Enhancing Flexibility in the Power Grid: A Study on Determining the Optimal Battery Size for Existing Wind Farms

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Abstract

The rapid expansion of intermittent renewable energy sources has introduced substantial challenges to both the stability of the electrical grid and the economic viability of incumbent wind farms. In light of recent regulatory amendments within the energy market, stakeholders are compelled to adjust their operational strategies. Concurrently, the expansion of wind power has exacerbated price cannibalization effects and increased price volatility, thereby heightening the imperative for enhanced system flexibility.

This thesis seeks to augment grid flexibility by determining the optimal integration of a Battery Energy Storage System (BESS) within existing wind-farm infrastructure, with the dual objective of improving producers' profitability. To this end, a Mixed-Integer Linear Programming (MILP) model is developed to identify both the optimal capacity and the dispatch strategy of a retrofit BESS. The model's objective function is formulated to maximize annual profit by (i) exploiting price differentials in the day-ahead and intraday markets, (ii) participating in Frequency Containment Reserve for disturbance (FCR-D) and normal operation (FCR-N) ancillary-service markets, and (iii) enforcing a stringent connection-point constraint that precludes charging from the grid. Six scenarios are systematically evaluated: a reference case; three variants prioritizing ancillary-service revenue streams; a scenario exploring variations in state-of-charge (SoC) operating ranges; and a case incorporating reduced BESS capital costs.

The results demonstrate the techno-economic feasibility of retrofitting BESS to existing wind farms. Under the reference scenario, the model identifies an optimal BESS rating of 15 MW/15 MWh for a size 200 MW wind farm, which cycles approximately 577 times per year. This configuration yields a 6.2 percentage-point improvement in capture rate, a Levelized Cost of Storage (LCOS) of €109 per MWh, and a net present value of €2.0 million, corresponding to a payback period of less than ten years. These findings substantiate the potential for BESS deployment to enhance both grid flexibility and wind-farm profitability under current market and regulatory conditions.

Keywords: Battery Energy Storage System, Energy markets, Wind farm integration, Grid flexibility, Mixed-integer linear programing, Renewable Energy

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Terminology

Abbreviations

AC - Alternative current
BESS - Battery Energy Storage System
BMS - Battery management system
BRP - Balance Responsible Part
BTM - Behind the meter
DC - Direct current
DSO - Distribution System Operators
ESS - Energy Storage System
FTM - Front of the meter
PPA - Power Purchase Agreement
SoC - State of Charge
SoH - State of Health
Settlement Period - The time after each operating hour when the TSO settles the cost for balancing the power supply and each DSO gets charged for the imbalance they caused
TSO - Transmission System Operators

Parameters names

A - Total profit obtained by the battery and wind farm per year [EUR]
$B_{BESS,exp}(t)$ - Total income from battery discharge [EUR/h]
$B_{BESS,cost}(t)$ - Battery cost [EUR/h]
C_{rate} - Multiplier of storage compared to power, ergo 1h, 2h, 3h battery, etc. [-]
$ConnectionPoint$ - Maximum allowed transmission through the grid-connection simultaneously at one point in time [MWh]
D_{avg} - Daily average price [EUR]
E_{batt} - Battery energy dimension [MWh]
$E_{effective}(t)$ - Placeholder variable to track energy degredation [MWh]
$F_{wind,exp}(t)$ - Income from the wind park [EUR/h]
$F_{FCR-D\&N}(t)$ - Income from the staked power to frequency regulation (FCR-D and FCR-N) [EUR/h]
L - Self-discharge of battery [%]
M - Big M factor [-]
η - Battery efficiency [%]

O&M - Operation and maintenance cost
$P_{Wind,tot}(t)$ - Wind power produced in total per hour [MWh]
P_{batt} - Battery power dimension [MW]
$R_{intra}(t)$ - Real-time intraday electricity price [EUR/MWh]
$R_{spot}(t)$ - Real-time day-ahead electricity price [EUR/MWh]
$SoC(t)$ - State of Charge each hour [MWh]
T - Total lifetime [h]
t - Time [h]
Δt - Delta time between two adjacent hours [h]
$X(t)$ - Discharged battery energy [MWh]
$Y(t)$ - Charged battery energy [MWh]
$z(t)_1$ - Binary decision variable [-]

Contents

List of Figures

List of Tables

1. Introduction

1.1 Problem

The Swedish electricity market and national energy supply are expected to undergo significant transformations in the coming decades [1]. Historically, Sweden's electricity system has been dominated by nuclear and hydropower, generation technologies characterized by their predictability and low volatility. However, since the mid-2000s, there has been a marked increase in the share of intermittent renewable energy, primarily wind power [2]. By 2023, such intermittent sources accounted for approximately 23 percent of total electricity generation. In line with its environmental ambitions, Sweden adopted a political framework in 2017 aiming for complete carbon neutrality by 2045 [3].

According to the long-term market analysis by Svenska Kraftnät, the national transmission system operator (TSO), electricity consumption in Sweden is projected to surpass domestic production across all modelled scenarios by 2045 [4]. This anticipated increase in demand is expected to affect all sectors of the Swedish economy, underscoring the urgency of transitioning away from fossil fuels toward more sustainable energy sources.

The existing electricity grid infrastructure was primarily designed to accommodate continuous, dispatchable power generation. However, the increasing share of variable renewable energy highlights the growing necessity for enhanced grid flexibility. As of 2025, a substantial number of Sweden’s wind farms remain within their expected 25-year operational lifespan [5], yet most operate without the integration of Energy Storage Systems (ESS). Retrofitting these assets with BESS presents an opportunity to enhance their role in grid stability and better align their output with market signals.

This thesis aims to address this challenge by identifying the optimal BESS configuration that can be integrated into existing wind farms. The dual objectives of the study are to improve grid flexibility and enhance the economic viability of wind power producers in an increasingly dynamic and decentralized electricity market.

1.2 Purpose

Currently, the installed wind power capacity in Sweden has on average, approximately 15 years remaining in its operational lifespan [5][6]. While the integration of energy storage systems into newly planned hybrid renewable energy parks has become a central focus in future development strategies [5], a disparity remains: many existing wind farms lack the technological and economic advantages inherent to these modern hybrid configurations. This thesis seeks to address that gap by investigating the potential of retrofitting pre-existing wind farms with battery energy storage systems to enhance their capture rate and overall market performance. In doing so, the aim is to bridge the divide between aging wind power infrastructure and the next generation of integrated renewable systems.

A critical constraint in this context is the limited grid interconnection capacity available to older wind farms, specifically, the inability to draw power from the grid for charging purposes. In nearly all cases, the BESS must be charged exclusively using the wind farm’s own generation. This constraint imposes unique design and operational challenges that necessitate a tailored optimization approach. Consequently, this thesis aims to determine the optimal BESS size under these conditions and evaluate its impact on the wind farm’s capture rate and profitability. The overarching goal is to provide insights that inform both retrofit strategies and broader policy discussions on grid flexibility and renewable integration.

1.3 Introduction to Bodecker Partners

Bodecker Partners is an independent advice and revenue risk management firm offering expertise within the Nordic Power markets. This includes management of merchant market risks to investors and asset owners of Nordic renewable power production as well as PPA advisory to industry sourcing sustainable renewable electricity.

1.4 Aim and questions

The primary objective of this master's thesis is to determine the optimal configuration of a Battery Energy Storage System for integration with pre-existing wind farms. The focus is placed on developing an optimization tool capable of processing input data from wind farms of varying sizes and characteristics together with market data. Based on this input, the tool identifies the BESS size that maximizes revenue through the combined energy export of the newly configured hybrid wind-storage system.

To achieve this, the model simulates BESS operation within the framework of the wholesale electricity market, incorporating factors such as price volatility, trading windows, and production variability. The analysis is limited to new battery systems; second-life or repurposed batteries are excluded from the scope of this study.

The optimal battery configuration identified by the model is further evaluated through a post-processing framework, which provides detailed insights into the economic and technical performance of the investment. The results of this analysis are presented and discussed in Chapter 4: Results.

The primary research questions addressed in this thesis are outlined below:

What battery size for a BESS is optimal for an existing wind farm?

Is there compability for BESS in the current market?

How does the future look for implementing batteries to wind parks, and their technological development?

After careful evaluation and discussion, the authors declare their recommendations concerning the questions in the final chapter, chapter 7. Conclusion.

1.5 Limitations & non-disclosure

The limitations of this project can be linked to three major areas: the market, the model, and the purpose. Within these categories, bounds were established to design a working optimization model during the time frame of this paper. Future development includes suggestions on how to improve and expand with fewer limitations. This can be found in the discussion chapter 6.5 Assumptions and 6.7 Future Work. Below each of the major areas will be presented with their respective limitations.

In addition, some information in this thesis is covered by a non-disclosure agreement between the authors and Bodecker Partners. Because of this, some sections are secluded in the public report: the code, as well as the data input used in the optimization model.

1.5.1 The market

In the optimization model developed for this thesis, frequency regulation revenue was treated conservatively. Although frequency services currently constitute a major component of battery income in practice [7], the model was intentionally structured to emphasize arbitrage potential. This design choice reflects projections that increased penetration of variable renewable energy sources in the Swedish power system will expand the scope for intraday market trading [8].

By assigning a conservative value to ancillary service revenues in the base case, the model was compelled to evaluate profitability primarily through market-based trading activity. This approach increased the reliability of the sizing optimization, as it ensured that the battery's economic performance was based on active power and energy utilization, rather than a steady, low-risk income from power staking on the frequency market.

For the intraday market, pricing is continuous, meaning that the market price for a given delivery hour evolves dynamically until the actual hour of operation. Due to data availability constraints, this thesis employed the average hourly price derived from the continuous pricing curve as the input for optimization. While this introduces a degree of simplification, the approach is justified by the same logic as the hourly-to-quarter-hour transition: greater price irregularity increases the number of profitable trading opportunities. Thus, using mean values results in a more conservative estimate, reinforcing the robustness of the model when applied in real-world contexts.

The most significant limitation concerning market assumptions lies in the post-optimization trading strategy. Once the optimal battery size is determined, implementing a practical trading model would require a forecasting mechanism, capable of estimating market conditions at least 24 hours in advance. This is essential for aligning charging and discharging operations with actual market signals. As it stands, the model relies on perfect foresight, which, while useful for theoretical benchmarking, is not directly applicable to operational planning.

Therefore, future development should focus on integrating predictive trading models that can simulate economically optimal behavior under real-world uncertainties. This would allow the tool to not only recommend an optimal BESS size, but also provide a complementary trading strategy to guide operators toward maximizing profitability within the market framework.

1.5.2 The model

During the development of the optimization model, several constraints were introduced to ensure compatibility with both the mathematical requirements of the modeling environment and the practical conditions of a realistic operational scenario. One of the most significant constraints is that the battery energy storage system (BESS) is only permitted to charge from the co-located wind farm, and not from the electrical grid. This constraint was implemented for two primary reasons.

First, it reflects the technical and contractual limitations of the existing grid connection point. In a pre-existing wind farm, the grid connection is typically dimensioned to accommodate exported generation and a limited degree of import capacity, sufficient only for auxiliary functions such as internal lighting and control systems [9]. Integrating a BESS with grid-charging capability, particularly at a scale of several megawatts, would necessitate an expansion of the grid connection agreement, involving both significant cost and lead time.

Second, the model assumes that the battery system is intended to be deployed without any modification or delay, operating solely within the current infrastructure.

By restricting the battery to charge exclusively from the wind farm, the model reflects a zero lead-time implementation scenario, avoiding the administrative and logistical complexities associated with upgrading grid access.

An additional constraint pertains to the mathematical structure of the model. Due to the use of linear programming techniques within the Pyomo-Gurobi framework, several inherently nonlinear relationships, such as those associated with battery degradation and lifetime performance, were approximated using linearized expressions. The implications and limitations of these approximations are discussed in detail in Chapter 6.6: Approximation Quality.

Together, these constraints were designed to preserve both model solvability and practical applicability, ensuring that the resulting optimization outputs are both mathematically robust and operationally feasible.

1.5.3 The purpose limitation

The primary objective of this master's thesis is to determine the optimal battery size for integration with a pre-existing wind farm. In such installations, the grid connection point is already defined based on the wind farm's rated maximum output, as agreed upon in prior connection agreements. This introduces a strict technical constraint, whereby the combined output of both the wind farm and the BESS must not exceed the connection point's capacity at any given time. Violating this limit would lead to grid imbalances, potentially incurring significant balancing costs and undermining the economic viability of the investment.

As a result, the optimal battery sizes identified in the reference scenario are relatively small when compared to those proposed for new hybrid projects that are co-designed from the outset to integrate wind and storage technologies [10]. This outcome is a natural consequence of the differing technical and regulatory environments under which existing wind farms were developed.

In summary, the optimal sizing of a BESS for a pre-existing wind farm must consider stricter operational constraints than would be present in a greenfield hybrid development. These limitations require a tailored modeling approach that accounts for legacy infrastructure and grid access restrictions, ultimately leading to smaller, yet feasible and economically justifiable storage solutions.

2. Theory and Literature review

2.1 Current outlook of the Swedish electricity market

Both in Sweden and in the rest of Europe the electricity market is deregulated, meaning that electricity is traded under free market competition [11]. This also means that the price for electricity is decided by supply and demand. The electricity grids, which transform the electricity from one point to another, are interconnected. The purpose of this interconnection and the deregulated market is to use the resources as effectively as possible and to meet the demands of the market.

2.1.1 Hedging/forward market

The Swedish electricity market can be divided into four main stages based on the trading timeframe. The first stage is the forward or hedging market. In this stage, market participants engage in price hedging, allowing them to secure electricity prices for future delivery, sometimes up to ten years in advance. This form of trading is financial in nature, meaning that no physical exchange of electricity takes place. Instead, it serves to mitigate price volatility and financial risk by locking in prices, thereby providing greater economic predictability for both producers and consumers.

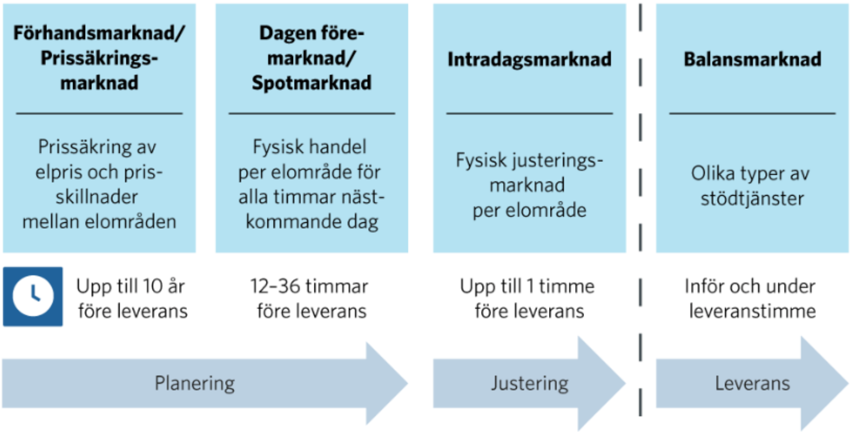


Figure 1. The four different stages on the electricity market

For an efficient electricity market, participants must ensure predictability in their future revenue streams by protecting themselves from unfavorable price movements and fluctuation. To do this protection participants can hedge against price fluctuation with forward contracts, for example futures. A future is a standardized contract that indicates that a buy or sell should be executed at a future date to a decided price [12].

2.1.2 Day-ahead market

The subsequent stage in the electricity market is the day-ahead market. In this market, participants submit bids and offers for electricity to be generated and delivered on the following day. The market operates as a blind auction, meaning that all participants place their bids without access to information about the bids submitted by others [13]. This mechanism promotes competitive pricing and efficient market outcomes by ensuring that supply and demand are matched based on marginal costs and willingness to pay, while maintaining market transparency and fairness.

