storage technologies with 80% to 65% lower investment costs than current Li-ion costs will make DAM arbitrage possible. However, this result doesn't take storage degradation or imperfect forecasts into account. Cost projections for utility-scale battery storage expect capital cost reductions ranging from 10 - 52% for 2025 and 21-67% for 2030 (Cole & Frazier, 2019). Furthermore, it has been shown that DAM arbitrage doesn't require storage technologies with high power ratings as the 8-hour battery performed best in terms of IRR. This is caused by the gradual changes in DAM prices throughout the day. The optimal operation typically sees 1 to 2 charge cycles a day. Increasing penetration of RES on the grid might cause DAM prices to become more volatile in the future making DAM arbitrage more interesting as a consequence.

Operation in the aFRR market has shown significantly more potential. It has been shown that a 6-fold improvement of the normalized IRR is the theoretical upper limit for Li-ion technology in the free-bid aFRR market. The sensitivity analyses for battery degradation show that reaching this theoretical potential is not probable at current cycle-life levels for Li-ion. Furthermore, it was shown that contracted aFRR has a lower theoretical upper limit but is less sensitive to storage replacement costs. Additionally, contracted aFRR is less sensitive than free-bid aFRR to imperfect market forecasts but due to the lower upper limit, the normalized IRR dropped below the break even point with imperfect forecasts. Free-bid aFRR retained a normalized IRR above break even with imbalance price forecasts that slightly outperform the current state of the art. The high potential for free-bid aFRR comes with the sidenote that the Netherlands is currently one of the only countries in the European grid area that allows for non-pre-contracted bids in aFRR. In conclusion, free-bid aFRR has a higher theoretical upper limit but due to lower sensitivities, it can be expected that contracted aFRR might earlier be adopted by market participants as a value-adding service.

Stacking of DAM arbitrage and aFRR shows little benefits over solely using the storage system to provide aFRR. This might change in the future if the DAM market's volatility increases to a point that the added revenue becomes significant compared to the added revenue from aFRR. If this occurs then it is recommend to stack DAM arbitrage with free-bid aFRR because this approach has the highest total amount of energy traded by the storage system.

Two arguments were given in the introduction for co-location over a standalone storage system. The first being the pre-existence of co-located storage for safety reasons and the second being imbalance mitigation. It has been shown that the potential for the latter is low. Imbalance costs accounted for 3% of total revenues. Therefore no strong arguments exist for geographically co-locating utility-scale storage. However, from the perspective of a WPP operator, there are other arguments for adding storage to the companies portfolio. The profitability of WPPs will come under pressure from declining DAM prices caused by the increasing share of RES in the energy mix. This same development drives the increasing price volatility and balancing costs that will fuel the profitability of storage systems. Therefore, it can be hypothesized that in the long run WPP operators would benefit from investing in storage research and pilots today.

Because no strong arguments for co-location exists, it is recommend that future master theses on business cases for grid-connected storage don't focus on co-located storage. The business case for storage is believed to be independent of being co-located with a RES when operated for DAM arbitrage of frequency support. Co-location does remain a relevant topic in other fields, such as micro-grids, congestion management or power-2-x technologies. Instead, future theses can look into the potential of adding intra-day trading as a market. Furthermore, the methods used to construct forecasts for imbalance price and regulation states in this project can be improved. Future theses can also look into optimization methods that can have stochastic forecasts as inputs. These methods can also include an element of risk management where the storage system is operated less aggressively when nearing the SOC boundaries. Lastly, the sensitivity to storage degradation was based on a highly simplified approach. It has been shown that the results are relatively sensitive to the storage replacement costs. Therefore, future theses should incorporate more accurate degradation models.

The business case for storage, as put forth in this project, might not exist today. However, strong clues exist that it will in the future. The predicted drop in costs of storage and the increased volatility in electricity markets will provide opportunities for the profitable operation of storage systems. When that time comes WPP operators should also be interested to operate these storage systems to further their goal of competing with traditional fossil fuel-fired power plants.

