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Dispatch Modelling of a Wind Power and Battery Energy Storage Systems Hybrid Park

Optimisation of Operational Strategy and Profitability under Multi-Market Participation and Imbalance Management

Master's thesis in Sustainable Energy Systems

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Abstract

The share of renewable electricity generation in modern power systems has increased significantly. Since renewable energy sources such as wind power are inherently intermittent, their integration into the electricity grid can lead to increased power fluctuations, voltage instability, and frequency deviations. Consequently, the demand for balancing services and system flexibility has grown. Battery energy storage systems (BESS) have emerged as a key technology for supporting renewable integration due to their fast and flexible power regulation capabilities. They can also be integrated with existing renewable generation assets, forming so-called hybrid parks.

The aim of this study was to dimension a hybrid park consisting of wind power and BESS. A techno-economic optimisation model was developed to evaluate the operational strategy and economic performance of different BESS sizes during the years 2023, 2024, and 2025 using historical and forecasted production and market data. The optimisation model considers the participation of the hybrid park in both the day-ahead and intraday electricity markets, including imbalance costs, and determines the optimal operational schedule to maximise total revenue.

The results show that, under given assumptions of input data, none of the evaluated BESS configurations generated sufficient revenue to recover investment and operational costs within the assumed lifetime. Nevertheless, larger BESS capacities provided increased operational flexibility, enabling greater opportunities for energy arbitrage and improved management of production imbalances. The results further indicate that battery utilisation varied depending on the BESS size, market conditions, and the year under consideration. The sensitivity analysis demonstrated that factors such as improved forecast accuracy and reduced investment costs could significantly enhance the economic viability of the hybrid park.

In general, the results show a great difference between the studied years, which suggests that dimensioning an optimal BESS configuration based solely on the results from a single year could lead to faulty deductions for long-term profitability and system performance. Overall, the study contributes to a greater understanding of how market structure, forecast uncertainty, and BESS sizing influence the economic performance of hybrid wind-storage systems.

Keywords: BESS, Dispatch Optimisation Model, Economic Evaluation, Electricity Markets, Hybrid Park, Imbalance, Rolling Horizon

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Henrik Reimer, Gothenburg, May 2026
Ellen Westberg, Gothenburg, May 2026

List of Acronyms

Below is the list of acronyms that have been used throughout this thesis listed in alphabetical order:

ANP	Annual Net Profit
aFRR	automatic Frequency Restoration Reserve
BESS	Battery Energy Storage Systems
BRP	Balance Responsible Parties
BSP	Balancing Service Provider
CAPEX	Capital Expenditure
CET	Central European Time
CRF	Capital Recovery Factor
FCR-D	Frequency Containment Reserve Disturbance
FCR	Frequency Containment Reserve
FFR	Fast Frequency Reserve
FRR	Frequency Restoration Reserve
MEPS	MetCoOp ensemble prediction system
MET Norway	Norwegian Meteorological Institute
mFRR	manual Frequency Restoration Reserve
FCR-N	Frequency Containment Reserve Normal operation
OPEX	Operating Expenditure
PBP	Payback Period
RES	Renewable Energy Solutions
SOC	State Of Charge
SvK	Svenska Kraftnät
TSO	Transmission System Operator
VRE	Variable Renewable Energy

Nomenclature

Below is the nomenclature of indices, sets, parameters, and variables used in the optimisation models.

Indices

t	Index for hour

Sets

T^{DA}	Set of hours in the day-ahead optimisation horizon [h]
T^{ID}	Set of hours in the intraday optimisation horizon [h]

Day-Ahead Model

Parameters

Φ_t^{DA}	Day-ahead electricity price at time t [EUR/MWh]
$\hat{\Phi}_t^{IB}$	Forecasted imbalance price at time t [EUR/MWh]
$\hat{G}_t$	Forecasted generation at time t [MWh]
$P^{\max}$	Battery power capacity [MW]
η^{ch}	Charging efficiency
η^{dis}	Discharging efficiency
$SOC^{\max}$	Maximum state of charge [MWh]
$SOC^{\min}$	Minimum state of charge [MWh]
SOC'	Initial state of charge for horizon [MWh]
N^{cyc}	Maximum number of cycles per day
P^{exp}	Maximum export capacity [MW]

P^{imp}	Maximum import capacity [MW]
L	Grid loss coefficient set by Svenska Kraftnät
R	Risk surcharge set by Svenska Kraftnät [EUR/MWh]

Variables

p_t^{gen}	Generated power injected to the main node at time t [MW]
p_t^{curt}	Curtailed generation at time t [MW]
p_t^{ch}	Battery charging power at time t [MW]
p_t^{dis}	Battery discharging power at time t [MW]
p_t^{res}	Reserved capacity for imbalance handling at time t [MW]
p_t^{buy}	Power purchased from grid at time t [MW]
p_t^{sell}	Power sold to grid at time t [MW]
soc_t	State of charge at time t [MWh]
r_t^{DA}	Day-ahead revenue at time t [EUR]
$\hat{r}_t^{IB}$	Predicted imbalance-related revenue at time t [EUR]

Intraday Model

Parameters

Φ_t^{DA}	Day-ahead electricity price at time t [EUR/MWh]
Φ_t^{ID}	Intraday electricity price at time t [EUR/MWh]
$\hat{\Phi}_t^{IB}$	Forecasted imbalance price at time t [EUR/MWh]
G_t	Realised/updated generation at time t [MWh]
P_t^{ch}	Planned charging (from day-ahead) at time t [MW]
P_t^{dis}	Planned discharging (from day-ahead) at time t [MW]
P_t^{buy}	Planned purchase (from day-ahead) at time t [MW]
P_t^{sell}	Planned sales (from day-ahead) at time t [MW]
$P^{\max}$	Battery power capacity [MW]
η^{ch}	Charging efficiency
η^{dis}	Discharging efficiency
$SOC^{\max}$	Maximum state of charge [MWh]
$SOC^{\min}$	Minimum state of charge [MWh]
SOC^{prev}	State of charge from previous horizon [MWh]

$N^{cyc,left}$	Remaining allowable cycles
P^{exp}	Maximum export capacity [MW]
P^{imp}	Maximum import capacity [MW]
L	Grid loss coefficient
R	Risk surcharge [EUR/MWh]

Variables

p_t^{gen}	Generated power injected to the main node at time t [MW]
p_t^{curt}	Curtailed generation at time t [MW]
Δp_t^{ch}	Adjustment to charging power at time t [MW]
Δp_t^{dis}	Adjustment to discharging power at time t [MW]
Δp_t^{sell}	Adjustment to day-ahead sales at time t [MW]
Δp_t^{buy}	Adjustment to day-ahead purchases at time t [MW]
$p_t^{sell,ID}$	Intraday market sales at time t [MW]
$p_t^{buy,ID}$	Intraday market purchases at time t [MW]
i_t	Imbalance at time t [MW]
soc_t	State of charge at time t [MWh]
r_t^{DA}	Day-ahead revenue (adjusted) at time t [EUR]
r_t^{ID}	Intraday revenue at time t [EUR]
$\hat{c}_t^{IB}$	Predicted imbalance cost at time t [EUR]

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1
Introduction

This chapter covers the background of the project to provide context and highlight the relevance of the work. The aim and research questions are also presented, along with the study's limitations.