The daily process works as follows, at 10:00 CET, the available capacities on interconnectors and the grid are published. Buyers and sellers then have until 12:00

CET to submit their final bids to Nord Pool or other market operator for the next day's delivery auction.

Submitted orders are matched with other orders through the pan-European market coupling process, known as the Single Day-Ahead Coupling (SDAC), using a common algorithm called Euphemia. This matching process determines a single price for each hour and bidding zone, where the supply and demand curves intersect, while also considering network constraints [14].

For example, consider a wind farm operator managing a plant with a total installed capacity of 200 MW. Each day, the operator must submit a day-ahead capacity bid, i.e., an hourly forecast of the generation they expect to deliver during the next 24 hours. Because the market operates as a blind auction, these bids are submitted without knowing the prices that will clear for each hour of the following day.

2.1.3 Intraday market

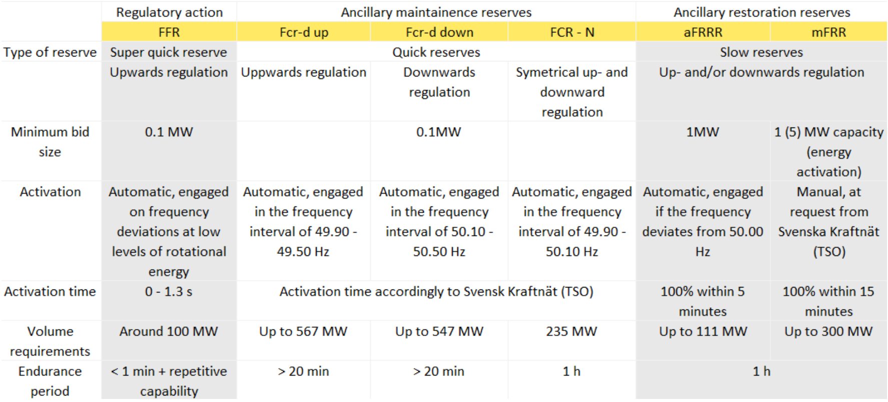
The intraday market is a short-term electricity trading market where market participants can buy and sell electricity close to real-time to adjust their positions based on updated forecasts and changing conditions. Typically, most market participants purchase their desired volume in the day-ahead market, while the intraday market primarily serves as a platform for adjusting positions. It complements the day-ahead market and enables greater flexibility in electricity supply [15].

The intraday market plays a crucial role in helping BRPs (Balance Responsible Parties) maintain balance, meaning that the traded volume aligns with the actual volume at their respective connection points, minimizing deviations [16].

2.1.4 Ancillary service market

The ancillary services market represents the final stage of the electricity market and plays a critical role in maintaining grid stability. In Sweden, as in the broader Nordic synchronous area, the system frequency is maintained at 50 Hz. To ensure this frequency remains stable, a continuous balance must be upheld between electricity generation and consumption. When deviations from this balance occur, the Transmission System Operator (TSO) intervenes by procuring and activating ancillary services. These services must be acquired through open and non-discriminatory market mechanisms.

Given the variable nature of frequency deviations, the ancillary services offered differ in terms of response time and operational characteristics. As illustrated in the figure below, the ancillary services market is segmented into six distinct categories. These categories are differentiated by the type of reserve provided, minimum bid size requirements, the frequency deviation thresholds that trigger activation, and the required speed of response. This structured framework enables the TSO to deploy the most suitable service in response to specific grid imbalances, ensuring both reliability and efficiency in system operation.



	Regulatory action	Ancillary maintainance reserves			Ancillary restoration reserves	
	FFR	Fcr-d up	Fcr-d down	FCR - N	aFRRR	mFRR
Type of reserve	Super quick reserve	Quick reserves			Slow reserves	
	Upwards regulation	Uppwards regulation	Downwards regulation	Symetrical up- and downward regulation	Up- and/or downwards regulation	
Minimum bid size	0.1 MW		0.1MW		1MW	1 (5) MW capacity (energy activation)
Activation	Automatic, engaged on frequency deviations at low levels of rotational energy	Automatic, engaged in the frequency interval of 49.90 - 49.50 Hz	Automatic, engaged in the frequency interval of 50.10 - 50.50 Hz	Automatic, engaged in the frequency interval of 49.90 - 50.10 Hz	Automatic, engaged if the frequency deviates from 50.00 Hz	Manual, at request from Svenska Kraftnät (TSO)
Activation time	0 - 1.3 s	Activation time accordingly to Svensk Kraftnät (TSO)			100% within 5 minutes	100% within 15 minutes
Volume requirements	Around 100 MW	Up to 567 MW	Up to 547 MW	235 MW	Up to 111 MW	Up to 300 MW
Endurance period	< 1 min + repetitive capability	> 20 min	> 20 min	1 h	1 h	

Figure 2. The different ancillary services provided.

The primary markets to operate for a BESS system are the mFFR, FCR-D up and down and FCR-N [17].

2.1.5 How buying and selling works

Trading takes place on a common European market. In Sweden, there are two electricity exchanges where market participants can submit buy and sell bids for Swedish electricity areas: Nord Pool and EPEX Spot.

All the electricity exchanges in the EU are interconnected, allowing bids from buyers and sellers across the EU to meet if there is transmission capacity between the electricity areas. This is known as market coupling [18].

2.1.6 Transition to 15-minute time resolution and new regulations

At the basis of this thesis is a 60-minute settlement period in the electricity market, meaning that the balance between electricity supply and demand is settled (i.e., measured and financially accounted for) in hourly intervals. The transition from a 60-minute to a 15-minute settlement period in electricity markets is a regulatory change aimed at harmonizing market operations across Europe and improving system efficiency. This shift aligns with the European Union’s Target Model for Electricity Markets, promoting a more integrated and competitive electricity system [19].

A shorter settlement period improves grid balancing by allowing more precise adjustments between electricity generation and consumption, reducing imbalances and enhancing frequency stability. It also facilitates the integration of renewable energy, enabling better management of intermittent sources like wind and solar power. Additionally, market harmonization across EU member states fosters cross-border electricity trade and increases market liquidity.

Svenska Kraftnät has already initiated the transition of the ancillary services mFRR, a process that has led to extreme price volatility and historically high market prices. At times, prices have surged to levels as high as €10,000/MWh, prompting concerns from industry experts regarding the financial viability of market participants under the new regulatory framework [20]. mFRR procurement is now conducted separately for each electricity area to enable greater use of cross-zonal transmission capacity. However, certain areas have very few bids, leading to elevated clearing prices due to limited market depth. Several commentators have cautioned that, without regulatory adjustments or temporary relief measures, some companies may face insolvency. In a press release issued on 14 May 2025, Svenska Kraftnät acknowledged the substantial increase in costs and highlighted that smaller wind farm operators are among those most adversely affected by the current market dynamics [21].

2.1.7 Historical fluctuations in the Swedish electricity market

Over the past five years, the Nordic and broader European electricity markets have experienced exceptional volatility in spot market prices. A range of global events has significantly influenced market dynamics, resulting in price behaviour that diverged drastically from patterns observed in the previous decade. Notably, the years 2020 and 2022 stand out due to external shocks with far-reaching effects. In particular, the 2022 Russian invasion of Ukraine triggered widespread sanctions against Russia—a major supplier of natural gas to Europe. This supply disruption placed considerable strain on countries with high dependency on natural gas, such as Germany, where the fuel accounted for 18.6% of total electricity generation in 2022 [22]. The resulting price surges rippled through interconnected electricity markets, including Sweden, leading to unprecedented price spikes [23].

In contrast, the Swedish market experienced lower-than-average spot prices in 2020. This was largely due to reduced electricity consumption [24] and hydrological conditions associated with a "wet year," in which elevated rainfall and snowmelt increased the output potential of hydroelectric plants. Additionally, total electricity production reached a high level that year [25], contributing to reduced marginal costs and yielding prices more consistent with those observed in the preceding decade—effectively marking 2020 as a return to a “typical year” in terms of pricing behaviour and market deviations [26].

Beyond the spot market, the ancillary services market has followed a distinct trajectory throughout the 2020s. The frequency containment market has shown a steady upward trend, particularly since 2022, when the FCR-D (Frequency Containment Reserve – Disturbance) market introduced a separate remuneration mechanism for downward regulation, in addition to the existing upward price component [27]. After a period of price decline leading up to 2020, the ancillary services markets began to recover, with prices rising from 2022 onward and, from 2024, surpassing previous historical levels [27].

2.2 BESS technology

A BESS is a system that stores energy for later use. The most usual form of BESS today is stand-alone and charged from the grid, but an increase is seen in so-called hybrid parks where the battery is being charged from wind or solar power. By having a BESS installed one can change the load and supply power during low-generation periods [28].

Recently, the installation of BESS in Sweden has seen exponential growth. According to a market research study conducted by Bodecker Partners during the summer of 2024, almost all surveyed producers and project developers of wind and solar power are now exploring the possibilities of integrating batteries into their facilities. In parallel to this, a huge development is being made with stand-alone BESS that offers ways to stabilize the grid [29].

2.2.1 Battery energy storage system components

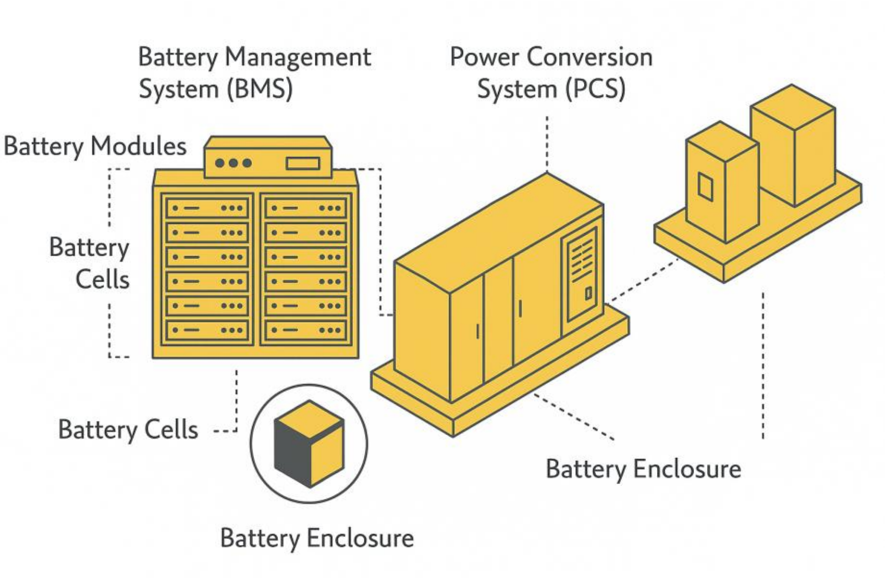


Figure 3. The components of a BESS, inspired from Lightsource bp, generated with ChatGPT.

Battery modules are the central component of a BESS, where energy is stored and subsequently charged or discharged. As seen in Figure 3, each battery module consists of multiple cells connected, the cells are often made of lithium-ion although other types may also be utilized. These modules are then stacked and assembled into a battery rack.

The Battery management system (BMS), it keeps track of the internal performance of the battery cells, including performance, temperature, SOC, and other safety parameters. It ensures optimal charging, prevents overcharging or deep discharge, and maximizes the battery's lifespan and safety.

Battery systems handle electricity as direct current (DC), whereas the electrical grid and most connected loads use alternating current (AC). To bridge this gap, a Power Conversion System (PCS) or bi-directional inverter converts DC electricity from the batteries into AC during discharge, and AC from the grid into DC when charging the batteries.

The battery is then covered by the battery enclosure, usually the size of a shipping container. Enclosures are often supplied with a liquid-cooled system that uses a combination of chiller and HVAC to keep batteries within certain temperature ranges. If dangerous temperatures are reached, the system then automatically shuts down to ensure safety [30].

2.2.2 Performance factors

Different parameters affect the lifetime of a BESS. The state-of-health or "SoH" refers to the difference between a completely new and fresh battery to an older, more used one in terms of cell aging and performance. A new battery starts with a SoH of 100%, which then gradually decreases over its lifetime. The end-of-life is reached at around 70% [31]. SoH is affected by different factors and how you operate the battery with one of the most important ones being battery degradation. It is a non-linear process where performance of the battery decreases as the number of cycles increases [32]. A battery cycle refers to one full charge and discharge process.

One of the other more important parts affecting the performance and SoH for a battery is the State of charge, SOC. The State-of-charge is usually defined as an actual available amount of charge in each battery, related to the maximum available amount of charge. The full charge of a battery is 100% and expressed as a percentage [33]. An optimal charging strategy does not exceed a certain percentage for both dis- and recharging, this optimizes the lifetime for the battery. This is also known as depth-of-discharge.

When regularly charging to the battery's maximum (100%) or discharging the battery to very low levels (<10-20%) it can lead to faster degradation. Overcharging leads to excessive voltage stress, which can damage the battery over time while deep discharges strain its internal components leading to capacity loss and heat generation [34].

2.2.3 BESS lifetime

According to Bodecker Partners the BESS lifetime can be assumed to be between 12 000 to 15 000 cycles. For a battery to be operational for 15 years this represents a yearly cycling of 800 to 1000 cycles every year. The national Renewable Energy Laboratory (NREL) indicates an operational lifetime of 15-20 years for a BESS asset with 6000 to 10 000 cycles in total [35]. According to Rao Konidema a battery that has two cycles per day reaches a SoH at 65 % after 16 years and more than 20 years for one cycle per day [36]. An article wrote by Ben Hardman; he assumes a cycling of 6000 to 10 000 cycles [37].

For the cycling rate, per year for batteries, findings from industry and research explains that the average cycling rate for BESS in the UK was 1.2 cycles per day for 2024 [38]. According to research from New York State Energy Research and Development Authority (NYSERAD), an evaluation of 42 BESS projects revealed that systems providing ancillary services averaged between 700 and 1 100 cycles per year [39]. As demonstrated by Yang et al. for BESS systems participating in energy arbitrage and ancillary services some systems achieved up to 1.5 cycles per day, depending on market volatility and operational strategies.

2.2.4 The battery C-rate

The C-rate of a battery indicates how quickly it can be fully charged or discharged, relative to its total energy capacity. For example, a C-rate of 1C means that the battery is charged/discharged from 0-100 % in 1 hour. Similarly, a 0.5C rate means the battery will take two hours to fully charge or discharge (from 0 to 100%).

In energy terms, this means if a battery has an energy capacity of 2 MWh and is rated at 1 MW power, it would be a 0.5C battery, since it takes two hours to deliver its full capacity of 2 MWh at 1 MW power. Increasing the C-rate results in faster charging ability, and vice versa [40].

2.2.5 Rapid development of battery technology

As the world transitions towards renewable energy production, the technology surrounding the depth of discharge and lifetime capacity evolves. It is estimated that within the near future batteries will be able to sustain a deeper depth of discharge, and full charge size. It will transition from the current industry standard, a working area between 20% to 80% in state of charge [41], to a higher capacity of 10% to 90%. It will do so by decreasing the speed of the cycle degredation [42], allowing for higher depths of discharge while still maintaining the same lifetime as current batteries.

2.2.6 Battery cost

The cost of batteries has decreased significantly over the last decade. BloombergNEF (BNEF) reported a substantial 40% year-on-year drop in BESS costs in 2024. In China, turnkey systems for 4-hour duration reached an average of $85/kWh, marking the first time prices fell below the $100/kWh threshold in that market [43]. The U.S. National Renewable Energy Laboratory (NREL) projects that utility-scale BESS costs could decline by up to 47% by 2030 compared to 2022 levels [44]. This shows that the levels have been decreasing and most probably will keep doing so in the future.