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A

Appendix: Preliminary Study (Mehta et al., 2021)

Technical and economic value of utility-scale wind-storage hybrid power plants

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***Abstract*—The potential technical benefits of wind-storage hybrids, mainly arbitrage, imbalance reduction, and frequency support, are convincing enough to launch demonstration projects. However, a quantitative analysis of these benefits, including economic considerations, is lacking. The aim of this study is to establish at what costs such technical benefits can be achieved, and whether developers reap sufficient economic advantage to make the development of such hybrid plants attractive. A wind-storage power plant is simulated for arbitrage, imbalance revenue maximization, and secondary frequency support using the Internal Rate of Return as a parameter to measure the economic performance. It is found that, for a wind-farm developer, deploying batteries just for arbitrage and/or imbalance revenue maximization does not improve profitability at current levels of battery costs. However, there is a strong economic incentive for a wind farm developer to deploy batteries to participate in the secondary frequency market.**

Keywords: Hybrid power plant, wind power, battery energy storage, energy markets, ancillary services

I. Introduction

The role played by renewables in meeting the decarbonization goals cannot be emphasized more. A large number of wind and solar farms are being deployed owing to the widespread presence of the resource and maturity of the technology. However, as the penetration of wind and solar energy in the energy system increases, the integration poses a major challenge. As wind and solar depend on the availability of the resource, which is uncontrollable, they are intermittent in supply. This leads to various issues related to high balancing reserves and their associated integration costs (upto $5/MWh, shown by W. Katzenstein and J. Apt [1]), inefficient use of the grid infrastructure, frequency fluctuations, forecasting errors, etc. Adding storage can alleviate some of these issues. Deploying storage at a generator or a system operator level can reduce power imbalances from forecasting errors, enable energy arbitrage, provide frequency support, flexibility of generation, congestion relief, etc. As mentioned in a report of IRENA [2], of all the storage types, battery storage (especially Li-ion) makes up the largest share of total installed storage capacity, mainly due to its rapidly declining costs. This research explicitly focuses on co-located wind-battery storage Hybrid Power Plants (HPP).

Adding storage to wind has seen a lot of positive light in the past few years in the form of both demonstration and commercially operational projects. As discussed by Wind Europe [3], about 400 MW of co-located wind-storage hybrids have already been made operational (or announced) globally, where battery is mainly used as the storage source. Petersen *et al.* [4] discuss the learnings from the hybrid power plant projects of Vestas. For instance, the Lem Koer project demonstrated the advantages of coupling wind with storage in the form of reduced penalties, reduced ramp rates, capabilities in providing ancillary services, etc. Klonari *et al.* [5] study the existing HPP around the world, of which most systems are a combination of wind and storage, and identify drivers and barriers followed by some probable policy changes that could be implemented. The authors identified capacity firming to be the most widely used functionality of a hybrid power plant, and they also state that the business case of having HPP, from a developer point of view, is still under development. An important conclusion drawn by the authors was that these utility-scale HPP are not fully rewarded by the current market incentives.

Extensive research has been carried out on detailed modelling of wind-storage HPP where the enhanced value of adding storage is discussed. B. Cheng and W. Powell [6] optimized the battery for arbitrage and frequency control using multi-scale dynamic programming. However, the main objective was to develop and display the functionality of the algorithm. Heredia *et al.* [7] developed a stochastic model to find the optimal operation of a wind-battery system in the day-ahead, intraday, and the secondary reserve market taking into account all the uncertainties. The authors concluded that profits from the reserve market exceed that of the day-ahead market, and the increase in total profit was about 10%, compared to the wind-only case, when the battery was used for the day-ahead and imbalance market. Similar results w.r.t revenue increase were reported by Kaushik *et al.* [8] where the optimal operation of a wind-battery system in the Danish market is shown. Bolado *et al.* [9] also analyze the value of storage in performing arbitrage including price forecasting using Artificial Neural Networks.