1.1 Background

In recent years, the share of renewable electricity generation in the energy system has increased significantly. Renewable sources, such as wind and solar, have great potential to generate low-cost electricity [1], but their production depends on weather conditions that do not always align with electricity demand. In 2024, the Swedish electricity system consisted of 25% generation from wind power and 1.5% from solar power [2]. Electricity demand is expected to increase substantially by 2045, with wind power anticipated to play a key role in meeting this demand [3]. However, the growing share of renewable generation can significantly affect the revenues of wind and solar park owners due to the cannibalisation effect. As new wind and solar capacity is added, it produces electricity with generation profiles similar to existing units, increasing supply during the same periods and thereby reducing market prices and overall revenue for producers.

Both wind and solar power are intermittent resources characterised by significant fluctuations. Wind power tends to vary irregularly over time, whereas solar power is strongly linked to specific hours of the day [4]. As their penetration in the energy system increases, these fluctuations can lead to voltage instability and frequency deviations, thereby increasing the need for reserve capacity [5]. Battery energy storage systems (BESS) have therefore emerged as a valuable technology for integrating these renewable sources, as they can provide multiple services within the electricity grid, such as Fast Frequency Reserve (FFR) and other ancillary services [6]. When BESS is integrated with generating units and shares a common connection point to the grid, it forms a hybrid park, enabling smoother and more controllable power delivery [7]. Consequently, the energy supplied to the grid from a hybrid park becomes less volatile and better suited to support grid balancing.

There are additional advantages associated with hybrid parks. Following the introduction of the 15-minute resolution in the imbalance market in spring 2025, imbalance costs for wind and solar park owners have increased significantly, in some cases reaching up to five times their previous levels [8]. This development reduces the economic attractiveness of renewable investments for potential owners. The integration of energy storage could mitigate these imbalance costs by enabling the park to better align its actual output with scheduled production [6]. In addition, storage introduces new revenue opportunities. Since the Swedish electricity market includes both energy trading and ancillary service markets [9], hybrid parks can participate in multiple value streams. Consequently, hybrid parks not only improve grid stability and reduce imbalances but also enhance profitability through energy arbitrage and the provision of ancillary services. Furthermore, studies show that additional benefits arise when multiple technologies share a common grid connection point. This allows grid capacity to be utilised more efficiently, while fixed connection costs can be distributed among several technologies [10]. However, BESS also has limitations, and their integration into hybrid parks leads to a considerable increase in investment costs [11]. Therefore, their economic viability and optimal integration require further investigation.

This thesis is done in collaboration with Renewable Energy Solutions (RES), one of the world's largest independent renewable energy solutions companies [12]. With more than 40 years of experience, the company has developed projects resulting in 29 GW of installed renewable energy capacity globally. RES has previously developed separate wind farms, solar parks, and BESS in Sweden, but is now exploring the possibility of integrating these technologies into a single hybrid park. However, determining the optimal operation of such a hybrid park is a challenging and relatively unexplored task, which constitutes the focus of this thesis.

1.2 Aim and Research Question

The objective of this thesis is to develop a techno-economic model of a hybrid energy park consisting of wind power generation combined with BESS. The purpose of the model is to determine the optimal operation and evaluate the financial performance of the park relative to the generation capacity and BESS system size. The following research question is the main topic of the thesis.

How does profitability depend on the operational strategy of the hybrid park?

The thesis will additionally answer the following subquestions:

- *How can BESS be optimally sized relative to generation capacity to ensure the profitability of a hybrid wind–storage system in the Swedish electricity market?*
- *How is revenue distributed across the different electricity markets?*
- *How does profitability vary under different yearly market conditions?*
- *Which factors affect the revenue of the hybrid park?*

1.3 Limitations

The project employs a linear optimisation investment model implemented in the Julia modelling framework. The model can be operated with both hourly and 15-minute time resolutions and is geographically limited to a single wind farm located in the price area SE2. It is solved over a one-year time horizon, and this procedure is repeated for the years 2023, 2024, and 2025. Historical day-ahead and intraday market prices from these years are used in combination with forecasted imbalance cost data.

Furthermore, the model does not explicitly represent the detailed behaviour of individual wind turbines. Instead, an hourly capacity factor profile is used to characterise the generation of the wind farm. This capacity factor is derived from the actual production patterns of the wind farm, thereby implicitly accounting for losses and efficiencies in the system components between the turbines and the grid connection. The corresponding power curves are constructed using data from 2023 and are assumed to remain constant for the subsequent years. Similarly, the tariffs for power and energy in the grid are based on the values for 2025, since these are the only ones publicly available.

2 Theory

This chapter covers the theory behind the study. Here, the characteristics of a hybrid park are presented, as well as some key characteristics of the components of the park. Additionally, it covers the structure of the Swedish electricity market.

2.1 Hybrid Parks

A hybrid park is an energy facility that integrates multiple technologies at the same site, most commonly wind turbines, solar panels, and BESS, with wind and BESS technologies being central to this study. In Sweden, hybrid parks are a relatively new concept, however, there are already some operational parks. One example is located in Skårmåla, where wind power is combined with solar power [13]. In Halmstad, there is also a hybrid park combining solar power and BESS, which is one of Sweden's first hybrid solar parks [14], and it was completed in 2025. In this study, the potential of converting existing wind farms into hybrid parks with BESS is investigated.

According to Bodecker Partners [6], a hybrid park can provide several advantages, such as delivering ancillary services, performing energy arbitrage, or providing other grid-support services, all of which may increase revenue streams from multiple markets for the park owner. In particular, by performing energy arbitrage, the grid connection point can be utilised more cost-effectively. This may help alleviate grid bottlenecks and thereby create opportunities to increase installed capacity within the park. In addition, the BESS enables the park to manage its imbalances and provide a more reliable power output, thereby reducing imbalance costs. Further advantages of hybrid parks include improved utilisation of existing infrastructure and increased operational flexibility. Finally, hybrid parks can mitigate the cannibalisation effect for wind and solar technologies, thereby increasing revenue.