2.3 Potential BESS revenue streams

2.3.1 Load shifting and energy arbitrage

An energy management method where energy production is offset to adapt towards consumption. Utilizing some form of energy storage, volatile production can supply peak consumption hours even though production might not align. By sending out the stored energy during hours of high consumption and low production and storing energy during hours of high production and low consumption, the distribution is evened out thus "shifting the load" [45].

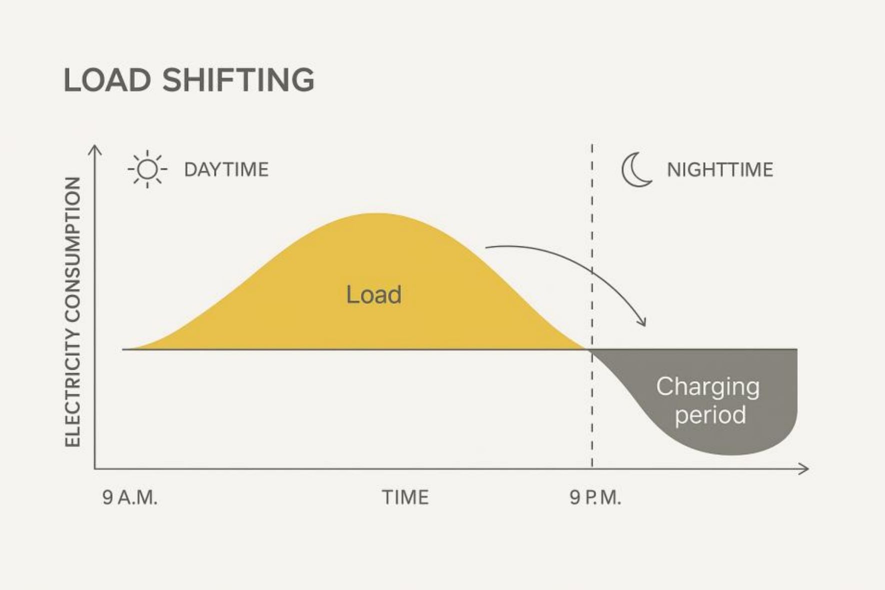


Figure 4. Visualizing of load shifting, inspired from Exro, generated with ChatGPT.

In electricity trading arbitrage is the utilization of differences over time, or geographical areas to profit from fluctuations in market price [46]. It can be seen from three different approaches.

- Time arbitrage: Using energy storage, electricity can be bought during hours of low price, stored, and then sold at a higher price during hours of high demand. The term arbitrage refers to the utilization of those differences during shorter times [47]. This is the day-ahead or intraday market when speaking of electricity trading. [48]

- Geographical arbitrage: Similarly, price differences in different regions, for example in Sweden's electricity region 1-4 or the European electricity market, can be used to profit from selling across those areas.*

- Arbitrage trading with certificates in the day-ahead market. The difference in predicted price can vary from the real-time price, creating margins for arbitrage [48].

* It should be noted that it differs from the trading normally conducted between these regions, driven by the need for extra electricity or the surplus that can be utilized elsewhere. Arbitrage trading is purely directed towards economic gain and might flow out of a region despite an internal demand, or vice versa, which can cause additional load on the transmission network [49].

Energy arbitrage or load shifting can be integrated both as a stand-alone battery solution but also together with a wind farm. The volatility is increasing on the spot market due to the variety in supply and demand. A drastic change in the supply of wind power during a period when demand is limited can result in low and even negative hourly prices because the surplus energy then can't be absorbed. This will then lead to a steeper curve for the merit order which leads to a higher spread in the spot prices, something that benefits energy arbitrage [50].

2.3.2 Peak shaving

Due to society becoming increasingly electrified, and the increase of end-users of electricity demands in consumption have increased. The hours when most end-users consume the most electricity simultaneously are referred to as the peak hours. The peak hours create an exceptional demand for electricity transfer, presenting a risk to the capacity of the electricity network. To mitigate this pattern the term peak shaving occurs, it envelopes techniques such as power tariffs for customers to incentivize less simultaneous consumption, and BESS systems to offset electricity for peaks. There are many more ideas and solutions as this is an area of focus worldwide [51].

2.3.3 Cannibalization and capture rates

The capture rate is the average electricity price a power producers achieve over time, based on geographical resources and the relation to market price fluctuations. In other words, how well the production captures the average market price. For a production that has its major output during less demanded consumer hours, the selling prices will on average be lower resulting in lower “capture rates” of the market price. This is common for renewable energy sources like solar- and wind power, in comparison to non-renewables which can be adjusted manually [52].

An effect that lowers the capture rates is the cannibalization effect. It can occur in different ways.

- Overproduction during high wind conditions: When many wind farms produce energy simultaneously during windy conditions, it can create an electricity surplus. This surplus drives down electricity prices during these periods, often to a price lower than the average price. Since wind production is concentrated to those windy periods with lower prices, wind power producers earn less money per produced MWh, which lowers their capture rates.

- Wind power´s price dependence on weather: Wind power producers do not have the ability to control production to match times when electricity prices are higher. Instead, they produce the most electricity when it's windy, which tends to be the times when prices are low due to increased production. This means that wind power often captures a lower price than other energy sources, negatively affecting their capture rate.

- Cannibalization through competition: With every new wind power plant being built in the same area, the competition to sell electricity at the same time increases. Since all wind turbines produce the most electricity simultaneously, they compete to sell their output, which further drives down prices. By doing this, new wind turbines “cannibalize” the revenues of existing wind farms, which then reduces capture rates even more [53].

2.3.4 Increased value of grid connection

Installing a BESS to an already existing grid connection point can increase its value. A land-based wind farm has a yearly capacity utilization of 35 to 40 %. This means that the battery can take advantage of the rest of the capacity. During the hours when production is high, and the wind farm operates close to full connection capacity, prices are usually low. When prices are low the battery is unlikely to discharge power to the grid, meaning that the maximum connection originally sized for the wind farm won't be a problem since they won't operate at the same time during this scenario. However, during low production from the wind farm prices tend to increase, and the battery then has the possibility to use most of the connection point due to low usage from the wind farm.

Increasing the capacity of a grid connection point for a wind farm can be a challenge depending on the bidding zone and network operator. A wind farm requires a limited network subscription for its self-consumption, meaning that charging the battery with energy from the grid becomes limited [54] [55].

2.3.5 Asset-backed trading

To understand asset-backed trading one must first know purely financial trade. A purely financial trade is the classic speculative approach commonly seen in stock markets, where the goal is to profit from market value fluctuations without physically delivering the traded commodity. The energy in a financial trade is bought and sold without direct ownership or control over the system. Instead, the trader sells third-party energy with the idea of buying it back cheaper and the other way around.

Since financial trades do not involve physical energy generation or consumption, they are typically asset-less and focus solely on market speculation. An asset-backed financial trade is like a financial trade, making money on market value without delivering energy. The difference is that, as the name says, the trade is asset-backed, which means support from a physical system to take energy from. A battery is one of the most common systems to back a trade with. Because if the market behaves unpredictably, this asset serves as a safeguard against significant financial losses. Such a scenario arises when prices rise after selling energy with the expectation of repurchasing it at a lower price or when prices drop after purchasing energy with the intent of selling it at a higher price. To mitigate potential losses, the seller utilizes the asset to physically supply the required energy volume [56], by doing so expensive corrective costs can be avoided, while staying in balance.

The battery in connection with a wind farm can perform such trades with the battery and speculate in the market, using the battery to “back up” potential miscalculations.

2.3.6 Ancillary services

As discussed in part 2.1.4 there are different ancillary services in Sweden depending on the type of reserve, minimum bid size, by what frequency deviation that starts them, and their responsiveness. The primary markets to operate for a BESS system are the mFRR, FCR-D up and down, and FCR-N. There are two ways to earn money from ancillary services availability of capacity and payments for actual delivered energy [57].

Svenska Kraftnät, which acts as the Swedish TSO, establishes ancillary services through a capacity market. In this market, external providers (partakers in the market) are compensated for making capacity available, regardless of whether it is activated or not. This applies, for example, to FCR-N and FCR-D, which are two services that a BESS can provide.

For services like aFRR and mFRR, there is an energy activation market, where compensation is based on the actual energy delivered when resources are activated. To quote Svenska Kraftnät: "A reserve market where volume is bid in. Bids are activated during the operating quarter. Energy payment is provided for the actual activated energy. No capacity payment is given." This means that payment is only made when the BESS is activated and discharged to the grid or charged from the grid.

2.4 Wind farm and BESS layout

2.4.1 Potential layouts

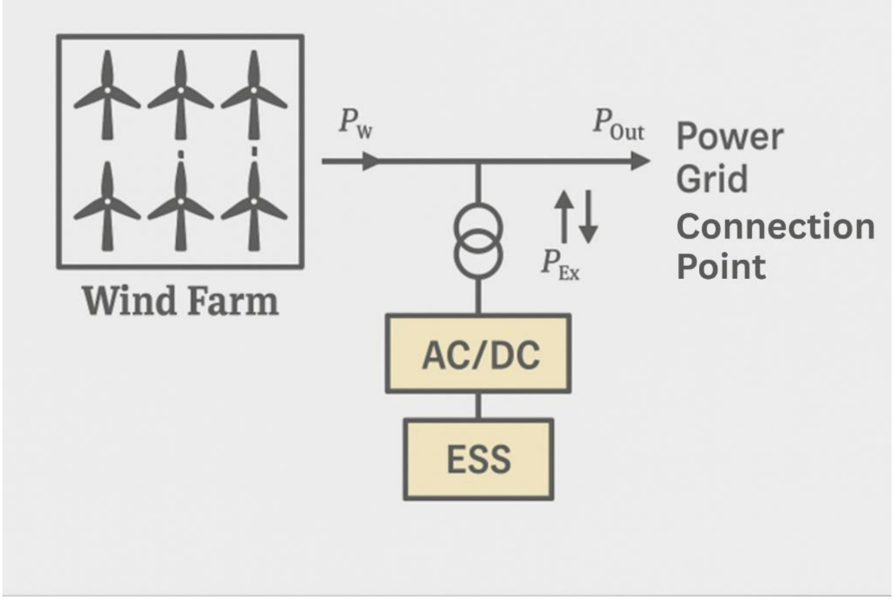


Figure 5. Layout of wind farm and battery towards the grid, inspired from work by Jannati and Vahidi, generated with ChatGPT.

In a work by Jannati and Vahidi called “A master-slave adaptive linear neuron-based approach for cost-effective use of battery energy storage systems in wind farms” they proposed the following layout of the hybrid park, showcased in the figure 5 above. Here, the wind farm and the battery are placed in front of the meter [58].

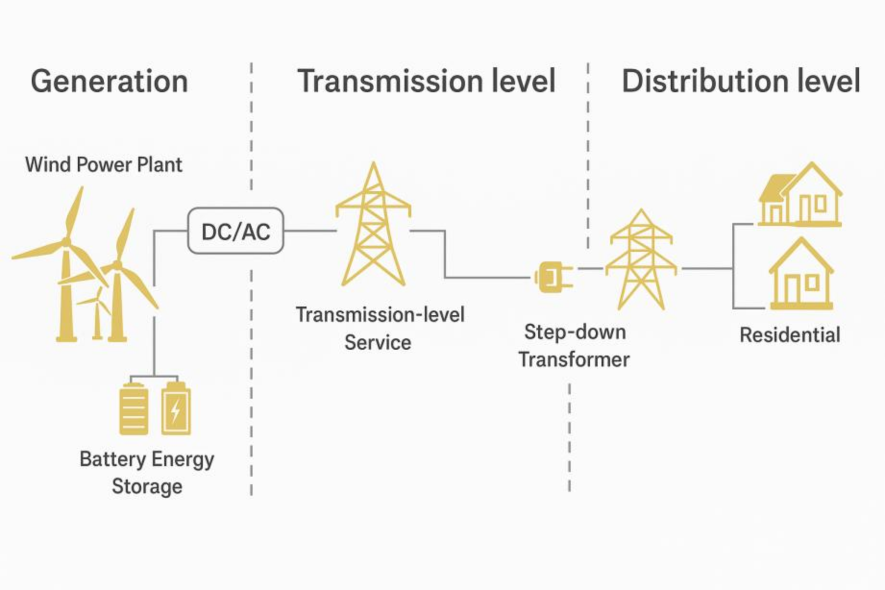


Figure 6. Layout of wind farm and battery towards the grid, inspired from study by Ngoenmeesri, Chidaruksa, Wangkeeree and Sirisamphanwong et.al, generated with ChatGPT.

In a study by Ngoenmeesri, Chidaruksa, Wangkeeree and Sirisamphanwong et.al named Power quality enhancement for Thailand's wind farm using 5 MWh Li-ion battery energy storage system [59], they propose a similar layout with the battery and wind farm in front of the meter, see figure 6.

2.4.2 Behind-the-meter and front-of-the-meter systems

BTM refers to energy systems that are installed on the customer's side of the utility meter, enabling local energy generation, storage, and consumption. These systems may include solar photovoltaic (PV) installations, BESS, and energy-efficient appliances, but most usually used only by consumers.

The primary function of BTM systems is to enhance self-consumption, whereby the energy generated or stored is utilized directly by the building or facility. By reducing dependence on electricity supplied from the grid, BTM systems contribute to lower electricity costs, increased energy resilience, and reduced grid congestion. Additionally, these systems may support demand-side management by optimizing energy consumption patterns and mitigating peak load demand [60].

Front-of-the-meter systems on the other hand are located on the utility side of the meter and are connected directly to the transmission or distribution grid, rather than being tied to a specific customer's meter. These systems are typically owned by utilities, independent power producers, or energy traders. FTM storage enables participation in wholesale markets, such as frequency regulation, energy arbitrage, and ancillary services [61].

The most used variant for larger utilities such as wind farms and battery parks are the front of the meter [62]. In the figure below, the difference between the two is visualized for better understanding.

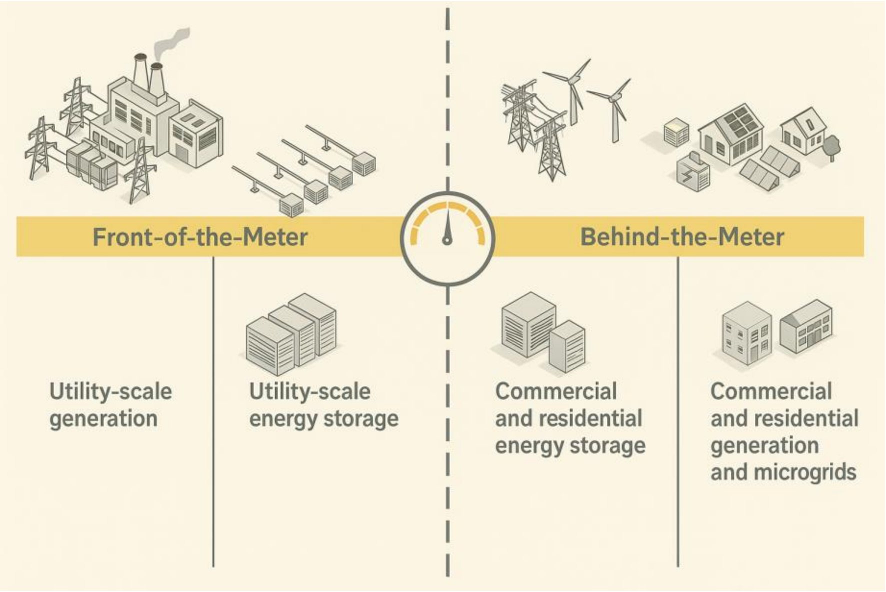


Figure 7. The differences between front and behind the meter, inspired from Power Sonic, generated with ChatGPT.