However, an analysis including storage costs is missing, which is also the case for many studies where the focus is the efficacy of the model/algorithm. Sioshansi [10] examined the use of storage for arbitrage. The author reported that the current costs of storage technologies may not justify this use. This conclusion is more relevant to this research as the aim here is to provide a preliminary techno-economic analysis in order to identify the use cases where adding storage would be economically beneficial to the developer:

'The objective is to establish, by quantitative analysis, the scenarios under which wind-battery HPP could be economically beneficial from a generator point of view.'

The paper first describes a generic bidding and real-time operation model for wind-storage HPP applied to a model of the electricity market of the Netherlands. The strategies for two specific storage applications, namely the energy market and the imbalance market (ancillary services), are then described. Finally, the case study definition is provided and the results for the two storage applications are discussed.

II. Generic model

This section discusses the general modelling approach used in this research.

A. Model overview

A complete setup of the model is shown in Figure 1. The red lines represent flow of information while the black lines represent actual power flow. The bidding block uses forecasts from the wind and the market to make predictions, day-ahead, and place the bid in the spot or imbalance market, depending on the application of storage. In real-time, the controller uses actual market information along with actual wind generation and battery energy status to make opportunistic decisions. The controller decides whether to send the wind power as it is to the grid, whether to charge the battery using wind, whether to discharge the battery along with wind, whether to take in energy from the grid, etc. This is indicated by the red signal that operates the switch.

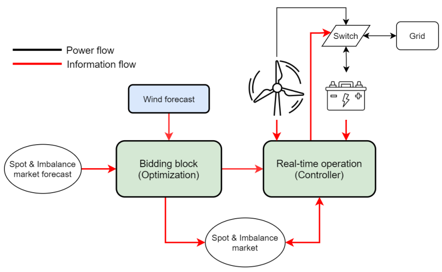

Fig. 1. Generic model of wind-storage HPP investigated

In this research, it is assumed that the controller has perfect knowledge of both the spot and the imbalance market while optimizing the bids day-ahead. It is known that this is not completely realistic but it sets the best economic case for wind-storage HPP. The objective is to have a preliminary model to find out applications that are economically profitable for storage which can then form as a basis for future detailed studies.

B. Wind

For wind speeds below cut-in, the power is zero while for wind speeds between rated and cut-out, the turbine operates at P_{rated}. For all the wind speed values between cut-in and rated, the power produced can be determined using equation (1), where v is the wind speed, C_p is the power coefficient, A_{rotor} is the area of the rotor, and η_{dt} is the drivetrain efficiency.

$$P(v) = 0.5 \cdot C_p(v) \cdot \rho \cdot A_{rotor} \cdot v^3 \cdot \eta_{dt} \tag{1}$$

To simulate the wind forecasts, an error signal is imposed on the actual wind generation. This error signal is based on the nationwide error between wind forecasts and actual generation. The Netherlands being a small country (by area), it is assumed that the forecasting errors made by all the wind generators are in the same direction. The histogram of forecasting errors normalized w.r.t the nationwide installed capacity is shown in Figure 2. The data used is open-source, provided by the European Network of Transmission System Operators for Electricity (ENTSO-E) [11].

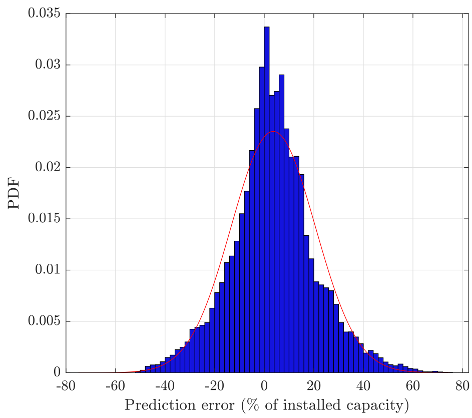

Fig. 2. Offshore wind forecasting error (as a function of installed wind capacity) in 2019

C. Storage

In this paper, storage is coupled with wind for two different applications. For each use case, a different objective function is implemented, and will be stated in the next chapter while the constraints implemented are nearly the same other than the case specific constraints.