Although hybrid parks and their optimal participation in electricity markets are relatively new topics, they have become increasingly relevant research areas. Varotto et al. [15] studied the optimal investment in BESS connected to a floating farm combining wind and solar power under three different cases of BESS integration. In that study, the batteries were modelled to enable energy arbitrage and to store electricity for sale at more favourable times. They showed that adding BESS to a wind farm can effectively reduce curtailment and provide a more stable power output to the grid.

In another study, Paul et al. [16] propose a multi-objective framework to determine the optimal battery capacity in connection with an offshore wind park. Their results provide an approach that can help decision-makers choose a suitable BESS configuration based on local requirements. For example, the study suggests that BESS with a longer storage duration is optimal when the objective is to avoid curtailment or loss-of-load hours. A similar study was conducted by Scrocca et al. [17], where solar panels coupled with BESS are analysed in the Italian electricity market. A stochastic model is used to optimise the participation of the park in the day-ahead and intraday markets to reduce imbalances. They conclude that when the BESS is only used to reduce imbalances, the net present value is negative, however, when arbitrage is included, the BESS becomes profitable.

In a further study by Senthilkumar and Jayasankar [18], the capabilities of hybrid solar–wind battery systems are assessed. They evaluate multiple optimisation approaches to determine the optimal sizing of park components to meet energy demand and conclude that the Secretary Bird Optimisation algorithm yields the lowest cost of electricity. They also find that a system including all three components generates more renewable energy, whereas configurations combining either wind or solar power with batteries result in lower costs.

Regarding optimal participation in the electricity market, Dennis et al. [19] studied a neighbourhood-sized BESS and its optimal participation in the Australian spot and ancillary services markets. More specifically, they examined the impact of using forecast data for optimisation instead of actual data and concluded that the use of forecasted data rather than historical can significantly decrease the revenue of the battery.

2.1.1 Generating Technologies

In this study, the modelled hybrid park uses wind power as the generation technology. Wind is an intermittent energy source and is highly dependent on weather conditions, where wind speed is essential for the operation of the plant [20]. This is because the power available in the wind is proportional to the cube of the wind speed, as shown in equation 2.1.

$$P = \frac{1}{2} C A \rho v^3 \tag{2.1}$$

where P is the theoretical power, C a constant factor depending on the design of the wind turbine, A is the rotor swept area, ρ the air density and v the wind speed.

A turbine is designed to operate from its cut-in speed up to its cut-out speed, with the rated speed somewhere in between. These speeds depend heavily on the turbine design, and the operating range can vary from approximately 4 to 17 m/s for a small turbine, while larger modern turbines can operate at wind speeds of up to 26 m/s [20]. Above this threshold, the risk of component damage increases, and the turbines are shut down. Together, these characteristic wind speeds create what is called a power curve, which illustrates the power the turbine can produce at each wind speed. Additionally, losses should be accounted for in the curve, and both internal and external losses exist [21]. The external losses are related to the grid and could therefore be used to normalise the curves when comparing different turbine models. The internal losses are specific to the turbine and park design. In this study, the power curve is constructed using measured power output data from the park at the grid connection point, ensuring that system losses are inherently included.

2.1.2 Battery Energy Storage System

A crucial component of the hybrid parks considered in this study is the battery system. How the battery can be utilised depends on its characteristics and how its operation affects its lifetime. The lifetime of BESS is mostly dependent on discharge rate, temperature, and depth of discharge [22]. Often, battery ageing is divided into calendar and cycle ageing [11]. Calendar ageing is the inherent degradation over time, primarily due to the state of charge (SOC) level and operating temperature. Cycle ageing arises every time the battery is charged and discharged. In this case, depth of discharge, cell temperature, and average SOC level of each cycle also influence the ageing. The end of the battery's lifetime is often defined as when the usable capacity falls below the end-of-life criterion, the most commonly used end-of-life threshold being 70% or 80% of the initial capacity. In this study, a fixed lifetime and a specified number of cycles per day are used, as this is often how warranties are defined [23].

The costs of battery systems are projected to decrease in the coming decades [24]. In a study conducted by the National Renewable Energy Laboratory at the beginning of 2025, three scenarios for future cost development for four-hour systems were presented. In the high-cost scenario, battery costs are expected to increase during the coming 5 years. However, in the medium- and low-cost scenarios, the costs are projected to decrease by approximately 20% and 40%, respectively, by the year 2030.

2.1.3 Grid Connection

In the Swedish electricity system, each producer connected to the grid must pay a transmission grid tariff to the transmission system operator (TSO) Svenska Kraftnät (SvK) [25]. The tariff includes charges both for capacity and energy, and the purpose of the charges is for the TSO to cover its costs for operation, maintenance, and to purchase electricity in case of losses. These tariffs vary in size depending on the geographical location of the connection point, although they are independent of where on the market the electricity is sold.

2.2 The Swedish Electricity Market

This section provides an overview of the Swedish electricity market structure from the perspective of hybrid parks with battery storage, highlighting the major revenue opportunities available.

The market consists of several time intervals, ranging from up to 10 years before delivery to real-time delivery [9]. The market with the longest time horizon is the forward market, where contracts are traded in advance to secure future prices. In the day-ahead market, electricity is traded based on forecasts 12–36 hours before delivery. Both the forward market and the day-ahead market are considered planning markets. The forward market will not be discussed further in this study. Next is the intraday market, where adjustments are made to correct imbalances or forecast errors from the planning markets. This market operates up to one hour before delivery. Finally, the balancing market ensures that supply and demand remain in balance during delivery. The balancing market operates shortly before and continuously throughout delivery in 15-minute intervals. For a visual representation of the Swedish electricity market, see Figure 2.1 below.

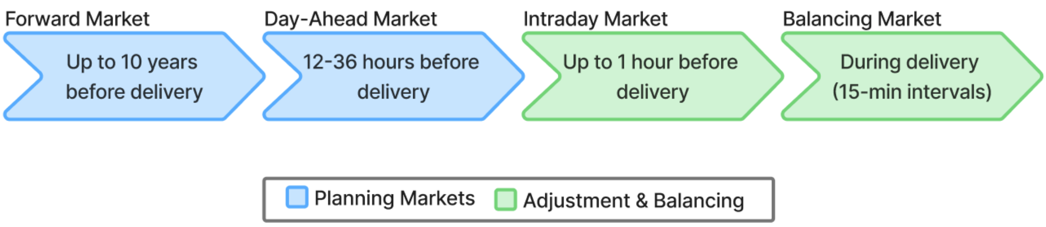


Figure 2.1: Overview of the Swedish electricity market.