2.5 Previous work

Previous research has focused on sizing BESS for renewable power generation. When analysing the outcomes of different studies, it is evident that comparing sizing results across different studies can be challenging. In an article by Yang et al., it is demonstrated that there is no universal method for sizing BESS. Instead, the choices depend on several factors, from the type of system (eg microgrid, sunpower hybrid etc.), the purpose of sizing, the amount of data available and the level of computational resources accessible for simulations and analysis.

In a research paper by Alberto Grimaldi, Francesco Demetrio Minuto, Alessandro Perol, Silvia Casagrande and Andrea Lanzini, it performed a Techno-economic optimization of utility-scale battery storage integration with a wind farm for wholesale energy arbitrage considering wind curtailment and battery degradation. Their results indicated that the highest net present value of 152k EURO is achieved with a 1h BESS of 4 MW /4 MWh. They simulated their results based on real wind and market data, though the specific capacity of the wind farm is not stated, it can be assumed by the annual yearly production of 90 000 MWh per year to be around 50 MW in size. The authors develop a Mixed-Integer Linear Programming (MILP) optimization model to determine the best battery size and optimal dispatch strategy [64].

The paper also examined previous scientific research in assessing the techno-economic performance of utility-scale renewable power plants combined with BESS. The two primary methods for doing this are price-taker and price-maker modelling. Price-taker simulations focus on optimizing resource dispatch based on historical or projected electricity prices, aiming to maximize net revenue for the energy facility owner. On the other hand, price maker models, instead optimize the commitment and dispatch strategies across a fleet of energy generators to minimize the overall system cost of meeting electricity demand. In this paper price-taker simulations will be performed. This is because BESS capacities usually are considered small relative to conventional electricity production and therefore can be modelled as a price-taker, which implies that one has to accept the prevailing market price [65].

Across multiple studies Mixed-Integer Linear Programming or (MILP) is the most used deterministic mathematical optimization framework for simulating BESS. MILP's ability to handle both continuous and discrete decision variables makes it particularly suitable for modelling the complex operational constraints and decision-making processes inherent in BESS applications [66] [67] [68] [69].

Previous research and evaluations on LCOS for BESS applications suggest a spread in value. Lazard’s levelized cost of storage analysis – version 9.0 suggests a LCOS of 125 to 221 €/MWh for a 2-hour battery [70]. According to PNNL LCOS Workbook for 2024, a LCOS of 195 to 258 €/MWh is estimated [71]. The National Renewable Energy laboratory’s cost projections for utility-scale lithium-ion BESS systems in the advanced scenario is 110 to 140 €/MWh [72].

3. Method

3.1 Explanation of model

3.1.1 Pyomo optimization tool

To incorporate mathematical logic into Python an optimization model-builder, pyomo, was utilized. Through it, expressions and constraints could be established. The model type was concrete, as the parameters were defined in the initial formulation [73]. A short explanation entails highlighting the key factors to better grasp the pyomo application.

Pyomo introduced different classes to enable the MILP approach, these key factors were defined as:

- Objective function: The mathematical function that was solved to find the optimal decision variables.
- Parameters: Predefined data, used as the input and constant values in the model.
- Variables: The variables in a Pyomo code were unknown specifications that were to be decided in pyomo when combined with a solver.
- Rules: The rule construct in pyomo was a supportive tool utilized to simplify mathematical relationships. It’s purpose was to define the method outside of the constraint- or expression call to allow for a better overview when handling advanced expressions. The rule method also allowed for conditional logic which was useful when creating conditional constraints.
- Expressions: Mathematical equations describing relationships between parameters and variables with potential factors.
- Constraints: The limitations of decision variables establish the range of allowed values. The constraints were applied to establish the “working area” for the solver.

The details of each key factor will be explained in more detail throughout the sub-headings below.

3.1.2 Gurobi solver and MILP programming theory

Once the pyomo optimization was built the solver was imported. In the context of this problem, Gurobi was the most sufficient solver because of its functionality when dealing with parameters that need binary decisions. Gurobi is a Mixed Integer Linear Programming solver. Linear programming implied that relationships in the optimization model had to be linear. The inclusion of mixed integer programming allowed for the use of binary decision variables, z1 in this case. It provided a way to express the practical limitations of charging and discharging, specifically to make sure that they didn't engage at the same time.

The way gurobi solved the objective function was through branch and cut decisions [74], it had a working area that was "cut" with mathematical constraints. In that working area it went through decisions each time a value was investigated, ultimately creating a path "a branch" that provided a solution with values for each decision variable, as well as an answer to the objective function. If the branch was solved it updated the best function, if the branch was unsolvable, it was pruned. This process repeated until the custom time limit was reached (120s), and then the best solution was presented. It also included software to control proof of optimality, deciding which solution was optimal. This was indicated by a gap value defining the percentual difference between the actual value and the theoretically maximum value if constraints were freely relaxed. This gap-value was integral in reassuring a feasible solution. A solution was only approved when it displayed a gap of 1% or lower.

3.1.3 Objective function

The end goal was to formulate an equation that the whole optimization would be fixed on. That formulation was passed on to the solver to define the optimal values. In this case, the final objective was defined as "The optimal battery size where profit is maximized for the wind and battery park". Running this model with a solver allowed for the identification of the optimal decision variables, ultimately resulting in the battery dimensions that were most optimal in the context of this thesis.

The maximization objective was fulfilled by generating a linear relationship between several variables. Included were:

- Revenues from battery trade on the intraday market.
- Revenues from the wind park on the day-ahead market.

- Staked power to frequency regulation profit.
- Costs from the battery investment.

The equation was formulated mathematically as:

$$A = \max \sum_{t=1}^{T_{BESS}} \left(B_{BESS,exp}(t) + F_{wind,exp}(t) + F_{FCR-D\&N}(t) - B_{BESS,cost}(t)\right) \; (1)$$

The total profit per year (A) was obtained by the revenue from the electricity exported from the battery to the grid, $B_{BESS,exp}(t)$, the wind parks additional revenue, $F_{wind,exp}(t)$, and the income from frequency regulation $F_{FCR-D\&N}(t)$. Each income model will be further detailed in the subheadings. Then the cost of investment for the battery, $B_{BESS,cost}(t)$, was subtracted. The summation included the hourly values for each of the expressions, throughout the whole lifetime.

3.1.4 Parameters

The parameters were taken as input in the solver and did not change after the solver. For this optimization, the parameters were the data given by Bodecker Partners on day-ahead market prices, Intraday market prices, and wind production aligned with the reference scenario which will be defined in (3.2 Reference scenario). It also included constant values required to implement full logic.

Ergo, the parameters, real-time intraday electricity price, $R_{intra}(t)$, real-time day-ahead electricity price, $R_{spot}(t)$, and wind power produced in total per hour, $P_{Wind,tot}(t)$, were obtained from real data in the format of data frames. To transcribe data frames into parameters lambda functions were used. The lambda function was a temporary method that operated within another method-call.

The other parameters were defined as:
Self-discharge of battery L = 0.042 [%]
Battery efficiency, η = 95 [%]
Delta time between two adjacent hours, Δt = 1 * [s]
Big M factor, M = 1 000 000 [-]
Total lifetime, $T = 15 \times 8760$ [h]

$ConnectionPoint$ = Maximum power in connection (Entered manually) [MW]
D_{avg} = Mean value of intraday prices for each day [EUR]

3.1.5 Decision variables

Each variable was initialized within a region. State of charge, $SoC(t)$, charged battery energy $Y(t)$, and discharged battery energy $X(t)$ were defined as non-negative real numbers that accounted for real-life applications, where numbers enabled higher precision in the solver than the alternative integer range. For example, when considering self-discharge in the state of charge, and efficiency in charging power. The battery energy dimension, E_{batt}, and the battery power dimension, P_{batt}, on the other hand, were meant to be rated factors and were formulated as non-negative integers to reflect how dimensions are constructed in real life, batteries were not sold with decimal rated power- and energy values.

The multiple of storage compared to power, C_{rate} was an integer variable, with an allowed range of one to five, it was used in the code to decide the relationship between E_{batt} and P_{batt} Finally, $z(t)_1$ was defined as a binary variable, which was useful for decision logic applied in charging constraints.

3.1.6 Expressions

The relationships used in the objective function were in turn described with expressions. The expressions were based on the decision variables as well as the parameters defined previously.

Effective energy degradation

$$E_{effective}(t) = E_{batt} \times \left(1 - \left(0.3 \times \frac{t}{T}\right)\right) \tag{2}$$

Degradation of battery over the lifetime, from 100% storage capacity to 70%, time based, ergo the time over total time factor, which resulted in a linear degradation with a percentual degradation each hour. This type of linear approximation had to be applied due to the static limitations of Pyomo, the quality of the linearization is discussed in chapter 6.6 Approximation Quality. $E_{effective}(t)$ was a placeholder variable to track energy degradation, in MWh, it appeared once more in the SoC tracking function

Battery cost function

$$B_{BESS,cost}(t) = \frac{c_1 \times (P_{Batt}) + c_2 \times (E_{batt} - P_{batt} \times 1h)}{T} \tag{3}$$

Where $c_1 = 3.5 \times 10^5$ €/MW and $c_2 = 2.0 \times 10^5$ €/MWh are constants.

The battery cost model was defined in collaboration with Bodecker Partners. The cost of battery power was estimated at €350,000 per MW, while the additional energy capacity, beyond the initial installed power, was priced at €200,000 per MWh. These numbers were based on present pricing data from Bodecker Partners as of spring 2025, the newest data available at the time of our thesis. The price was then divided over the full lifetime to enable division of costs on a more flexible basis.

Battery revenue function

$$B_{BESS,\mathrm{exp}}(t) = R_{intra}(t) \times X(t) \tag{4}$$

The battery exported the electricity available to the intraday price at that specific time.

Wind revenue function

$$F_{wind,exp}(t) = R_{spot}(t) * \left(P_{wind,tot}(t) - Y(t)\right) \tag{5}$$

The new wind export revenue represented the electricity generated and sold by the wind farm itself minus the energy that went into charging the battery. Every hour where wind was available, it was sold to the grid, with subtraction of the battery. Note that this production is promised day ahead and sold to the day ahead market $R_{spot}(t)$ price.

Frequency regulation income-function

$$F_{FCR-D\&N}(t) = C_{FCR} \times 0.2 \times P_{batt} \tag{6}$$

Constant revenue for staking the excess 20% of SoC on the frequency regulation market. This number is an assumption made by the authors based on historical prices, it accounts for a hypothetical revenue from a combined staking for FCR-D up and down, and FCR-N services. In the reference case it was decided to $C_{FCR} = 20$ €/MW. The function for frequency regulation was defined conservatively to increase safe predictions while modelling. The risk of having a too liberal model for frequency regulation income could influence the result by overpowering the arbitrage trade and potentially miss-size the battery. The quality of the approximation is further explored in chapter 6.6 Approximation Quality.

3.1.7 Constraints

The constraints were applied to establish the "working area" for the solver. The constraints were established to facilitate the solver's optimization; the range unloaded the solver of unnecessary computations and streamlined branching so that the algorithm could work faster.

Battery power and energy

$$\mathrm{E_{batt}} = \mathrm{C_{rate}} \times \mathrm{P_{batt}} \times 1\mathrm{h} \tag{7}$$

Charging rate was a value between 1-5, defined in the parameters. A strict constraint could hide errors in the logic by forcing $\mathrm{E_{batt}}$ it to a reasonable value. In practice the installed power and additional modules expanding the battery energy in BESS follow a proportional relationship. For the sake of practicality the power was deemed to never have a size exceeding the storage capacity, the real-life application would become difficult - there would never be enough capacity to discharge for a full hour in an hourly-based market. Therefore, $\mathrm{E_{batt}}$ was constrained to be at least one times $\mathrm{P_{batt}} \times 1h$ and up to five times larger. The final range was concluded through a discussion with prof. Martin Andersson.

Availability in connection point

$$\mathrm{P_{batt}} + \mathrm{P_{wind,tot}}(t) \leq \mathrm{ConnectionPoint} \tag{8}$$

Pre-existing parks had a limit on the output they were allowed to send through their connection to the grid. It was adapted for maximum rated production and created a hard limit on how much the battery could transmit at one point in time. Since the purpose of this thesis was to research compatibility with pre-existing parks it was an integral part of the constraints. To ensure compatibility with real-life scenarios, the park and battery together cannot transmit more power than they are rated for at the connection point, at any point in time.

Charging & Discharging Constraints

The two constraint that were applied on the discharge and charge parameters had an "if, elif, else" logic that constituted the market trading strategy for the battery, in turn dictating how the profitability of the battery was determined.

Charging code

$$\begin{gathered}\text{if}\left(\mathrm{R}_{\text{intra}}(t) \leq \mathrm{D}_{\text{avg}}\right)\\ \mathrm{Y(t)} \leq \mathrm{P}_{\text{batt}} \times 1h\\ \text{elif}(\mathrm{t} = \text{first hour})\\ \mathrm{Y(t)} \leq \mathrm{P}_{\text{batt}} \times 1h\\ \text{else}\\ \mathrm{Y(t)} \leq \mathrm{Y(t-1)}\end{gathered} \tag{9}$$

For the coded charging-constraint the logic was implemented in the following way: If the actual price for the hour on the intraday market was lower than the daily average spot price, of the day-ahead market, the charging variable was allowed to transmit less or equall power as the P_{Batt} throughout the hour.

"Else if", alternatively, if it's the first hour of the data input, then the criteria were the same as for the if-statement. This was added to avoid an error that was occurring when the else statement was activated in the first hour.

Else, in all other cases, the current charging amount for the actual hour was allowed to be equally large as the last hour or less, to accommodate for inertia in the system. Looser constraints for the model allowed for better optimization. The alternative of reducing it to zero in all other cases resulted in a too constrained model.

Since the binary decision, which is presented below, also constrained the model there would not be a charge and discharge at the same time. These constraints together fulfilled the prerequisites for a practically functioning optimization model.

The discharging-constraint was implemented in a similar way to the charging.

Discharging

$$\begin{gathered}\text{if}\left(\mathrm{R_{intra}}(t) > \mathrm{D_{avg}}\right)\\ \mathrm{X(t)} \leq \mathrm{P_{batt}} \times 1h\\ \text{elif}(\mathrm{t} = \text{first hour})\\ \mathrm{X(t)} \leq \mathrm{P_{batt}} \times 1h\\ \text{else}\\ \mathrm{X(t)} \leq \mathrm{X(t-1)}\end{gathered} \tag{10}$$

If the intraday price for the hour was lower than the daily average the size of the discharge could be less or equal to the rated power. This constraint allowed the battery to determine whether it would be profitable to discharge electricity, or not.

"Else if", the first hour required the discharge size to be less or equal to the rated power, to avoid the error of the else statement tracking the state of charge to a non-value for previous hour, since it would be beyond the before first point in the dataset.

Else, in all other cases the discharge method was the same as the charging method. The discharge size could be equally large or smaller than the last hours' discharge-size. Similarly, this inertia and the loose constraint allowed the model itself to find the best discharge-case.

State of charge
For the state of charge, several logical constraints had to be applied to ensure proper battery function. The following was implemented in pyomo

SoC Range

$$0.2 \times E_{effective}(t) \leq SoC(t) \leq 0.8 * E_{effective}\ (t) \tag{11}$$

With the current battery technology, as mentioned in 2.2.5 Rapid development of battery technology, it was at the time of this thesis common practice to limit the available energy between 20% and 80% of rated energy to sustain a full lifetime of battery usage. With the constraint above SoC was limited to staying within these boundaries. In the results below alternative scenarios will explore how the limits of SoC can affect the optimization, 4.3. SoC Variation.