The battery energy level (E_{batt}) and the normalized State Of Charge (SOC) at any given time stamp are given by equation (2) & equation (3), respectively.

$$E_{batt}(t) = E_{batt}(t-1) + x_{cha}(t-1) \cdot \eta_b - x_{dis}(t-1) \cdot \frac{1}{\eta_b} \tag{2}$$

where x_{cha} and x_{dis} is the power with which the battery is being charged and discharged, respectively. Also, depending on charging or discharging, the efficiency term (η_b) is adjusted.

$$SOC(t) = \frac{E_{batt}(t)}{E_{cap}} \tag{3}$$

where E_{cap} is the total battery energy capacity.

D. Market

This study deals with two different markets, namely the spot market and the imbalance market. In the bidding phase, it is assumed that the controller has perfect forecast of both markets. Using this information along with the wind forecast, it places a bid. The bid being placed in the spot market or the imbalance market depends on the storage application. If the battery is used for arbitrage, it places the bid in the spot market while if the battery is used to provide ancillary services, it places a bid in the imbalance market. In real-time, using the real-time wind generation, battery energy state, and market information (which, due to the assumption, is the same as the forecast), the controller decides how to re-iterate the operation of the hybrid plant so as to maximize the revenue.

E. Bidding & real-time operation

The bidding block uses an optimization algorithm so as to optimize the operation of the hybrid plant to maximize the revenue while in real-time, the controller simply re-iterates the operation based on actual information of the market, wind generation, and battery energy state. These two blocks can be best explained for the given storage application and will be discussed in detail in the next chapter.

F. Economic figure of merit

The figure of merit chosen in this study to evaluate the economic feasibility of a particular configuration is the Internal Rate of Return (IRR). It is the rate at which the Net Present Value (NPV) of a project is zero, as shown in equation (4), where Cf_n represents the cash flows over the years and C_0 represents the initial investment. Thus, by comparing the IRR values of different cases, the better performing case can be identified.

$$0 = NPV = \sum_{n=1}^{N} \frac{Cf_n}{(1+IRR)^n} - C_0 \tag{4}$$

The IRR values for different wind-storage configurations have been normalized with the wind-only case. In this case, an IRR lower than 1 does not mean the business case has negative value, or isn't profitable. It simply means that the case is not as profitable as the wind-only case.

III. Storage applications

The purpose is to use storage to enhance the value of an existing wind farm by tapping into two different possible revenue streams. To guide the reader with some nomenclature, a generator participating in the day-ahead energy market is referred to as the Balance Responsible Party (BRP) while a generator providing frequency restoration services to the grid operator, by placing bids in the imbalance market, is referred to as the Balancing Service Provider (BSP). It should be noted that an asset can also be registered both as a BRP and as a BSP so as to provide services in multiple markets.

A. Energy arbitrage with imbalance revenue maximization

Energy arbitrage is a concept wherein the instants of production and consumption are separated. To maximize the revenue, battery storage can be used to store some energy when the day-ahead market prices are low and sell energy when the market prices are high. Also, as the developers place their bids day-ahead, the prediction of overall farm output needs to be done 12-36 hours in advance, which could result in a significant deviation between forecasted power and actual power generation. This is where battery storage could add value by maximizing the revenue from imbalances. Here, the wind-storage plant is solely acting like a BRP, placing bids in the spot market.

To place the bids in the day-ahead market, a simplex optimization algorithm is used to determine the combined power of wind and batteries in order to maximize the revenue. The bids are then placed in the market by 12 pm on the previous day. The most basic form of optimization for arbitrage using storage can be summarized by equation (5), where x is the design vector, consisting of battery charge (x_{cha}) and discharge (x_{dis}) values (adjusted w.r.t efficiency), λ_{DAM} is the day-ahead market price, 96 is the number of Imbalance Settlement Periods (ISPs) in a day, and P_{cap} is the maximum battery power capacity, depending on the duration and battery energy capacity. Also, the battery SOC obtained as a result of the last charge/discharge value of a given day is set as the initial SOC level for the new optimization to be carried out for the next day.