There have been two major developments in the electricity market in recent years. First, in October 2024, the capacity calculations were updated to be flow-based [26], allowing for more efficient use of the grid. Second, from spring 2025 onwards, the day-ahead, intraday, and balancing markets operate with a 15-minute resolution [8], whereas they previously operated with an hourly resolution. The model will be adapted to handle both time resolutions.

2.2.1 Day-Ahead Market

Most of the electricity on the market is bought and sold on the day-ahead market, also known as the spot market [27]. In Sweden, there are two power exchanges where market participants can trade, Nord Pool and EPEX Spot. These exchanges are connected to other European markets through market coupling, meaning that prices are set in a joint European auction each day. In Sweden, electricity is traded for physical delivery in four bidding zones: SE1, SE2, SE3 and SE4. Buyers and sellers submit bids for how much electricity they want to buy or sell in each bidding period of the following day, at a given price and in a specific bidding zone. The bids from variable renewable energy (VRE) sources are based on forecasts. Prices are determined according to the marginal pricing principle, where the cost of producing the last kilowatt-hour needed to meet demand sets the price. The auction takes place at 12.00 Central European Time (CET) the day before the delivery day, and the prices are set individually for each bidding zone.

The prices on the day-ahead market can be both positive and negative. Negative prices occur when there is an oversupply of electricity, which often happens during peak production periods for VRE sources [28]. Negative prices create volatility in the market and can pose challenges for producers, as there may be situations where they effectively pay to sell their electricity. For an actor to be able to participate in the day-ahead, or intraday, market, they need to be a member of either Nord Pool [29] or EPEX Spot [30].

2.2.2 Intraday Market

The day-ahead market is based on forecasts of production and demand, and since forecasts never perfectly match reality, the intraday market exists to adjust closer to the delivery time [31]. The intraday market is smaller in volume and is mainly used by balance responsible parties (BRPs), who are financially responsible for any deviations between their traded volumes and the actual measured consumption and production. BRPs can therefore trade on the intraday market to reduce their imbalances and avoid imbalance settlement charges. This is done by purchasing additional electricity on the market, meaning that the cost of correcting the imbalance corresponds to the price of electricity on the intraday market [32]. The intraday market in Sweden is traded on the same exchanges as the day-ahead market, Nord Pool and EPEX Spot, and is also connected to other European markets through market coupling [31].

There are three intraday auctions on the delivery day [31]. After the first auction, continuous trading starts and continues until one hour before delivery. Trading is conducted in the same periods as the day-ahead market, i.e. 15-minute intervals since 2025. In the continuous intraday market, prices are set according to the pay-as-bid principle, while the auctions use marginal pricing. Cross-border trading between bidding zones requires available transmission capacity, which limits how much power can be transferred between areas. In connection with each intraday auction, continuous trading across borders is temporarily closed to reserve transmission capacity.

2.2.3 Balancing Market

The intraday market closes one hour before delivery, meaning that some imbalances may remain [33]. These are managed on the balancing market, which is used to maintain a real-time balance between consumption and production. The TSO is responsible for procuring and activating ancillary services in this market.

Ancillary services are services required to ensure the stable operation of the power system, such as upward or downward regulation of production or consumption. There are six types of ancillary services, each with specific requirements regarding activation time, duration, and capacity [33]. These include Frequency Restoration

Reserve (FRR), which can be activated either automatically (aFRR) or manually (mFRR), Frequency Containment Reserve (FCR), which is divided into FCR for normal operation (FCR-N) and FCR for disturbances (FCR-D), and FFR. All services except FFR can be used for both upward and downward regulation, whereas FFR is only used for upward regulation.

Balancing service providers (BSPs) participate in the market by offering these services, which the TSO procures as needed. The demand for ancillary services is increasing as the share of VRE generation grows [33]. However, the market for ancillary services is also expected to saturate within a couple of years [6]. After each delivery period, an imbalance settlement is carried out to calculate the costs associated with each BRP. Each BRP is financially responsible for the imbalances they cause, and the purpose of imbalance pricing is to provide an incentive for BRPs to remain in balance.

To be able to bid in as a balancing service, the BSP must meet certain requirements. These are presented in Table 2.1.

Table 2.1: Requirements for BSP on the ancillary market, endurance requirements vary depending on activation type and service characteristics. [34]

	aFRR	**mFRR**	**FCR-N**	**FCR-D up**	**FCR-D down**	**FFR**
Minimum bid size	1 MW	1 MW	0.1 MW	0.1 MW	0.1 MW	0.5 MW
Endurance	1 h	15/30 min	1 h	$\geq$ 20 min	$\geq$ 20 min	5/30 s

Note. mFRR endurance depends on whether activation is scheduled (15 min) or direct (30 min). FFR also requires repeatability within 15 minutes.

The hybrid park model developed in this thesis participates in both the day-ahead and intraday markets. Although the park does not directly participate in the balancing market as a BSP, its operation is influenced by the imbalance costs resulting from the balancing market. Consequently, the optimisation strategy aims to minimise these costs by correcting forecast deviations and reducing the park's own imbalances through intraday market actions and BESS operation. While it would be possible for a hybrid park to participate directly in the balancing market as a BSP, this functionality was not included in the scope of this study, as participation in the day-ahead and intraday markets was considered to be of greater importance for the investigated operational strategy.

3
Method

This chapter covers the developed optimisation model as well as a description of how different data was obtained and managed. The economic calculations are described, and the sensitivity analysis is presented.

3.1 Optimisation Model

This section presents the optimisation model developed in this thesis. The model is a rolling optimisation framework consisting of two-part models. The overall framework of the model is visualised in Figure 3.1.