SoC Tracking

An assumption was made that the battery arrived fully charged. SoC updated with regards to the previous hour's value, charge- or discharge amount, and losses from the vampire drain effect. First hour, no tracking. Remaining time.

$$SoC(t) = SoC(t-1) \times (1-L) + Y(t) \times \eta - \mathrm{X(t)} \times \eta \tag{12}$$

The actual hour took its value from the SoC of the previous hour with the addition of either newly charged, or discharged, energy. Efficiency limited the amount that could be transferred into the battery, which was accounted for by the lambda-parameter multiplied by the size variables.

Binary decision

To ensure no charging and discharging happened at the same time

$$Y(t) \leq M \times z(t)_1 \tag{13}$$

&

$$X(t) \leq M \times (1 - z(t)_1) \tag{14}$$

The binary decision variable determined if a battery were to charge (define a Y-value) or discharge (define an X-value) for each hour. It was physically impossible to have them simultaneously. To apply this conditional logic the binary value could be either 1 which implied that the charging logic was true (battery charges), or 0 which implied that the discharging logic was true (battery discharges). The big M factor was used to increase the value of the binary decision so to not actually limit the capacity of X(t) and Y(t).

3.1.8 Post-processing parameters

The post-processing parameters were picked to cover as much of the investment details as possible and to evaluate a technoeconomic analysis of the optimal size.

The LCOS represents the total lifetime cost of a battery system divided by the total volume of energy throughput, measured in megawatt-hours (MWh). It provides a standardized metric to evaluate the economic efficiency of a battery by capturing the cost per unit of stored and discharged energy. To determine at what average cost, in today's euros, of delivering one megawatt-hour of energy from a storage system over its entire lifetime, the metric levelized cost of storage was used. It covered all key cost drivers into a single unit in €/MWh delivered. The formula for the levelized cost of storage was the following:

$$\mathrm{LCOS} = \frac{\mathrm{B_{BESS,cost}}(\mathrm{t}) + \sum_{\mathrm{t}=1}^{\mathrm{T_{BESS}}} \frac{\mathrm{O\&M_t}}{(1+\mathrm{r})^{\mathrm{t}}}}{\sum_{\mathrm{t}=1}^{\mathrm{T_{BESS}}} \frac{\mathrm{B_{BESS,exp}}(t)}{(1+\mathrm{r})^{\mathrm{t}}}} \tag{15}$$

Where $\mathrm{B_{BESS,cost}}$ represents the total cost over the batterys lifetime, $\mathrm{O\&M}$ represents the annual operations and maintenance costs associated with the BESS in year t. In this context, "operations" refers to all activities required to keep the storage system in service, such as system monitoring, dispatch coordination, and routine inspections, while "maintenance" covers scheduled and unscheduled repairs, component replacements, and performance testing throughout the battery's lifetime. It is defined as €/MWh.

To evaluate the total money the BESS generated over its lifetime, after covering all costs and the required discount rate, the net present value was calculated. The $\mathrm{B_{BESS,cost}}$ represented the initial investment, $\mathrm{B_{BESS,exp}}$ the net cash flow each year exported from the battery to the grid, which according to assumptions was set to be constant from year-to-year. "r" represented the discount rate and $\mathrm{T_{BESS}}$ the project lifetime. The formula for net present value was the following:

$$\mathrm{NPV} = -\mathrm{B_{BESS,cost}} + \sum_{\mathrm{t}=1}^{\mathrm{T_{BESS}}} \frac{\mathrm{B_{BESS,exp}}}{(1+\mathrm{r})^{\mathrm{t}}} = 0\ \mathrm{EUR} \tag{16}$$

To understand at what value the discount rate made the present value of all future cash inflows equal to the initial investment, internal rate of return was calculated. The higher the internal rate of return, the more desirable an investment would be to undertake. For the calculations of IRR, the same equation was used for calculating NPV.

To cover the time for the investment to pay itself off the metric payback time, PBT, was introduced. The definition of a simple, undiscounted payback period was defined as the number of years it took for cumulative nominal cash inflows to equal the initial investment.

$$\sum_{\mathrm{t=0}}^{\mathrm{PBT}} \mathrm{B_{BESS,exp}(t)} = \mathrm{B_{BESS,cost}(t)} \tag{17}$$

To make the payback period take the discount rate into consideration, the discounted payback, DPBT, time was introduced. It was defined as the number of years it took for discounted, present value, cash inflows to equal the initial investment.

$$\sum_{\mathrm{t=0}}^{\mathrm{DPBT}} \frac{\mathrm{B_{BESS,exp}}(t)}{(1+\mathrm{r})^{\mathrm{t}}} = \frac{\mathrm{B_{BESS,cost}}(t)}{(1+\mathrm{r})^{\mathrm{t}}} \tag{18}$$

The final post-processing parameter was the change in capture rate. As described in section 2.3.3, the capture rates were decreasing for wind farm owners. This was due to the cannibalization created when more renewable, and specifically wind power, was introduced into the Swedish electrical system. To evaluate how the BESS solution together with the wind farm affects the capture rate, it was introduced as the final post-processing parameter.

The capture rate was calculated by taking the day-ahead price to what was sold every hour multiplied with the specific production that same hour summarized for a month. That amount was then divided by total production for that specific month. Simply put, it generated the average market price that specific power produces captured for each MWh generated.

When a battery was added to the wind farm a new capture rate price was calculated. Since some of the generated electricity was stored instead of sold directly to the grid, the wind farms contributed to the capture rate differently. The electricity stored in the battery was sold at other hours (arbitrage), contributing to another capture rate. This was then added to the calculated capture price for the wind farm generating a new total capture rate for that month.

$$\text{Capture rate} = \frac{\text{Avarage price recived by the wind farm (and battery)}}{\text{Avarage market price}} \tag{19}$$

3.2 Scenario-based analysis

In the Data Analysis chapter, a scenario-based approach was utilized to give a rigid exploration of impacting factors. The purpose of the paper was to find the optimal battery storage for an existing wind park. Throughout this work one park was used for reference to find the optimal solution. This was also called the reference scenario. For the results to cover a wider, more realistic, outcome different parameters were varied and compared to the reference scenario. These were the alternative scenarios presented below. They were based on relevant changes happening in the battery and energy market.

As explained in (2.2.6 Battery Cost), the price of batteries was projected to decrease, which was accounted for in a "lower cost" scenario. The impact of revenues from frequency regulation was gathered in its own group of scenarios, since the frequency revenue was predicted to play a large role in total profitability, and as specified previously had seen an alternative progression compared to the spot market. Different prices were incorporated in scenarios to see the potential effects of less conservative pricing ranges. In addition, battery technology was altered to see improvements in useful capacity, by relaxing the constraints on SoC boundaries, which resulted in one last additional scenario.

To conclude, the analysis was split into three main areas, SoC scenario, lower price scenarios, and frequency revenue scenarios. Each area will be examined in further detail in the subheadings.

Perfect foresight was continually used during the different scenarios, meaning that the model already knew all the values for the whole year, and could apply them to optimize the battery size. In contrast to reality where predictions must be made, perfect foresight allowed for more certainty when optimizing. The drawback was that it was based on the data for 2024, which could not represent how the present market evolved. More discussion around perfect foresight can be found in chapter 6.2 Perfect foresight and future forecasting requirements.

3.2.1 Reference scenario

The purpose of the paper was stated in the introduction (1.2), based on this a reference scenario could be described. A wind park was chosen where production was rated at 200MW, and the connection point was limited to 220MW of simultaneous transfer. The market area was SE3 in Sweden and the market prices were taken from hourly data for 2024.

The SoC was limited to current standards and operated between 20% and 80% of the rated energy in the battery. The operational life for the battery was set to 8 000 cycles with the current SoC. The total cost of battery was estimated according to Bodecker Partners evaluation. With the number of cycles solved by gurobi the economic lifetime was calculated to 15 years.

3.2.2 SoC scenario

When exploring the future development of battery technology (2.2.5), it created an interest in exploring how the SoC boundaries could be expanded to utilize more of the battery capacity during its lifetime. As it was observed to have major effects on the profitability and degradation of the battery. Because of this a future scenario was dimensioned where SoC was increased. In conclusion, a technical improvement scenario was made with SoC varying between 0.1 - 0.9 of the rated energy.

3.2.3 Ancillary services scenario

To cover the differences in earnings from ancillary services three additional scenarios were made. In the reference scenario, a specific price for the ancillary service was used. This value was argued to be a low estimate and conservative compared to the levels witnessed in the last years on the market. Therefore, three extra scenarios, covering a wider range of observed prices, were added. The price for the reference scenario was 20 /MW and the three other scenarios generated had a price of 25, 30 respectively 40 €/MW.

3.2.4 Battery cost scenario

As described in section 2.2.6, the cost of batteries has decreased significantly over the last decade. To account for a potential future decrease in battery prices, an additional scenario was created, representing this decrease. In the new scenario a power cost of €250,000 per MW, and an additional energy storage cost of €150,000 per MWh for the storage capacity beyond one hour (1C), was added.

4. Results

The results of the reference scenario, as defined in the preceding sections, are presented and evaluated in the following chapter. This includes all post-processing parameters, such as economic performance indicators, cycle count, and capture rate, as well as visualizations of trading behavior throughout the year.

Subsequently, a comparative analysis is conducted, in chapter five, between the reference scenario and each of the alternative scenarios, namely the lower cost, SoC variation, and ancillary service cases. For each scenario, the corresponding post-processing results are examined to assess the impact of key parameter variations on the performance and profitability of the battery system.

4.1 Reference scenario

For the reference scenario, see chapter 3.2.1 for defintion of scenario, the optimal battery storage was dimensioned to 15MW/15MWH ($C_{rate} = 1$, which will be condensed as "1C" in forthcoming results). The battery cycled a total number of 577 times per year, which equalled 1-2 charge/discharges per day.

For the economical post-processing parameters, a discount rate of five percent was assumed, and the operational cost was estimated to be €6 per KWh. There was also zero end-of-life salvage assumed meaning that the battery did not have any value remaining at end of life. Constant cash flow was assumed accordingly to the model that iterates yearly. This resulted in the following:

Table 1. Post-processing parameters for the reference scenario.

	LCOS (€/MWh)	NPV (M€)	Payback time simple (years)	Payback time discounted (years)	Cycles	IRR (%)
Reference Scenario	109	2.01	7.5	9.6	577	10.2

Furthermore, the capture rate was visualized for every month of the year, and compared to the wind park itself, without any battery.

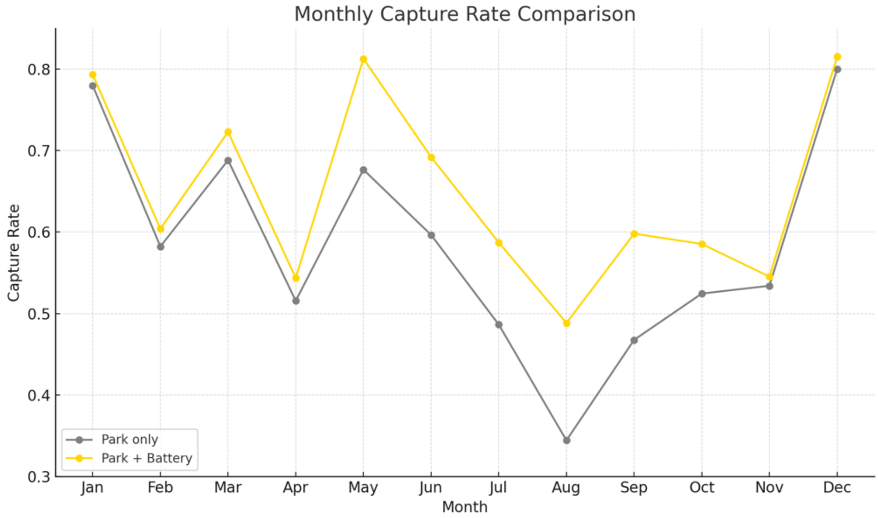


Figure 8. Monthly capture rate comparison.

The yellow curve in figure 8 represents the performance of the new hybrid park with an integrated battery energy storage system. Over the course of the year, a consistent increase in the capture rate was observed compared to the non-hybrid configuration. Seasonal variations, particularly between winter and summer months, are further examined in Chapter 5.1: Reference Scenario Analysis.

The optimization model generated hourly data for battery charging, discharging, and state of charge (SoC) throughout the year. These outputs were used to create visualizations illustrating the battery's operational strategy.

In figure 9, the daily average values for charging and discharging are presented. Charging activity is depicted in yellow, while discharging activity is shown in grey. These visualizations provide insight into the temporal dynamics of battery usage and its contribution to improved energy capture and market participation.

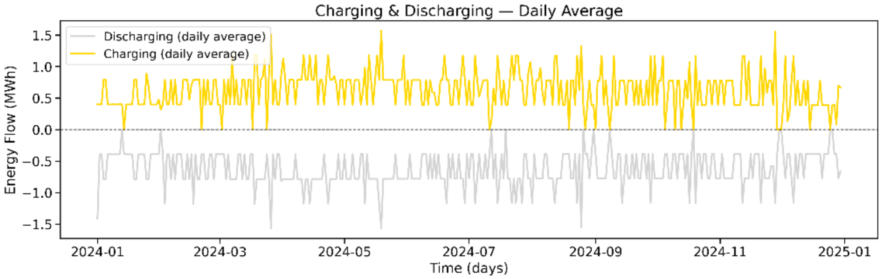


Figure 9. Daily average of charging and discharging over a year.

The energy flow in the previous figure is presented as a daily average, indicating that multiple charge-discharge cycles could occur within a single day. The y-axis reflects the average net energy trade per day, with charging represented as positive values and discharging as negative values. This convention explains the symmetrical scale of the axis. A more detailed interpretation of these trends is provided in Chapter 5.1: Reference Scenario Analysis.

To further illustrate the operational behaviour of the battery, the figure below presents a representative week of battery activity. Charging is shown in yellow and discharging in grey. The power levels do not reach the full rated capacity of 15 MW in either direction due to system constraints, including a round-trip efficiency of 95% and a maximum usable SoC limited to 60% of total capacity. The specific charge and discharge values were determined endogenously by the optimization model based on the input parameters, ensuring operation remained within technical and economic bounds.

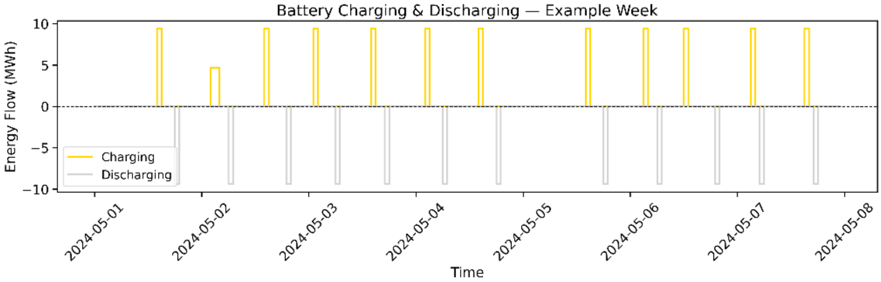


Figure 10. Example week of charging and discharging.

The example week presented corresponds to the first week of May 2024. The observed trading patterns indicate that certain days were less economically favourable for charging the battery, most notably on May 2nd and May 5th. Despite these fluctuations in profitability, the battery's SoC at the beginning of the week enabled discharging on all days but one, and prevailing market prices generally provided incentives for trading activity.