$$\begin{aligned} \max_{x} \quad & f(x) = \sum_{t=1}^{96} (x_{dis}(t) - x_{cha}(t)) \cdot \lambda_{DAM}(t) \\ \text{s.t.} \quad & 0 < x_{dis}(t) < P_{cap} \\ & 0 < x_{cha}(t) < P_{cap} \\ & 0.3 < SOC(t) < 1 \\ & SOC(t=97)_{new} = SOC(t=97)_{opt} \\ & SOC(t=97)_{D} = SOC(t=1)_{D+1} \end{aligned} \tag{5}$$

In real time, the actual wind generation, spot prices, and the imbalance price for every 15 mins (ISP) are checked. Based on the power deviations between wind generation and the placed bid (P_{diff}), and the price difference between imbalance and spot price (δ), a decision is made whether to re-iterate the battery operation or to stick to the original battery schedule.

For a situation where wind generation is higher than the bid volume ($P_{diff} > 0$):

- If $\delta > 0$, sell the excess to the imbalance market instead of charging the battery.
- If $\delta < 0$, charge the battery to minimize P_{diff} and if some imbalances still remain, sell to the imbalance market.

For a situation where wind generation is lower than the bid volume ($P_{diff} < 0$):

- If $\delta > 0$, discharge the battery to minimize P_{diff} and if some imbalances still remain, buy from the imbalance

market.
- If $\delta < 0$, buy the deficit from the imbalance market instead of discharging the battery.

B. Ancillary services

Frequency regulation, voltage control, black-start capabilities, are some examples of ancillary services that can be provided by storage. The imbalance market in the Netherlands comprises of the primary, secondary, and tertiary frequency market. The primary frequency market responds to the real-time grid frequency, at a time resolution of one second, while the secondary frequency market operates at a time resolution of 15 minutes. In this paper, a preliminary analysis for the secondary frequency support market, also known as the automatic Frequency Restoration Reserve (aFRR) market is performed. According to Tennet [12], the TSO of the Netherlands, the secondary frequency market is about thrice the size of the primary frequency market, which is also a reason why it was chosen.

For a contracted BSP in the aFRR market, there exists a capacity and an energy remuneration. The BSP bids a fixed capacity in the upward and downward direction for the entire day, day-ahead, for which it receives the capacity remuneration, and every time the BSP is activated in real time to resolve the imbalances in the system, it receives an energy remuneration as well. In this analysis, it is assumed that the wind side of the HPP acts as a BRP while the battery serves a dual purpose where it acts as a BSP and also tries to maximize the imbalance revenue, where the imbalances are due to the errors in the wind power prediction. It is assumed that the BSP has perfect knowledge of the imbalance market day-ahead. It is known that this assumption is not realistic but it sets the best possible economic case for battery storage. It is also assumed that the BSP is always activated hence receiving an energy payment for each Imbalance Settlement Period (ISP) along with the capacity payments.

Based on the perfect information assumption of the imbalance market, the aFRR optimizer decides the up and down bids to be placed in the market. The wind forecast is directly used to bid in the day-ahead market. The objective function is given by equation (6) and the optimization can be summarized by equation (7). The two variables x_{up} and x_d represent the capacity bid in the imbalance market in the upward direction (battery discharge) and downward direction (battery charge) respectively. The activation state of the bid is represented by two boolean vectors, β_{up} and β_d. The imbalance market in a state of up-regulation for a particular ISP would result in the β_{up} for that ISP being 1 and β_d being 0, and the reverse for down-regulation. The capacity remuneration can be determined by multiplying λ_{cap}, the capacity revenue in Euro/MW/hr, with the capacity offered (the same for 24 hours) while the energy remuneration can be obtained by multiplying the net energy delivered in a particular ISP and λ_{imb}, the imbalance market price. The division by 4 converts the power delivered to energy for a given ISP (15-min).