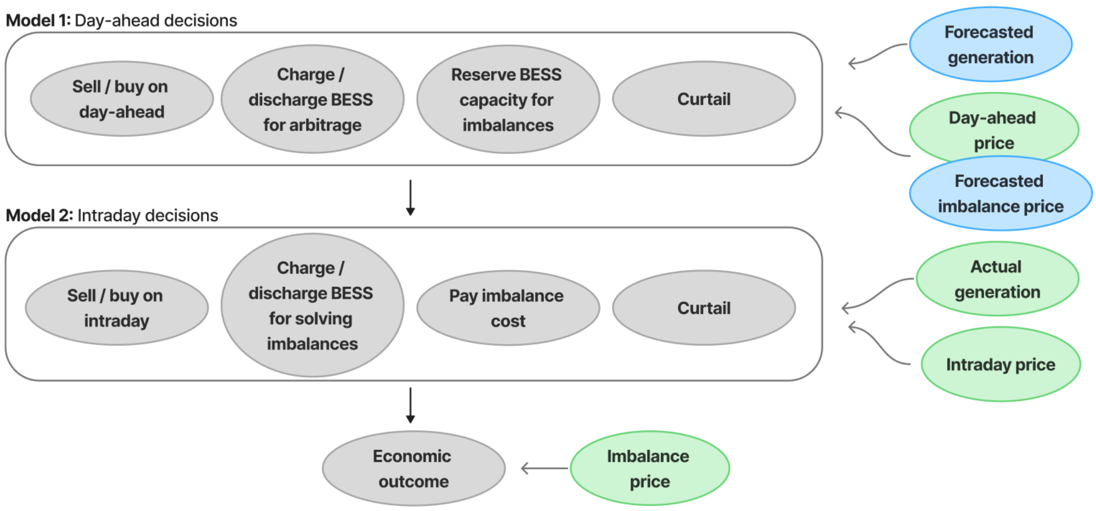


Figure 3.1: Visualisation of the framework for the two-part models.

The first part concerns the day-ahead planning. In this part, the model makes a plan for the day-ahead. The model could choose to trade on the day-ahead market, charge or discharge the BESS for arbitrage, reserve BESS capacity for eventual imbalances, or curtail production. These decisions are based on power generation from wind forecasts, day-ahead prices, and forecasted imbalance prices. The second part of the model concerns the intraday plan, where the model gets access to updated production data and intraday prices, and thus, imbalances between expected and actual production are known. The model decides whether to utilise the potential BESS reserve for imbalances, trade on the intraday market, accept imbalances and pay the forecasted imbalance cost, or curtail production. When all decisions have been made, the actual imbalance prices are used to calculate the economic performance of the park.

In more detail, the first model optimises day-ahead trading operations, as well as the planned charging and discharging of the BESS, based on wind forecasts, day-ahead prices, and forecast imbalance prices. This model generates a schedule for day-ahead trading and BESS operations, including reserved capacity to manage potential imbalances over the 00:00–24:00 period.

This schedule is then used as input to the second model, which re-optimises intraday operations based on the realised production of the wind farm. During the first three hours of the optimisation horizon, actual production data is available. Beyond this period, the model relies on forecasted values, which are adjusted to incorporate the average forecast error observed during hours with known production on the same day. This average forecast error is updated for each new horizon to include all known production values from that day. If the forecasted value is 0 MW, the forecast error is set to 0% for that specific hour.

The Intraday Model determines the actual SOC of the BESS. The SOC is extracted at 11:00 from the Day-Ahead Model, after which the planned charging and discharging schedule is used to calculate the SOC' at 24:00. This SOC' is then used as an input to the day-ahead optimisation for the subsequent 24-hour period. If the estimated SOC exceeds either the maximum or minimum limit, it is set to the corresponding boundary value. The intraday optimisation, however, runs continuously over the full 24-hour period, and the actual SOC is used throughout this model.

Additionally, to preserve battery health, the number of cycles per day is constrained. To account for this within the shrinking horizon formulation, an additional parameter is introduced to track the accumulated cycles and is passed as input to each updated optimisation horizon.

The rolling optimisation was implemented using eight update periods. In each period, the model is updated with three hours of realised wind production data, while retaining the planned values, along with the added average forecast error, for the remaining horizon. After each optimisation, the first three hours are fixed, and the optimisation horizon is shifted forward. This process continues until the full 24-hour period has been updated. This process is illustrated in Figure 3.2.

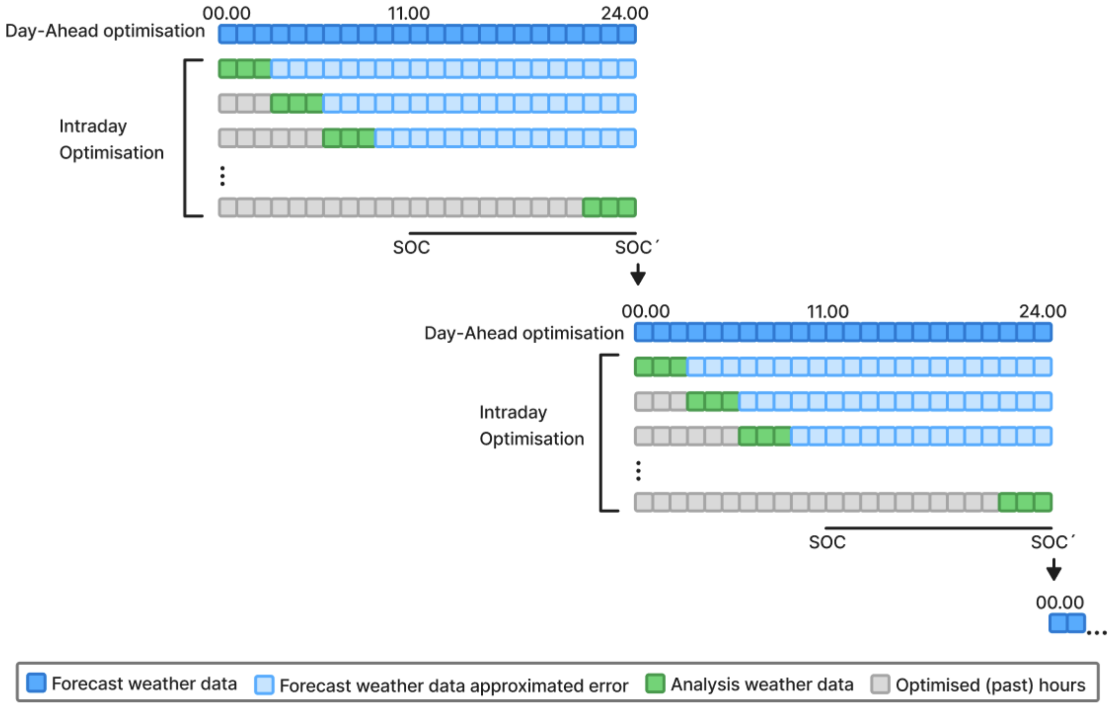


Figure 3.2: Visualisation of the time scopes of the rolling horizon.

3.1.1 Day-Ahead Model

The Day-Ahead Model is an optimisation model based on a system with the structure illustrated in Figure 3.3. The system consists of a wind farm, BESS, and a grid connection. All energy flows through a main node. Energy inflows to the node comprise forecasted generation, BESS discharge, imbalance reserve, and purchased electricity. Energy outflows from the node include electricity sales and BESS charging. The model also has a turbine node, where production and curtailment are balanced.