To provide a more comprehensive view of battery operation over time, two heatmaps were developed to visualize trading patterns. In these visualizations, the y-axis represents the hour of the day, while the x-axis denotes the month of the year. The colour intensity of each cell corresponds to the average energy charged or discharged (in MWh) during that specific time interval. These heatmaps reveal distinct temporal patterns: charging activity peaked around midnight and midday, with heightened activity during the summer months. Conversely, discharging was most prevalent during morning and evening hours and occurred more consistently throughout the year.

These operational trends closely mirror typical electricity price profiles, where prices tend to be lowest around midnight and midday and highest during morning and evening demand peaks. A more detailed analysis of this behaviour is provided in Chapter 5.1: Reference Scenario Analysis.

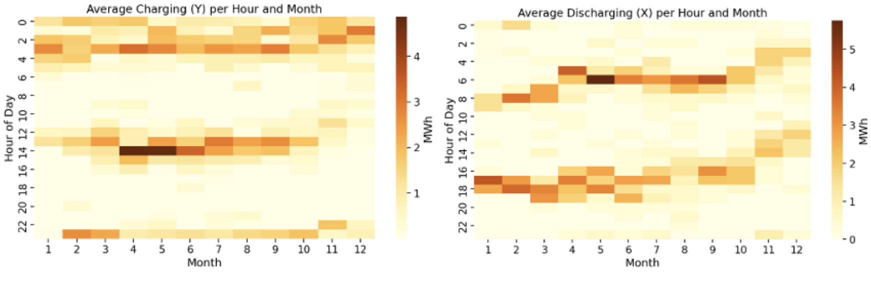


Figure 11. The heatmaps for the most common hours to charge respectively discharge during the day for each month of the year.

Proceeding from the reference case into the alternative scenarios the results took a parameter-oriented approach, where each subheading included all alternative cases and highlighted one of the post processing parameters each. The first one was the levelized cost of storage.

4.2 Levelized cost of storage (LCOS)

Levelized cost of storage, LCOS, presented in EUR per MWh. See chapter 3.2 for definition of scenarios.

Table 2. LCOS for all scenarios.

Reference scenario	Lower cost	SoC variation	Ancillary 1	Ancillary 2	Ancillary 3
109	57.7	63.9	108.4	109	109

The documented variation in cost was directly linked to the battery size, which in turn influenced the total investment cost. The lower-cost scenario resulted in the largest battery configuration, a 3C system rated at 15 MW/45 MWh and also produced the lowest LCOS. This outcome is likely attributed to the greater trading volume, allowing a larger total energy throughput over the battery's operational lifetime. A more detailed analysis of this dynamic is presented in Chapter 5.1: Reference Scenario Analysis.

The SoC scenario produced the second-largest configuration, with a 2C battery rated at 15 MW/30 MWh, benefiting from an extended usable state-of-charge range. In contrast, the ancillary service scenarios maintained the same configuration as the reference case, a 1C battery of 15 MW/15 MWh, reflecting consistent operational limits and a focus on revenue from grid services rather than expanded energy trading.

4.3 Net present value (NPV)

Net present value presented in millions of Euros. See chapter 3.2 for definition of scenarios.

Table 3. NPV for all scenarios.

Reference scenario	Lower cost	SoC variation	Ancillary 1	Ancillary 2	Ancillary 3
M€2.01	M€5.58	M€4.71	M€4.01	M€5.36	M€8.18

Across all scenarios, the NPV increased as battery performance improved, regardless of which specific parameter was adjusted. For example, increasing the allowable SoC led to a higher NPV than in Ancillary Case 1. However, both scenarios still resulted in lower NPVs compared to the lower-cost battery scenario, which had the second-highest overall value. The scenarios that included participation in ancillary service markets showed the most significant increase in profitability.

4.4 Payback time

The simple payback time presented in years. See chapter 3.2 for definition of scenarios.

Table 4. Payback time for all scenarios.

Reference scenario	Lower cost	SoC variation	Ancillary 1	Ancillary 2	Ancillary 3
7.5	6.19	6.61	5.89	5.14	4.09

The simple payback time referred to the payback time without taking the discount rate into account. All alternative scenarios saw a decrease in payback time, which was positive from an economic perspective. The lower cost and SoC scenarios were similar, and the ancillary scenarios were noticeably lower. All cases had a payback time below 15 years, which was the economic lifetime of the battery.

The discounted payback time presented in years.

Table 5. Discounted payback time for all scenarios.

Reference scenario	Lower cost	SoC variation	Ancillary 1	Ancillary 2	Ancillary 3
9.6	7.6	8.23	7.15	6.08	4.68

The increase in payback time indicated a healthy relationship between the discount rate and the initial investment, the payback time was still below 15 years, meaning that from the last year of payback, and onward, the battery would have recovered its own costs through revenue. As seen in the NPV the Lower cost scenario had a higher NPV as it would earn back its own costs quicker than the SoC case. In the ancillary cases a large upside was found when the revenue increased.

4.5 Capture rates

Capture rates were presented as an increase or decrease compared to having no battery, a “delta” in percentage points. See chapter 3.2 for definition of scenarios.

Table 6. Capture rates for all scenarios.

Reference scenario	Lower cost	SoC variation	Ancillary 1	Ancillary 2	Ancillary 3
6.62	9.15	8.80	7.77	9.03	11.4

The data showed that all future scenarios had a large upside in capture rate performance. The Alternative scenarios did not differ drastically from each other. But all scenarios saw an increase compared to the reference case. An important note was that the capture rate percentage was purely calculated with the difference in total change, it was not volume weighted.

4.6 Internal rate of return (IRR)

The internal rate of return presented in percentages. See chapter 3.2 for definition of scenarios.

Table 7. IRR for all scenarios.

Reference scenario	Lower cost	SoC variation	Ancillary 1	Ancillary 2	Ancillary 3
10.2	13.8	12.6	14.9	17.8	23

The internal rate of return reflected the expected profit, across all scenarios a return above 10% was observed. This profit was solely from the battery covering its own investment, where the added profit for the wind-park was secluded. A choice was made to visualize the battery performance on its own to present a nuanced result considering both the battery itself and the hybrid combination.

4.7 Yearly cycle count

The total cycles made with the battery throughout the whole year. A cycle count measured in terms of accumulated energy to and from the battery, where one cycle was defined as the total energy to complete a full charge and discharge within the bounds of the SoC. See chapter 3.2 for definition of scenarios.

Table 8. Yearly cycle count for all scenarios.

Reference scenario	Lower cost	SoC variation	Ancillary 1	Ancillary 2	Ancillary 3
577	540	548	579	579	575

One thing that had to be accounted for when inspecting the cycle count was that the way a cycle was counted varied in the SoC case, because of the increased range of operations. Therefore, even though there were less cycles, the battery still circulated more energy. The lower cost scenario, on the other hand, had the same threshold as the reference case, and still displayed a lower cycle count. Potential underlying factors are explained in further detail in chapter 5.2.6 Cycle Count.

5. Data analysis

5.1 Reference Scenario Analysis

The assumptions defined in the reference case were based on the most up-to-date investment costs and technology performance metrics available for the spring of 2025. The scenario was designed to reflect a situation in which a BESS could be implemented immediately under current market conditions. The optimization results suggested moderate feasibility, with the optimal configuration being a 1C battery rated at 15 MW/15 MWh, sufficient for one hour of full discharge at rated power. When compared to the wind farm's total installed capacity of 200 MW, this battery corresponds to only 7.5% of the maximum instantaneous generation capacity. As discussed in the limitations section, this relatively small size is primarily due to charging constraints, as the BESS could only be charged using energy produced on-site and was limited by the connection point's capacity to the grid.

A key indicator of system-level performance was the capture rate, defined as the share of electricity sold during periods of favorable market prices. This metric reflects the value of the hybrid park as a whole, independent of the BESS's stand-alone financial returns. In this respect, the reference scenario yielded promising results.

With the BESS in operation, the wind farms capture rate never dropped below 48% over the course of the year, a notable improvement over the baseline scenario, which recorded a low of 35% in August 2024. These results indicate a compelling case for retrofitting BESS to existing wind farms, even when economic constraints necessitate relatively small battery sizes. However, it is important to note that the capture rates were not volume-weighted; monthly averages were calculated independently of the amount of electricity generated in each period.

A closer inspection of the results revealed that the most significant improvements occurred during the summer months, where capture rates increased by more than 10 percentage points. In contrast, improvements during winter were more modest, often limited to a few percentage points. This seasonal trend can be explained by two key factors: first, higher trading volumes typically occur during winter, when electricity demand is greater; second, wind production in Sweden tends to be higher during the winter months due to increased wind speeds. Consequently, the relative contribution of a small battery is diminished during high-output winter periods, while it becomes more significant during summer, when wind generation is lower and BESS output represents a larger share of total energy exported to the grid.

Overall, the average annual capture rate increased from 58.3% to 64.5%, corresponding to an estimated additional revenue of approximately €400 000 per year. This highlights the potential added value of a BESS, even one of limited size, when paired with an existing wind asset. As the battery also has the ability to recover its capital cost over its lifetime, the case for investment becomes substantially stronger.

The economic performance of the BESS was assessed using four key metrics: LCOS, NPV, IRR, and Payback Time. Despite the relatively high capital cost of battery systems at the time of analysis, the results showed that the BESS could generate value over its 15-year lifetime. The LCOS was calculated to be €109/MWh, consistent with or slightly lower than comparable figures reported in the literature (see Chapter 2.5: Previous Work). This cost level is challenging to recover through energy arbitrage alone, indicating that participation in ancillary service markets is currently an integral part of the economic viability in the reference scenario.

Assuming an ancillary service income of €20/MW, the NPV of the reference scenario reached €2.01 million. The initial investment of €5.25 million was recovered after 9.6 years, considering appropriate discount rates. This financial outcome was made possible by a combination of revenue from frequency regulation services, arbitrage trading, and load shifting. The remaining 5.4 years of the battery's lifespan could thus be considered as net profit, representing approximately one-third of the total operational lifetime.

Nevertheless, the financial risk should not be overlooked. With a relatively high upfront investment, a modest NPV, and a nearly 10-year payback period, the project's financial profile could be considered risky, especially in the context of the electricity market's inherent volatility (as discussed in Chapter 2.1.7). However, it is important to frame the BESS not as a standalone asset, but as a strategic enhancement to the wind farm. Since the system improves both the wind farm's capture rate and recovers its own costs, the hybrid configuration presents a compelling case for upgrading aging wind infrastructure.

It is also worth emphasizing that this analysis is based on market conditions in 2024. Future fluctuations in electricity prices, regulatory frameworks, and technology costs could significantly alter the outcomes. A more detailed discussion on the implications of using 2024 as the baseline is presented in Chapter 6.4: Market Fluctuations.

Additionally, an important aspect to consider, particularly in light of developments in 2025, is the increased value of battery storage in scenarios where wind power production forecasts deviate from actual output. This topic has been highlighted in recent media coverage and underscores a potential benefit not fully captured in the reference case. As Svenska Kraftnät has initiated a transformation of the ancillary serices market to 15-Minute time resolution, extreme price volatility has emerged, with prices reaching up to €10 000/MWh. These dynamics have raised concerns over the economic sustainability of smaller producers, particularly in the absence of adaptive strategies such as energy storage. This context strengthens the case for batteries, not only as tools for arbitrage and ancillary services but also as risk mitigation assets when forecast errors lead to exposure in high-price balancing markets. This aspect should be acknowledged as an added value of battery integration and is addressed in Section 2.1.6: Transition to 15-Minute Time Resolution and New Regulations.

The final operational parameter evaluated in the reference case was the annual cycle count of the battery, which totalled 577 full equivalent cycles corresponding to approximately 1.58 cycles per day. This figure is slightly lower than anticipated when compared to the theoretical capability of future battery technologies, which are expected to achieve up to 12 000 cycles over a 15-year lifespan, or roughly 800 cycles per year (see Section 2.2.3: Battery Lifetime). However, this observed discrepancy warrants further discussion and contextualization.

The optimization model used in this study was designed to identify the most economically advantageous charging and discharging strategy based on hourly electricity prices in the intraday market. The battery was only activated when market prices deviated significantly either above or below the daily average of the day-ahead market, and only when sufficient wind generation was available to charge the system. As such, the model prioritized profitability over utilization, and avoided cycling the battery unless economic conditions were favorable. This operational logic helps explain the lower-than-expected cycle count.

The fact that the battery cycled approximately 1.5 times per day suggests that substantial price volatility sufficient to justify trading, occurred roughly twice per day, which is consistent with typical price dynamics observed in the Swedish electricity market. These daily patterns were further confirmed by the heatmap visualizations included in the analysis.

So why does the total number of cycles fall short of the expected 800 cycles per year? There are several factors contributing to this outcome. First, the analysis is based on market and production data from a single year (2024), and thus does not capture interannual variability. Electricity prices, wind patterns, and trading opportunities fluctuate from year to year; in some years, more frequent cycling could be justified, while in others, fewer opportunities may arise. Consequently, the cycle count of 577 should be interpreted as a representative figure for the conditions observed in the reference year, not as a definitive operational limit. It provides an approximate indicator of battery behavior under specific market and generation scenarios, rather than a universal benchmark.

Additionally, the model's conservative approach, designed to avoid unnecessary degradation and prioritize long-term value, may further constrain the number of cycles. Unlike theoretical cycle capacity, which assumes constant usage under ideal conditions, real-world operation involves trade-offs between profitability, battery wear, and grid constraints.

When benchmarked against similar studies, the cycle count obtained in this thesis aligns well with empirical data for batteries operating in hybrid applications focused on energy arbitrage and ancillary services. This indicates that while the technical limit of 800 cycles per year may be feasible under certain conditions, the operational cycle count observed here is consistent with current real-world BESS deployments.

This final section of the reference case analysis presents a detailed interpretation of the trading performance, based on the graphical results provided in the Results chapter. The analysis begins with figure 9 illustrating the daily average trade throughout 2024. In this graph, the y-axis represents net energy flow, where charging is depicted as positive values and discharging as negative. The daily variation is clearly visible: on some days, the battery exhibits a net charge, while on others, it discharges more energy than it absorbs. This variability reflects the model’s flexibility and responsiveness to market signals across different timescales.

Notably, the model is not restricted to balancing operations within a strict 24-hour cycle. Instead, it demonstrates an ability to optimize battery usage across multiple days. For example, one day might feature net discharging with a lower SoC maintained, while the following day might emphasize charging, reflecting the model's sensitivity to broader price trends and trading opportunities. This behavior indicates a well-functioning optimization algorithm capable of adjusting its operation dynamically to maximize profitability.

To further illustrate the model’s operational logic, a randomly selected week was plotted. Figure 10 highlights the variation in charge and discharge levels from day to day, underscoring the model’s ability to make economically rational decisions. The model was observed to fully charge or discharge the battery when profitable, and to abstain from trading when market conditions did not justify it. This is an important confirmation that the system is not over-utilizing the battery, but rather acting prudently in response to prevailing conditions.

The analysis then turns to the two heatmaps in figure 11, which offer a high-resolution overview of battery activity by hour and month. These visualizations revealed that the battery's discharge was most concentrated during early mornings (04:00–08:00) and early evenings (16:00–18:00). These time windows correspond with typical peaks in electricity demand in the Swedish market, when consumers are most active. The most significant discharging activity was observed between April and September, coinciding with the lower seasonal wind generation during summer months. This supports the earlier observation that the BESS plays a more prominent role when the wind farm’s output is reduced, enhancing the system’s contribution to market alignment.

Conversely, the charging heatmap showed that battery charging was most active during periods of low electricity prices, typically around midnight and midday. These times align with demand troughs in the daily consumption cycle and therefore represent favorable periods for cost-effective energy storage. Like the discharging behavior, charging activity was most pronounced between April and September, further reflecting the system’s seasonal responsiveness.