$$
\begin{aligned}
f(x) = (x_{up} + x_d) \cdot 24 \cdot \lambda_{cap} + \\
\sum_{t=1}^{96} (x_{up} \cdot \beta_{up}(t) - x_d \cdot \beta_d(t)) \cdot (\frac{1}{4}) \cdot \lambda_{imb}(t)
\end{aligned}
\tag{6}
$$

$$
\begin{aligned}
\max_{x} \quad & f(x) \\
\text{s.t.} \quad & 0 < x_{dis}(t) < P_{cap} \\
& 0 < x_{cha}(t) < P_{cap} \\
& 0.3 < SOC(t) < 1 \\
& SOC(t = 97)_{new} = SOC(t = 97)_{opt} \\
& SOC(t = 97)_D = SOC(t = 1)_{D+1}
\end{aligned}
\tag{7}
$$

In real time, depending on the actual wind generation and the imbalance situation in the country, the battery decides whether to mitigate the forecasting error in the wind generation or whether to settle it via the imbalance market. It should be noted that the battery mitigates the error only if doing so does not hamper the aFRR schedule of the battery for the rest of the day.

IV. Case study definition

This section discusses the general set of assumptions, and the wind and storage parameters used in this research.

A. Generic assumptions:

Some general assumptions that are adopted throughout the study are listed below:

- All studies are performed for the Netherlands.
- Wind speed, spot price, and imbalance price data have a temporal resolution of 15-min.
- Cesar observatory measurement data for the wind speeds are used.
- The data points are temporally correlated, and are from 2019.
- The study assumes utility-scale HPP.

B. Wind power

The system specifications used for the analysis are listed in Table I where P_{rated} is the rated power of the turbine and D_{rotor} is the rotor diameter.

TABLE I
Assumptions related to wind

	System assumptions	
Wind	Turbine P_{rated}	5 MW
	Turbine D_{rotor}	128 m
	Total installation costs	$1870/kW

The Power coefficient (C_p) of the turbine used is based on the power curve of the Siemens Gamesa G128-5 turbine.

C. Storage

The system specific assumptions pertaining to storage are listed in Table II. A battery lifetime model has not been included in this analysis. The intent however is to carry out a preliminary analysis using the best possible conditions and identify if the use case has some potential value.

TABLE II
ASSUMPTIONS RELATED TO STORAGE

Storage assumptions	
Storage type	Li-ion
Duration	1,4 & 8 hour battery
Energy costs	$ 165/kWh
Power costs	$ 125-365/kWh (duration dependent)
Round-trip efficiency	90 %
SOC limits	0.3 - 1

V. Results & Discussion

This section discusses the economic value of wind-storage HPP, from a developer perspective, for the two described storage applications. For each storage application, a working example of the algorithm is shown first followed by the economic value of storage.

A. *Energy arbitrage with imbalance revenue maximization*

A plot displaying the behaviour of various parameters is shown in Figure 3. In the first subplot, the blue line is the wind power forecast while the red bars are the bids placed in the day-ahead market along with battery charge/discharge values, optimized to maximize the revenue. A value higher than the blue line indicates battery discharge, which can also be seen as a positive red peak in the third subplot. The blue line in the third subplot indicates the re-iterated battery operation taking into account real time wind generation and imbalance prices. The second subplot shows the prices in the spot and the imbalance market while the fourth plot shows the ideal (planned) and new battery SOC.

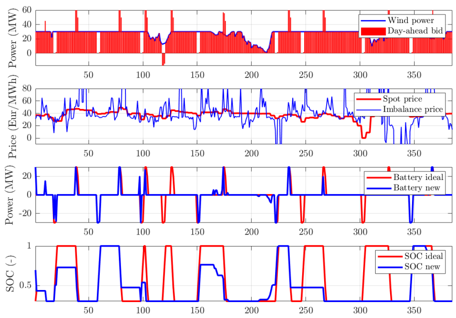

Fig. 3. Typical parameters plotted over time to illustrate the working of the algorithm for arbitrage along with imbalance revenue maximization

As an example, just before the 250^{th} time stamp, the bid indicates that the wind power charges the battery so as to discharge at a later point when the spot prices are higher. However, in real time, the controller observes that the imbalance prices are extremely high (as the country was in an overall deficit) which is why it chooses to ignore the original bid and instead sells the wind power directly in the imbalance market. In such a case, the battery state remains unchanged as seen by the flat blue line in the third subplot and the flat SOC line in the fourth subplot.