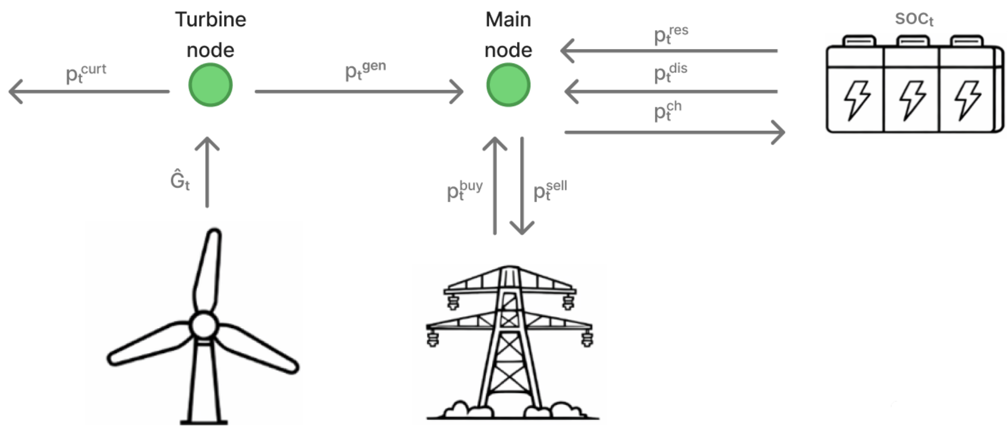


Figure 3.3: Energy balance for the day-ahead plan.

The optimisation is carried out for every 24-hour period over a year. The objective of the day-ahead optimisation, as described in Equation 3.1, is to maximise the total daily revenue of the park.

$$\max \sum_{t \in T^{DA}} (r_t^{DA} + \hat{r}_t^{IB}) \tag{3.1}$$

where r_t^{DA} denotes the revenue in the day-ahead market based on electricity sold and purchased, as defined in Equation 3.2, and $\hat{r}_t^{IB}$ is a prediction of the potential savings by imbalance reserve. Lastly, T^{DA} denotes the time horizon of the day-ahead optimisation, namely 24 hours.

$$r_t^{DA} = (p_t^{sell} - p_t^{buy}) \cdot \Phi_t^{DA} - (\Phi_t^{DA} + R) \cdot L \cdot (p_t^{sell} + p_t^{buy}), \qquad \forall t \in T^{DA} \tag{3.2}$$

where the first term represents the gross day-ahead market revenue, while the second term accounts for grid tariffs associated with electricity purchases and sales on the market. The p_t^{sell} denotes electricity sales, p_t^{buy} denotes electricity purchases, Φ_t^{DA} is the day-ahead electricity price, R is the SvK risk surcharge, and L is the SvK loss coefficient.

The $\hat{r}_t^{IB}$ variable is dependent on predicted imbalance prices and the capacity that the model chooses to set aside as a reserve for imbalances, as defined in Equation 3.3.

$$\hat{r}_t^{IB} = p_t^{res} \cdot \hat{\Phi}_t^{IB} - (\Phi_t^{DA} + R) \cdot L \cdot p_t^{res}, \qquad \forall t \in T^{DA} \tag{3.3}$$

where the first term represents potential earnings from resolving future imbalances, and the second term accounts for grid tariffs. The p_t^{res} denotes the capacity reserved for handling imbalance related to a generation deficit. This equation does not represent actual physical or financial flows within the park, rather, it balances the trade-off between reserving the BESS for imbalance management and using it for arbitrage. The imbalance reserve is not a traded product and therefore does not generate revenue, but is introduced solely to incentivise the preservation of battery capacity, ensuring consistent treatment of day-ahead and imbalance prices. This was also the rationale for introducing the tariff.

The Day-Ahead Model is governed by several constraints. The first is the energy balance of the turbine node, as defined in Equation 3.4.

$$\hat{G}_t = p_t^{gen} + p_t^{curt}, \qquad \forall t \in T^{DA} \tag{3.4}$$

where $\hat{G}_t$ denotes the forecasted generation of the wind farm, p_t^{curt} signify how much is planned to be curtailed, and p_t^{gen} stand for how much generation is planned to be used in the main node.

The energy flowing into the main node must strictly equal the energy flowing out of the node, ensuring that the park remains balanced.

$$p_t^{buy} + p_t^{gen} + p_t^{dis} + p_t^{res} = p_t^{sell} + p_t^{ch}, \qquad \forall t \in T^{DA} \tag{3.5}$$

The BESS is subject to several constraints. In particular, the charging and discharging rates must be limited so that they do not exceed the capacity of the BESS, which is enforced through Equation 3.6.

$$p_t^{ch} + p_t^{dis} + p_t^{res} \leq P^{max}, \qquad \forall t \in T^{DA} \tag{3.6}$$

where P^{max} is the BESS power capacity.

The model also tracks the SOC of the BESS. This is described by Equations 3.7 and 3.8. For the first hour of the horizon, the SOC from the previous horizon is used as input, as described in Section 3.1. For subsequent time steps, the SOC is updated based on the charging, discharging, and imbalance reserve variables.

$$soc_1 = SOC' + p_1^{ch} \cdot \eta^{ch} - \frac{p_1^{dis} + p_1^{res}}{\eta^{dis}} \tag{3.7}$$

$$soc_t = soc_{t-1} + p_t^{ch} \cdot \eta^{ch} - \frac{p_t^{dis} + p_t^{res}}{\eta^{dis}}, \qquad \forall t \in T^{DA} \setminus \{1\} \tag{3.8}$$

where soc_t is the decision variable, SOC' is the estimated value of the initial step for the horizon, η^{ch} is the charging efficiency, and η^{dis} is the discharging efficiency.

The model allows both the sale and purchase of electricity through a limited grid connection. Equations 3.9 and 3.10 enforce these capacity limits.

$$0 \leq p_t^{sell} \leq P^{exp}, \qquad \forall t \in T^{DA} \tag{3.9}$$

$$0 \leq p_t^{buy} \leq P^{imp}, \qquad \forall t \in T^{DA} \tag{3.10}$$

where P^{exp} denotes the maximum power that the park can export to the grid and P^{imp} denotes the maximum power that the park can import from the grid, which is set to the power capacity of the BESS. This is because the main use of the imported electricity is to charge the battery. The export capacity was set equal to the aggregated production capacity of the park, namely 164 MW.