In summary, the trading behavior of the battery under the reference scenario aligns well with known consumption and pricing patterns in the Swedish electricity market. The model successfully identifies and exploits periods of high and low market value, adjusting its operations accordingly. This demonstrates not only the robustness of the optimization approach but also the potential for BESS systems to generate meaningful value by following predictable, data-driven patterns in energy demand and price variability. The results underscore the system's ability to trade efficiently and logically, maximizing profitability while supporting the integration of intermittent renewable energy.

5.2 Alternative Scenario Analysis

Proceeding to investigate the alternative scenarios, an indicator-based analysis was applied, where each of the investigated post processing parameters is handled separately considering the outcome of all the alternative scenarios. In this way an overview of the impacts of different variations was intended to be easier to grasp and present. The headings below will contain further analysis of the post processing results.

5.2.1 LCOS

In the reference scenario, the LCOS was calculated to be €109/MWh. This value exceeds the average market price for electricity in 2024, which was €40.9/MWh, suggesting that, under current conditions, it is challenging to recover the full investment through battery operation alone. However, when considering the combined revenue streams from energy arbitrage, ancillary service participation, and the prevailing revenue from the wind farm, the overall economic viability of the investment becomes more favorable.

Among the evaluated scenarios, the reference case exhibited the highest LCOS, reflecting its relatively conservative configuration and current market limitations. In contrast, the lower-cost scenario and the high-SoC scenario produced significantly lower LCOS values, €57.7/MWh and €63.9/MWh, respectively. These reductions can be attributed to the two key components of the LCOS formula: total cost and total energy throughput.

In the lower-cost scenario, the reduced capital cost directly lowered the numerator in the LCOS calculation. Although the battery system was larger in absolute terms, the lower unit cost resulted in a higher total installed capacity at a competitive investment level. This increase in capacity translated into higher energy throughput over the system's lifetime, which further reduced LCOS. In essence, more energy was delivered per euro invested.

The high-SoC scenario, by contrast, maintained the same battery cost of investment as the reference case but benefited from a broader usable state-of-charge range (0.1 to 0.9, compared to 0.2 to 0.8 in the baseline). The battery was rated at 15 MW/30 MWh, effectively doubling the storage duration to 2 hours (2C configuration). This increase in usable energy enabled greater energy throughput across the same investment cost, leading to a reduced LCOS.

An interesting comparative insight emerges when evaluating the configurations of these two scenarios. The SoC-enhanced battery, although smaller than the 15 MW/45 MWh lower-cost battery, was able to trade more effectively at key moments. Thanks to its extended SoC range, it could access up to 80% of its capacity for trading, compared to 60% in the lower cost (and reference-) case. This allowed it to respond more effectively to high-price events in the market, effectively "capturing" more value during peak conditions. From a system perspective, this performance was comparable to that of a larger, cheaper battery. Notably, both the SoC and lower-cost scenarios had equal investment levels of €8.25 million (undiscounted), emphasizing that enhanced technical performance via greater usable capacity can deliver value equivalent to purely financial savings.

The ancillary service scenarios displayed LCOS values that were closely aligned with the reference case. This outcome may appear counterintuitive, given their higher total revenue. However, it is explained by the fact that the hourly energy export remained approximately the same as in the reference scenario. The optimization model did not increase battery capacity or trading volume; instead, it modeled ancillary service income as a fixed revenue stream based on available power. Consequently, while total income increased positively impacting metrics like Net Present Value, Internal Rate of Return, and Payback Time, the LCOS remained largely unchanged due to static throughput and unchanged investment cost.

It is also important to note that in the context of hybrid systems, LCOS alone may not fully reflect the battery's overall value contribution. In hybrid wind-battery configurations, the battery’s role extends beyond standalone energy storage, it acts as a system integrator, smoothing output variability and enhancing the capture rate of the wind farm. In such cases, LCOS should be interpreted as a supplementary indicator of economic performance, rather than the sole determinant of investment feasibility. For instance, if LCOS were to fall below the average market electricity price (approximately €40.9/MWh in 2024), it could signal unrealistic assumptions or computational errors, as such values are not currently achievable with existing technologies.

Lastly, it should be noted that a slight deviation in the LCOS for Ancillary Case 1 was identified. This minor difference is likely due to rounding inconsistencies during post-processing and does not significantly impact the overall conclusions of the scenario.

In summary, the LCOS analysis underscores that both cost reductions and performance enhancements, such as expanded SoC ranges, can significantly improve the cost-effectiveness of battery storage. However, in hybrid applications, it is essential to evaluate LCOS alongside other metrics that reflect the broader system benefits of battery integration.

5.2.2 NPV

The NPV represents the current value of a project’s total expected profitability over its operational lifetime, incorporating the effect of a predefined discount rate. For wind farm owners, it serves as a direct financial indicator of the economic viability of investing in a BESS at present. As anticipated, the reference scenario yielded the lowest NPV. Under 2024 market conditions, the investment case for battery storage is relatively modest, yet still financially feasible.

The alternative scenarios, however, demonstrated significant improvements in NPV, highlighting the potential upside under plausible future market developments. Each scenario was based on credible assumptions regarding cost reductions, regulatory changes, or technological advancements. The results underscore the substantial opportunity for enhancing profitability through BESS integration in pre-existing wind farms, should any of these developments materialize.

In contrast to LCOS, which evaluates the cost per unit of energy throughput, NPV offers a more direct assessment of the investment's economic return, independent of technical performance metrics. Among all scenarios, Ancillary Case 3 produced the highest NPV, primarily due to stable and substantial income from power staking in ancillary service markets. The lower-cost scenario ranked second, suggesting that, purely from an economic standpoint, a future characterized by reduced battery investment costs offers the most favorable outcome.

The SoC-enhanced scenario also showed a strong improvement in NPV. It is arguably the most realistic in the short term, as it maintains the same capital cost assumptions as the reference case while benefiting from technological advancements that are already being realized in commercial battery systems. As discussed in Chapter 2.2.5: Rapid Development of Battery Technology, improvements in usable capacity and performance are expected to accelerate, making this scenario particularly relevant to near-term investment planning.

5.2.3 Payback time

The results indicated that scenarios with higher ancillary service revenues experienced the most significant reductions in payback time. However, as proposed in this thesis, future market dynamics are expected to shift gradually away from a strong reliance on ancillary services toward a more arbitrage-focused revenue model. The key takeaway from current data is that, under present conditions, batteries participating in frequency regulation markets can achieve favorable short-term returns, thereby supporting a positive investment outlook in today's market environment.

In a longer-term perspective, should ancillary service revenues diminish, the greatest potential for improved payback times will likely stem from reductions in battery manufacturing costs or advancements in battery technology. Both of these factors would enhance profitability through lower capital expenditure or improved energy throughput.

Notably, reductions in payback time were also observed in other alternative scenarios. The scenario with an increased SoC operating range showed a payback time reduction of over one year. This highlights an additional benefit of expanding the SoC interval, a technically feasible and relatively straightforward modification using current battery technologies.

5.2.4 Capture rates

The alternative scenarios all demonstrated a clear improvement in capture rates when compared to the reference case. Notably, both the lower-cost and wider SoC range scenarios resulted in the optimization model selecting larger battery configurations. Specifically, the lower-cost scenario produced a 3C-rated battery of 15 MW/45 MWh, while the SoC variation scenario resulted in a 2C battery of 15 MW/30 MWh, as previously discussed. These larger storage capacities enabled greater hourly trading volumes, thereby improving the system's ability to capitalize on price fluctuations and enhance the overall capture rate.

These benefits were particularly pronounced during the summer months, when wind generation volumes are typically lower. During these periods, energy is often transferred from the wind farm to the battery at reduced prices. The increased storage capacity in the alternative scenarios allowed for more effective shifting of this lower-value energy to periods of higher market prices, amplifying the relative improvement in trading performance. Even in the ancillary service revenue scenarios, a modest improvement in capture rates was observed, further supporting the economic rationale for BESS integration.

A recurring pattern across all scenarios was the greater relative improvement in capture rates during summer, particularly in May and August. These two months displayed the largest deviations from the baseline values. In total, the alternative scenarios achieved an average increase in capture rate of 18.3% in May and 18.7% in August. This can be attributed to the combination of lower generation volumes and, especially in August, generally low market prices, conditions under which even a relatively small battery system can provide significant marginal benefits.

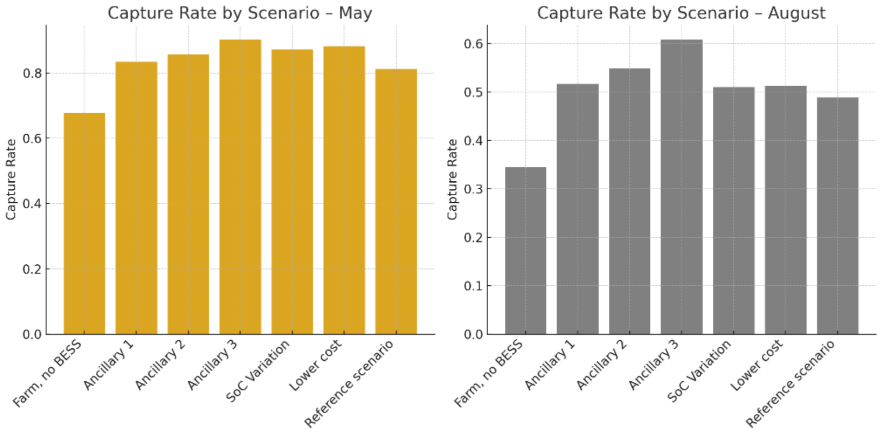


Figure 12. Difference in capture rate for each scenario for the months May and August.

As shown in Figure 12, these seasonal trends are clearly reflected in the monthly capture rate comparisons across scenarios. The results reinforce the conclusion that the relative value of battery integration is highest during periods of reduced wind generation, when the system's ability to optimize energy dispatch has a more pronounced impact on economic performance.

5.2.5 IRR

Among the alternative scenarios, the highest improvements in IRR were observed in the ancillary service cases, where increased revenue from staking power in the FCR-D and FCR-N markets was assumed. Even Ancillary Case 1, which included only a modest increase in ancillary income, yielded a higher IRR compared to both the lower-cost and SoC-enhanced scenarios. This outcome aligns with previous findings, reinforcing the significant role that ancillary service revenues play in enhancing the economic viability of battery storage systems.

It is important to note that the IRR values presented here were calculated based solely on the standalone performance of the battery system. The analysis does not account for the combined economic performance of the hybrid wind-battery configuration. If the battery's charging activity, drawn from wind turbine production, were to be considered as a cost in terms of foregone direct wind power sales, the resulting IRR would differ. Additionally, the overall financial return from the full wind park would vastly exceed the contributions from the smaller BESS component. Thus, the values reported for IRR in each scenario reflect only the self-sufficiency and investment viability of the battery on its own.

Each scenario produced a solid rate of return of 10% or more, indicating that under various plausible future conditions, BESS can be considered a financially sound investment. The greatest IRR improvements occurred in the ancillary service scenarios, while more modest gains were observed in the lower-cost and SoC scenarios. This is likely attributable to the fact that these latter cases involved larger battery systems, which required higher capital investment. Although these configurations achieved increased revenue through higher throughput, the proportional increase in returns was somewhat offset by the higher initial cost resulting in a more limited improvement in IRR.

5.2.6 Cycle count

The cycle count analysis revealed a slightly lower number of full equivalent cycles in the lower-cost scenario compared to the reference case. At first glance, this might appear counterintuitive, as one might expect a larger, lower-cost battery to be utilized more frequently. However, the deviation is minor and falls within a reasonable range, indicating no inconsistency in the model's logic. In the lower-cost scenario, the optimized battery was a 3C configuration with a capacity of 15 MW/45 MWh, enabling up to three hours of continuous discharge. This increased storage duration allowed the battery to store larger energy volumes and engage more selectively with high-value trading opportunities. Instead of cycling frequently, the model appears to have favored fewer but more profitable trades, conserving energy for peak market price events.

A similar explanation applies to the SoC-enhanced scenario, where the optimal battery was a 2C configuration (15 MW/30 MWh). The increased usable capacity allowed for extended operation and flexible scheduling, leading to slightly fewer cycles overall. The differences, 37 fewer cycles in the lower-cost scenario and 29 fewer in the SoC variation scenario, are relatively minor compared to the annual total (577 cycles in the reference). These small variations suggest that the effect of battery sizing on cycle count is limited and should not be overinterpreted.

For the ancillary service scenarios, the number of cycles was nearly identical to the reference case. This is expected, as all three scenarios used the same battery size and were not configured for greater arbitrage activity. Instead, their increased revenue came from additional ancillary service income, not from increased trading frequency.

A key reason for the similarity in cycle counts across all scenarios lies in the underlying input data. Each scenario was based on identical market price data for the SE3 bidding zone in 2024, and the same wind generation profile for the reference wind farm. As a result, all battery configurations were responding to the same market and production dynamics. Even with variations in battery size, SoC range, or revenue streams, the number of profitable trading windows in a fixed year remains constrained by the actual price and generation patterns. To observe significant differences in cycling behavior, either the price data or the generation input would need to change, such as through modeling other years or regions.

Furthermore, it is important to emphasize that the objective function of the optimization model is designed to maximize economic return, not to maximize the number of battery cycles. The model may therefore favor larger, more strategic trades over frequent low-margin cycling. This profit-driven approach explains why even technically more capable batteries do not necessarily cycle more often, they are used more effectively, not more frequently.

In summary, the slight variations in cycle count between scenarios are consistent with the model’s structure and input assumptions. They reflect rational trade-offs made by the optimization algorithm in response to uniform market and production conditions, highlighting that battery performance must be evaluated not only by usage frequency but by the economic value of its operation.

6. Discussion

6.1 A thought on pushing the limits

While present-day investors cannot yet capitalize on reduced battery costs, an important insight emerges when evaluating operational strategies under current technological and market conditions. Specifically, even with the existing investment cost structure, increasing the usable SoC range could offer significant economic advantages. The results indicate that a wider SoC range, despite accelerating battery degradation, leads to higher Net Present Value, improved Internal Rate of Return, and a reduced payback period. These enhancements suggest that, in certain cases, it may be economically rational to accept a modest reduction in battery lifespan in exchange for increased revenue generation in earlier years.

Under the reference scenario, the battery completes approximately 577 cycles per year. Given industry projections that anticipate a technical cycle life of up to 12,000 cycles, this implies a theoretical economic lifetime exceeding 20 years. Expanding the SoC range would naturally lead to faster cycling and earlier degradation, potentially reducing the lifespan to approximately 15 years. However, the decrease in payback time, coupled with improved annual returns, would likely preserve, or even enhance, the overall investment profitability.

Moreover, increasing the SoC range not only improves direct battery economics but also contributes to higher capture rates at the system level. In the context of retrofitting pre-existing wind farms with battery storage, capture rate enhancement is arguably the most critical metric, as it reflects the overall hybrid system's ability to align production with market demand and maximize value. As such, the SoC extension strategy may be particularly appealing for wind farm operators aiming to optimize the performance of their hybrid assets.

In conclusion, the trade-off between accelerated degradation and increased revenue should be carefully evaluated in light of project-specific priorities. In the case of hybrid wind-BESS systems, where system-level performance gains, such as improved capture rate, amplify overall value, operating with an extended SoC range represents a viable and potentially advantageous strategy for maximizing the return on investment.