Figure 4 shows the increase in revenue, with the majority stemming from arbitrage, due to added battery storage. It should be noted that in the Netherlands, a developer is not charged a direct penalty for a deviation made from the bid value. As long as the deviation mitigates the system imbalance, the developer is rewarded. This is why even for the wind-only case, a forecasting error may be beneficial as long as it helps restoring the system imbalance. For instance, if a wind farm generator produces more than the forecast at a time when the country is in a deficit, the generator would receive the imbalance price (higher than the spot price) for the additional power generated.

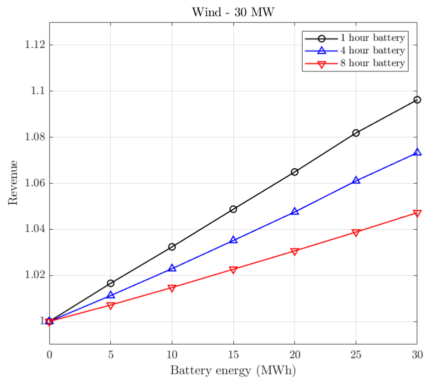

Fig. 4. Normalized increase in revenue due to storage

Similar results w.r.t revenue have been reported by Kaushik *et al.* [8] where the authors performed extensive simulations for the day-ahead market case including effects of battery lifetime, wind forecasts, and market forecasts on the revenue.

Figure 5 shows a complete picture of the economics of the system.

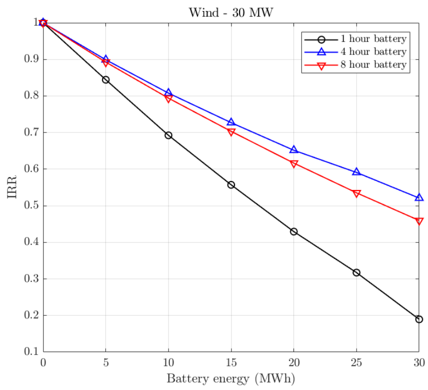

Fig. 5. Economics of a wind-storage system for arbitrage with imbalance revenue maximization

When the battery costs are taken into account, the IRR drops compared to the wind-only case. This indicates that there is no added incentive for a wind farm developer to deploy storage for arbitrage along with imbalance revenue maximization.

It is estimated that the battery costs need to drop by about 50% in order for the arbitrage case to be more profitable than the wind-only case. Also, day-ahead market prices have a major influence on this result. With a higher share of renewables in the grid, there may be more margin for arbitrage resulting in an added value for storage.

B. *Ancillary services*

A plot displaying the behaviour of various parameters is shown in Figure 6. The first subplot shows the capacity bids activated for a given day. A positive value indicates discharge (or power to be sold in the market) while a negative value indicates charge (or power to be bought from the market). It should be noted that all the charge bids need to have a constant capacity for a given day, and the same also holds for all the discharge bids. For some ISPs, the bidding optimizer does not place a bid (e.g. at time stamp 105). These rare instances correspond to a regulation state where the Transmission System Operator (TSO) does not activate any bids or a situation when both upward and downward bids are activated. The second subplot shows the difference between wind forecast and actual generation. The third subplot shows the old SOC value (optimized for the aFRR market) and the new SOC value (after iterations made to maximize imbalance revenue).