To preserve battery health, the BESS must be maintained within certain levels of charge, and cycling is limited to a fixed amount each day. The SOC is constrained according to Equation 3.11, and the cycling is limited according to Equation 3.12.

$$SOC^{min} \leq soc_t \leq SOC^{max}, \qquad \forall t \in T^{DA} \tag{3.11}$$

where SOC^{max} and SOC^{min} denote the maximum and minimum allowable SOC, respectively.

$$\sum_{t \in T^{DA}} p_t^{ch} + p_t^{dis} + p_t^{res} \leq 2 \cdot (SOC^{max} - SOC^{min}) \cdot N^{cyc} \tag{3.12}$$

where N^{cyc} denotes the total number of cycles allowed during the horizon. Lastly, to prevent the model from becoming unbounded, bounds are imposed on the decision variables according to Equations 3.13–3.17.

$$0 \leq p_t^{gen} \leq \hat{G}_t, \qquad \forall t \in T^{DA} \tag{3.13}$$

$$0 \leq p_t^{curt} \leq \hat{G}_t, \qquad \forall t \in T^{DA} \tag{3.14}$$

$$0 \leq p_t^{ch} \leq P^{max}, \qquad \forall t \in T^{DA} \tag{3.15}$$

$$0 \leq p_t^{dis} \leq P^{max}, \qquad \forall t \in T^{DA} \tag{3.16}$$

$$0 \leq p_t^{res} \leq P^{max}, \qquad \forall t \in T^{DA} \tag{3.17}$$

3.1.2 Intraday Model

In the Intraday Model, updated information regarding the realised imbalance of the park is incorporated. For the first three hours of the optimisation horizon, the forecast errors are known for each hour. Based on these errors, an average value is computed and applied to the remaining hours within the horizon. This enables the model to anticipate future imbalances and to schedule the use of the BESS. Consequently, the decision variable for imbalance reserves is no longer required, and since this variable was only used to prepare the BESS to manage imbalances during favourable price conditions, it does not reduce the available capacity, thereby allowing the model to replan accordingly. The updated system is illustrated in Figure 3.4.

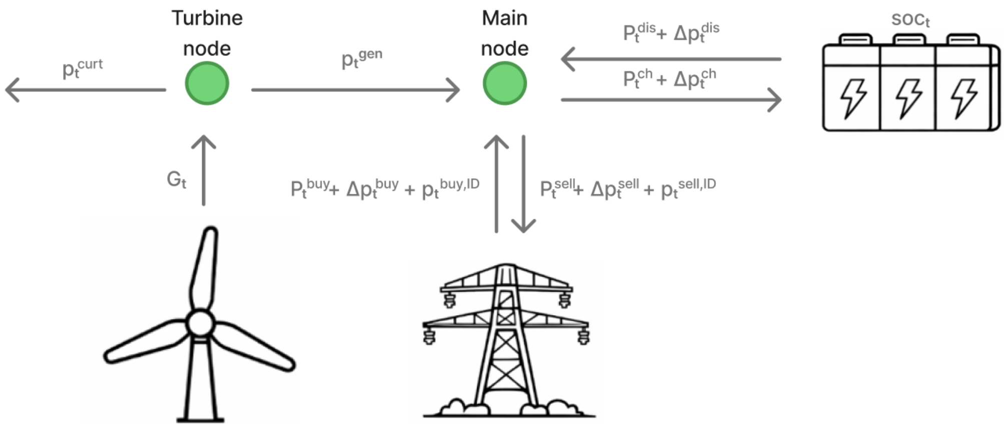


Figure 3.4: Energy balance for intraday optimisation.

The objective of the intraday optimisation, as described in Equation 3.18, is to maximise the total revenue within the current optimisation window.

$$\max \sum_{t \in T^{ID}} (r_t^{DA} + r_t^{ID} - \hat{c}_t^{IB}) \tag{3.18}$$

where, similarly to the Day-Ahead Model, the r_t^{DA} denotes the day-ahead revenue, and r_t^{ID} the intraday revenue. The $\hat{c}_t^{IB}$ denotes the imbalance costs based on predicted imbalance prices. The day-ahead revenue r_t^{DA} is described by equation 3.19.

$$\begin{aligned} r_t^{DA} = &((P_t^{sell} - \Delta p_t^{sell}) - (P_t^{buy} - \Delta p_t^{buy})) \cdot \Phi_t^{DA} + \\ &- (\Phi_t^{DA} + R) \cdot L \cdot ((P_t^{sell} - \Delta p_t^{sell}) + (P_t^{buy} - \Delta p_t^{buy})), \qquad \forall t \in T^{ID} \end{aligned} \tag{3.19}$$

where P_t^{sell} denotes the quantity sold on the day-ahead market, and Δp_t^{sell} denotes the adjustments to these sales. Since additional sales on the day-ahead market are not possible, these adjustments are restricted to downward revisions. Furthermore, P_t^{buy} denotes the quantity purchased in the day-ahead market, and Δp_t^{buy} denotes the downward adjustments to these purchases, with the same rationale as in the sell case. The variable Φ_t^{DA} represents the day-ahead market price at time t.

The intraday revenue r_t^{ID} is described in Equation 3.20.

$$r_t^{ID} = (p_t^{sell,ID} - p_t^{buy,ID}) \cdot \Phi_t^{ID} - (\Phi_t^{DA} + R) \cdot L \cdot (p_t^{sell,ID} + p_t^{buy,ID}), \qquad \forall t \in T^{ID} \tag{3.20}$$

where $p_t^{sell,ID}$ denotes the sales on the intraday market, $p_t^{buy,ID}$ the purchases on the intraday market, and Φ_t^{ID} the intraday market price. The tariffs in the intraday market are still based on the day-ahead price, thus, the cost per MWh remains the same as in Equation 3.19.

The imbalance costs $\hat{c}_t^{IB}$ are calculated according to Equation 3.21.

$$\hat{c}_t^{IB} = i_t \cdot \hat{\Phi}_t^{IB}, \qquad \forall t \in \{1, 2, 3\} \tag{3.21}$$

where i_t denotes the imbalances arising from the difference between what the park can deliver and what it sold on the day-ahead market, and $\hat{\Phi}_t^{IB}$ is the forecasted price, the same as that used in the Day-Ahead Model.

The Intraday Model is subject to several constraints, many of which are similar to those of the Day-Ahead Model. The turbine node, where generation and curtailment are balanced to determine the amount of energy transferred to the main node of the park, is described in Equation 3.22.

$$G_t = p_t^{curt} + p_t^{gen}, \qquad \forall t \in T^{ID} \tag{3.22}$$

where G_t is the production data for the intraday, p_t^{curt} denotes the curtailment, and p_t^{gen} denotes the energy injected into the main node of the park.