6.2 Perfect foresight and future forecasting requirements

An important observation from the reference scenario was the model's apparent awareness in trading decisions, specifically its ability to anticipate future market conditions and strategically plan net charging or discharging. This behavior reflects the use of perfect foresight within the optimization framework. The model was able to accurately determine when each trade would yield the highest return because it had full knowledge of future electricity prices and wind generation. While this assumption is common in techno-economic studies aimed at identifying optimal system configurations, it presents practical challenges when translating the results to real-world operations.

In practice, predicting long-term electricity price evolution and wind generation with high accuracy is extremely difficult. Therefore, while the model demonstrates the theoretical economic potential of BESS integration and identifies the optimal battery size under idealized conditions, it does not represent a directly implementable trading strategy. Rather, the optimization model was used as a design tool, with perfect foresight enabling a consistent benchmark for battery sizing and potential profitability. For this purpose, the assumption was deemed appropriate.

Importantly, the combination of perfect foresight and conservative revenue assumptions, particularly in the pricing of ancillary services and arbitrage opportunities, results in a balanced and realistic estimate of the upper bound of system performance. The model thus functions as a blueprint, illustrating how a battery could operate under ideal circumstances while maintaining credible economic outcomes.

To transition this work into a practical decision-making tool, future development would require the integration of forecasting capabilities. Specifically, a real-world trading model would benefit from price forecasts that extend at least one day ahead of the day-ahead market, allowing for a complete dispatch plan to be developed in advance. This would enable producers to schedule hourly trading activities with a forward-looking strategy, replicating the optimized behavior of the perfect foresight model as closely as possible. Moreover, such a system would help mitigate the risk of imbalance costs, by ensuring that battery charging and discharging align with market commitments.

Additionally, wind generation was also treated with perfect foresight in the current model. In a realistic setting, forecasting wind output would be essential to achieving comparable optimization results. Wind farm operators are already required to submit hourly production estimates to the Nord Pool market, implying the existence of internal forecasting models. By integrating these with price prediction models, the perfect foresight assumption could be replaced with a more robust and realistic predictive framework reducing error and improving the practical applicability of the trading strategy.

In summary, while the assumption of perfect foresight is a limitation in terms of direct applicability, it served a valuable function in this thesis by providing an idealized benchmark for optimal sizing and profitability assessment. Future work should focus on building predictive models to bridge the gap between theoretical optimization and operational feasibility.

6.3 Conservative modelling

The optimization model developed in this thesis adopts a deliberately conservative approach, particularly with respect to ancillary service revenues and the maximum export capacity constrained by the grid connection point. These limitations are discussed in greater detail in Chapter 6.5: The Assumptions. This modeling choice was made to ensure scientific rigor and to establish a realistic and cautious baseline for potential investment in BESS. By designing a model with conservative output assumptions, the risk of overestimating profitability is minimized, thereby reducing the likelihood of misleading stakeholders or incentivizing premature or ill-informed investment decisions.

However, one of the consequences of this conservative framework is the potential for battery undersizing. In a hypothetical variation conducted for the purposes of this discussion, the battery sizing was determined based on the maximum grid connection capacity and the average annual wind production, while still adhering to the constraint that total output (wind plus battery discharge) must not exceed the connection point limit at any time. Under these relaxed assumptions, the optimal battery size in the reference case was determined to be 161 MW/161 MWh 1C, a significantly larger system than the baseline result.

While this larger configuration reveals the technical feasibility of a higher-capacity battery, it also raises valid concerns regarding capacity utilization. In practical terms, such a large battery may be underutilized, as the available wind generation and grid export constraints rarely permit full utilization of the battery’s charge and discharge capacity. This highlights the need for further investigation into the operational efficiency of oversized systems, specifically how often a battery of this scale would be fully activated, and whether the increased capital investment would be justified by the additional revenue.

Returning to the original modeling rationale, the decision to adopt a stricter, more conservative approach was intentional. The objective was to provide a stable and scientifically grounded benchmark that could serve as a foundation for future research and practical investment analysis. By erring on the side of caution, this thesis contributes a reliable point of reference for wind farm operators and policymakers considering the integration of battery storage into existing infrastructure.

6.4 Market Fluctuations

As discussed in Section 2.1.7: Historical Fluctuation in the Swedish Electricity Market, the electricity market has experienced significant volatility over the past five years, making future price forecasting increasingly complex. Relying exclusively on spot-price data from a single year, 2024 in this case, for the purpose of optimization introduces inherent uncertainty. Such an approach, while methodologically clear, does not fully capture the spectrum of possible market outcomes.

A wide array of external factors influences electricity prices, including seasonal and weather variability, fuel costs, regulatory changes, international interconnections, supply-demand imbalances, and geopolitical events, among others. Therefore, basing an investment optimization solely on one year’s data, regardless of how representative, carries a high degree of risk.

That said, while elevated market uncertainty complicates forecasting efforts, it simultaneously enhances the strategic value of BESS. A well-designed BESS offers flexibility and can respond dynamically to volatile market conditions, thereby mitigating financial risk and improving system resilience.

This point is further emphasized by the recent introduction of 15-minute settlement periods in Sweden's ancillary service markets by the Transmission System Operator, Svenska Kraftnät, as discussed in Section 2.1.6: Transition to 15-Minute Time Resolution and New Regulations. Since the implementation of this reform, price volatility has increased markedly. For example, prices in some mFRR auctions have reached as high as €10,000/MWh, severely impacting market participants particularly wind power producers, who are most exposed to imbalances.

Although the same settlement reform for the day-ahead and intraday markets was originally scheduled for mid-2025, it has since been postponed. Nevertheless, it is reasonable to anticipate similar volatility once these changes are implemented. This evolving regulatory environment further underscores the strategic importance of flexible assets such as BESS, which are uniquely positioned to navigate price instability and enhance the economic viability of variable renewable energy sources.

6.5 The assumptions

As previously discussed, a conservative modelling approach was deliberately adopted in this thesis to ensure the results would not inappropriately incentivize investment or mislead wind power producers considering Battery Energy Storage Systems. Just as importantly, the model was designed to be immediately applicable for current wind farm operators, enabling practical implementation under existing technical and regulatory constraints. The rationale behind these modelling guidelines is further elaborated in Section 1.5 Limitations.

One of the key assumptions was that the battery could only charge from the wind farm's own generation, and not from the grid. This reflects real-world limitations related to existing grid connection agreements and the readiness of many wind farms to retrofit BESS without modifying their grid infrastructure. As observed in the results, this restriction significantly influenced battery utilization: the optimized BESS operated at 577 full equivalent cycles per year, or approximately 1.5 cycles per day. Figure 9 illustrates the average daily energy flow over the course of one year, revealing periods of underutilization, intervals where no charging or discharging occurred. These idle periods are largely a consequence of the constraint that prohibits grid charging, thereby preventing the battery from exploiting low or even negative market prices during surplus conditions.

If the model had allowed grid charging, particularly during low-price events, a larger battery with potentially a higher C-rate would likely have been selected. However, the second major constraint, the connection point capacity, reinforced the conservative stance. In many existing wind farms, the connection point is defined by long-standing agreements with the Transmission System Operator (TSO) or Distribution System Operator (DSO), which specify allowable export and import levels. Modifying these contracts often involves lengthy approval processes, making them a practical barrier to immediate implementation.

To illustrate the impact of relaxing these constraints, a hypothetical scenario was introduced in Section 6.3: Conservative Modelling, where the connection point and charging restrictions were relaxed. In this case, the model generated a battery size of 161MW/161MWh 1C for the reference year, demonstrating the significant potential for larger BESS installations if grid access were extended. However, such configurations would also delay deployment, requiring time-consuming approvals and infrastructure upgrades. Therefore, the decision to retain a conservative setup was justified by the aim to create a tool applicable from the outset, without requiring major changes to existing operational structures.

Another modelling simplification was the use of one year of market and production data, specifically hourly spot and intraday prices from 2024. This dataset was applied consistently throughout the battery's lifetime for the purpose of optimization. The decision was primarily due to time limitations and data availability challenges. Historical market data with sufficient resolution and consistency, especially intraday pricing, proved difficult to obtain. A more comprehensive analysis using multiple years of data would provide deeper insight into inter-annual variability and improve robustness. However, the single-year model still served its purpose of establishing a foundational investment benchmark.

A core objective of this thesis was to develop an optimization tool that generates practically implementable results, rather than a purely theoretical solution. If the model were instead intended solely for pre-project planning, a more experimental approach could be taken, one that explores various combinations of battery size, land usage, and connection point capacity, possibly including grid charging scenarios. In such cases, the emphasis would shift from immediate applicability to long-term feasibility. Nonetheless, the modelling tool developed here is adaptable to alternative constraints and future developments, and the hypothetical case clearly illustrates its flexibility and potential for broader application in wind farm planning and hybrid system design.

6.6 Approximation Quality

The optimization framework developed in this thesis was implemented using Pyomo, an open-source Python-based mathematical modeling language, in combination with the Gurobi solver. This setup required all objective functions and constraints to be expressed in a linear and static form. While effective for many applications, this requirement imposed certain limitations, particularly when modeling complex system behaviors that inherently follow nonlinear or dynamic patterns, such as battery degradation.

To account for degradation, a simplified linear approximation was applied across the battery's operational lifetime. In practice, battery degradation tends to follow an initial exponential decay, which later transitions into a more stable, near-linear decline. As the early nonlinearity is confined to a relatively short initial phase, the average degradation profile over a 15-year lifetime closely resembles a linear trend. Therefore, the linear approximation was considered sufficient for this study’s purpose, specifically to evaluate long-term economic performance and optimal battery sizing. While the model may slightly underestimate degradation in the earliest operational phase, this deviation has a negligible effect on the overall investment outcome, given that all financial metrics (e.g., NPV, IRR, payback time) are calculated over the entire project lifespan.

All such simplifications were carefully considered and motivated through discussion with academic supervisors, ensuring that the modeling approach remained scientifically sound and aligned with the scope and goals of the thesis.

An additional modeling challenge involved estimating the battery’s operational lifetime as a function of its cyclic behavior. Since the annual cycle count is an output of the optimization, it could not be used as an input to dynamically adjust the battery’s expected lifetime. Due to Pyomo’s static optimization structure, recursive relationships between inputs and outputs could not be directly implemented. Instead, an iterative approach was employed: an initial lifetime estimate was assumed, and the resulting cycle count was then used to validate or adjust this assumption in subsequent runs. This method ensured internal consistency between input assumptions and model outputs.

Similar to the linear approximation used for degradation, this iterative process was necessitated by the static nature of the modeling environment. Pyomo and Gurobi solve the optimization problem simultaneously and do not support real-time feedback or looping structures typical in dynamic simulation environments.

Looking ahead, one of the most promising areas for future work lies in developing a more dynamic modeling framework for battery degradation and lifetime estimation. Incorporating more detailed, nonlinear degradation curves and lifetime-cycle interdependencies could improve the realism and precision of the optimization outcomes. However, despite these limitations, the chosen toolset offered significant advantages: strong compatibility with mathematical formulations, robust performance, and the ability to deliver meaningful, scientifically valid outputs within the time constraints of the thesis project.

In summary, while certain trade-offs were made in model fidelity to accommodate the constraints of the selected optimization tools, the final framework proved to be both practical and reliable for determining optimal battery sizing and evaluating economic feasibility in hybrid wind-BESS configurations.

6.7 Future work

The battery size identified in the reference case is relatively modest when compared to the total installed capacity of the wind farm. This outcome stems from the conservative modeling approach adopted in the optimization framework. To strengthen the discussion, preliminary exploratory tests (not included in the core results) were conducted, which revealed that the two primary limiting factors in the model were the connection point capacity and the dependency on wind park production levels.

When the model was adjusted to base sizing on average wind production and the connection point limit, rather than on peak wind generation, a significantly larger battery configuration was selected. This scenario represents a more liberal design approach, which, while deviating from the conservative baseline, illustrates the potential for greater storage capacity if grid constraints and generation profiles are more flexibly interpreted.

As outlined earlier in the discussion, the conservative path was intentionally chosen to deliver a scientifically robust and implementable result. However, if the model is to be used in future as a decision-support tool for investment planning, we recommend that a more liberal sizing approach also be explored.

There is a trade-off to be considered: a larger battery may increase revenue potential but may not maintain a high utilization rate throughout the year. In the current reference case, the relatively small battery achieves high annual utilization. If similar utilization rates can be achieved with a larger system, the liberal approach may become economically advantageous, particularly in its ability to buffer production volatility and enhance the overall revenue profile of the hybrid system.

We also identify several areas for further development in the modeling framework:

Battery Degradation Modeling:
The degradation process was linearized to comply with the requirements of the Gurobi solver, which only accepts linear constraints. In future work, more accurate degradation representations could be integrated, either through linear regression models based on empirical lithium-ion degradation data or by transitioning to alternative solvers capable of handling non-linear optimization problems.

Ancillary Service Revenue Modeling:
The ancillary service component could be further refined by incorporating dynamic market behavior, such as mFRR (manual Frequency Restoration Reserve) participation and variable staking capacity. These enhancements would allow the model to better reflect the operational and financial variability observed in real markets. This is particularly relevant at present, as extreme prices are increasingly affecting wind farm owners who find themselves on the unfavorable side of the balancing market.

Multi-Year Optimization Horizon:

The current model is based on a single year of electricity price and wind generation data. Expanding the model to simulate multi-year scenarios would provide a more robust foundation for investment decisions, particularly by accounting for interannual variability in prices and production. Additionally, with the ongoing transition toward 15-minute market resolution, future versions of the model should be updated to accommodate sub-hourly data inputs, better aligning with evolving intraday and day-ahead market structures.

In conclusion, while the present model offers a conservative yet viable roadmap for BESS integration in existing wind parks, significant opportunities remain for refinement and expansion. These improvements would not only enhance the accuracy and realism of the results but also increase the practical relevance of the model as a tool for future energy investment strategies.

7. Conclusion

The reference scenario demonstrated that a 15 MW/15 MWh (1C) battery energy storage system (BESS) achieved a Levelized Cost of Storage (LCOS) of €109/MWh, a Net Present Value (NPV) of €2.01 million, and an Internal Rate of Return (IRR) of 10.2%. Additionally, the integration of the battery increased the wind farm's capture rate by over six percentage points, with the most pronounced improvements observed during the summer months, when wind production is lower. The battery operated with a cycle count of 577 per year, a value that aligns well with known patterns in the Swedish electricity market.

As the electricity market evolves toward 15-minute settlement periods, increased price volatility is anticipated. This transition will likely expand arbitrage opportunities, further enhancing the relevance and strategic value of BESS in hybrid configurations.

In the current market, however, ancillary services continue to play a dominant role in ensuring the profitability of battery investments. Given the upward trend in ancillary service revenues over the past five years, the results of this thesis suggest that hybrid wind-battery systems represent a viable and timely investment opportunity. Battery integration should therefore be seriously considered by existing wind farm operators, not only as a means of improving economic resilience but also as a contribution toward achieving Sweden's national climate neutrality target for 2045.

Among the most practical and immediately implementable strategies for improving battery economics is the expansion of the usable State-of-Charge (SoC) range. Unlike other technological enhancements that rely on future developments, an increased SoC range is feasible with current technology. The findings of this thesis demonstrate that extending the operational range of SoC can lead to significant gains in profitability, even when accounting for the associated impact on battery degradation. For wind farm owners seeking to maximize return on investment, increasing the SoC range represents a viable and actionable improvement.

In summary, this thesis offers a conservative yet forward-looking evaluation of BESS integration in pre-existing wind farms. The results show that a front-of-the-meter hybrid configuration can substantially enhance the performance and economic viability of renewable energy systems. With ongoing market reforms and continued technological progress, the outlook for wind-battery hybrid solutions is expected to become even more promising in the near future.

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