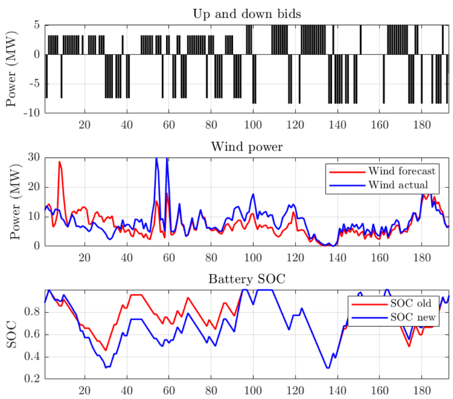

Fig. 6. Key parameters plotted over time illustrating the working of the aFRR algorithm

As an example, before the 20^{th} time stamp, the actual generation is lower than the forecasted value. At the same time, the battery had placed a positive bid (indicating a market need for up-regulation in the system). This is a situation where the imbalance prices are usually higher than the spot price and hence, the battery tries to minimize the fluctuation by discharging more than predicted (seen by the deviation between the blue and the red SOC curve). An example of the opposite effect can be seen at the 90^{th} time stamp, where the actual generation is higher than the forecast and the battery had placed a negative bid (indicating a need for down-regulation in the system). This is why the battery decides to charge (seen by the blue SOC curve ramping up quicker than the red SOC curve).

Figure 7 shows the complete economic scenario of this particular use case where it can be seen that under the assumption of perfect market information, participation in the aFRR markets is highly profitable for a wind-storage system.

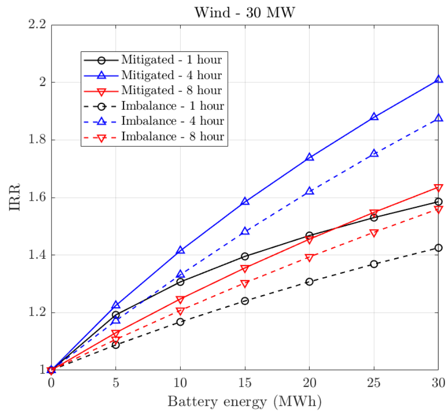

Fig. 7. Economics of a wind-storage system for the aFRR market with imbalance reduction

Due to the assumption of perfect imbalance market information, day-ahead, this case sets the upper bound to the profitability that can be achieved by using storage for contracted aFRR services. It is also observed that for the current battery costs, a 4-hour battery proves to be more beneficial than a 1-hour battery owing to the high battery power costs for a 1-hour battery with a marginal added benefit. The dashed lines represent the case where the battery is used only for bidding in the aFRR market while the solid lines represent the dual-use case where the battery is also used to maximize the imbalance revenue where the imbalances are generated from the wind forecasting errors.

VI. Conclusion

The analyses performed identified the value of adding storage to a wind power plant for two specific applications and recognized the economic benefit, if at all, to the developer. For wind-storage HPP, based on the above results and additional sensitivity studies, the following application-specific conclusions can be drawn:

A. *Arbitrage with imbalance revenue maximization*

- Adding a 1-hour battery for arbitrage and imbalance reduction, with an energy capacity roughly the size of the wind farm, can increase the revenue by about 10% compared to that of the wind-only case. However, in

terms of IRR, a 4-hour battery has a better economic case.
- Extra revenue/value added by energy arbitrage is about three times the revenue generated by mitigating the imbalances. The overall combined value still does not result in a business case better than the wind-only system.
- A reduction of about 50% in battery costs would be required to make it economically attractive (compared to the wind-only case).

B. Ancillary services

- Using battery storage to bid in the aFRR market along with its use to mitigate the imbalances has a strong economic case.
- A positive business case for storage is due to the assumption of having perfect information of the imbalance market day-ahead. A more realistic case, when the BSP has little prior information of the imbalances, would reduce the added value by storage. The realization of this maximum potential is highly dependent on the state of the art market forecasting capabilities.

This preliminary research suggests that providing ancillary services is a more attractive economic case for adding battery storage to an existing wind plant than arbitrage. It also shows that using the battery for maximizing imbalance revenue where the imbalances result from wind forecasting errors, has a significant added value. However, for an accurate estimate of the IRR and the true economic potential, other factors like imperfect market knowledge, battery lifetime, grid connections costs, limited grid capacity, etc. must also be included in the analysis.

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