Next, the main node energy balance is defined as described in Equation 3.23. Here, the parameters imported from the Day-Ahead Model, together with the updated production, are balanced, and the park may either remain in equilibrium or enter an imbalanced state through the i_t, which is dependent on the Δp_t^{sell} and Δp_t^{buy} variables.

$$\begin{aligned} &(P_t^{buy} - \Delta p_t^{buy} + p_t^{buy,ID}) + p_t^{gen} + (P_t^{dis} + \Delta p_t^{dis}) \\ &= (P_t^{sell} - \Delta p_t^{sell} + p_t^{sell,ID}) + (P_t^{ch} + \Delta p_t^{ch}), \qquad \forall t \in T^{ID} \end{aligned} \tag{3.23}$$

where P_t^{dis} denotes the planned discharging, and Δp_t^{dis} the adjustments to discharging. Similarly, P_t^{ch} denotes the planned charging, and Δp_t^{ch} the adjustments to charging.

The imbalance of the park can arise in several ways. Either the park fails to generate the amount of energy already sold on the day-ahead market, or the park has purchased energy in the day-ahead market, but when the hour arrives, it cannot import it because, for example, the battery is full. In the first case, the result on the market is a deficit, and in the second, a surplus, which is reflected in the negative sign in Equation 3.24.

$$i_t = \Delta p_t^{sell} - \Delta p_t^{buy} \tag{3.24}$$

The park can also choose to create an imbalance by not delivering or importing the energy, this is only chosen when the forecasted imbalance cost shows profit in being in imbalance.

The total sales and purchases after the intraday adjustments are constrained according to Equations 3.25 and 3.26, ensuring that the allowed export and import limits are not exceeded.

$$P_t^{sell} - \Delta p_t^{sell} + p_t^{sell,ID} \leq P^{exp}, \qquad \forall t \in T^{ID} \tag{3.25}$$

$$P_t^{buy} - \Delta p_t^{buy} + p_t^{buy,ID} \leq P^{imp}, \qquad \forall t \in T^{ID} \tag{3.26}$$

Similar to the Day-Ahead Model, the BESS is subject to several constraints. Equation 3.27 ensures that the battery capacity is not exceeded. Equations 3.28, 3.29, and 3.30 govern the battery dynamics, and finally, Equation 3.31 ensures that the maximum warranted number of cycles per day is not exceeded.

$$(P_t^{ch} + \Delta p_t^{ch}) + (P_t^{dis} + \Delta p_t^{dis}) \leq P^{max}, \qquad \forall t \in T^{ID} \tag{3.27}$$

where P^{max} is the power capacity of the BESS.

$$SOC^{min} \leq soc_t \leq SOC^{max}, \qquad \forall t \in T^{ID} \tag{3.28}$$

where SOC^{min} is the minimum allowed threshold and SOC^{max} is the maximum.

$$soc_1 = SOC^{prev} + p_1^{ch} \cdot \eta^{ch} - \frac{p_1^{dis}}{\eta^{dis}} \tag{3.29}$$

where SOC^{prev} represents the actual value after the final operational decision for the previous horizon.

$$soc_t = soc_{t-1} + (P_t^{ch} + \Delta p_t^{ch}) \cdot \eta^{ch} - \frac{(P_t^{dis} + \Delta p_t^{dis})}{\eta^{dis}}, \qquad \forall t \in T^{ID} \tag{3.30}$$

$$\sum_{t \in T^{ID}} (P_t^{ch} + \Delta p_t^{ch}) + (P_t^{dis} + \Delta p_t^{dis}) \leq 2 \cdot (SOC^{max} - SOC^{min}) \cdot N^{cyc,left} \tag{3.31}$$

where $N^{cyc,left}$ denotes the remaining cycles in the current optimisation horizon.

Lastly, to prevent the model from becoming unbounded, bounds are imposed on the decision variables. The p_t^{gen} variable is constrained according to Equation 3.32, and p_t^{curt} according to Equation 3.33. The Δ variables are constrained by Equations 3.34–3.37. The downward adjustment of charging and discharging is limited to the scheduled levels, while upward adjustments cannot exceed the maximum capacity of the BESS. The market interaction variables on the intraday are constrained by Equations 3.38 and 3.39. The import and export capacities remained constrained by the battery capacity and the aggregated turbine power, respectively, as per the day-ahead case.

$$0 \leq p_t^{gen} \leq G_t, \qquad \forall t \in T^{ID} \tag{3.32}$$

$$0 \leq p_t^{curt} \leq G_t, \qquad \forall t \in T^{ID} \tag{3.33}$$

$$-P_t^{ch} \leq \Delta p_t^{ch} \leq (P^{max} - P_t^{ch}), \qquad \forall t \in T^{ID} \tag{3.34}$$

$$-P_t^{dis} \leq \Delta p_t^{dis} \leq P_t^{dis}, \qquad \forall t \in T^{ID} \tag{3.35}$$

$$0 \leq \Delta p_t^{sell} \leq P_t^{sell}, \qquad \forall t \in T^{ID} \tag{3.36}$$

$$0 \leq \Delta p_t^{buy} \leq P_t^{buy}, \qquad \forall t \in T^{ID} \tag{3.37}$$

$$0 \leq p_t^{sell,ID} \leq P^{exp}, \qquad \forall t \in T^{ID} \tag{3.38}$$

$$0 \leq p_t^{buy,ID} \leq P^{imp}, \qquad \forall t \in T^{ID} \tag{3.39}$$

3.2 Julia

The modelling in this study was carried out using Julia (version 1.12.4). Julia is a high-performance programming language designed for numerical and scientific computing, with features such as numerical stability and precision that make it well-suited for optimisation tasks. The linear optimisation model is implemented in Julia using the JuMP modelling framework and solved with Gurobi (version 13), a state-of-the-art optimisation solver, under an academic license.

3.3 Economic Calculations

To evaluate the economic performance of the BESS, each size has been compared to a base case of no BESS. For each studied year and BESS size the total annual revenue, annualised capital expenditure (CAPEX) and operating expenditure (OPEX) were calculated. The different CAPEX and OPEX costs, as well as the capital recovery factor (CRF), were provided by RES Group. From this, the annual net profit (ANP) and payback period (PBP) were calculated using Equations 3.40, 3.41 and 3.42.

$$\text{Total annual cost} = \text{Total CAPEX} \cdot \text{CRF} + \text{Total OPEX} \tag{3.40}$$

$$\begin{aligned}\text{ANP} = {} & \text{Total annual revenue} \\ & - \text{Total annual revenue}^{\text{Base case}} - \text{Total annual cost}\end{aligned} \tag{3.41}$$

$$\text{PBP} = \frac{\text{Total CAPEX}}{\text{ANP}} \tag{3.42}$$

In the case of a negative ANP, the PBP was set to non-existent.

3.4 Data Collection

In the following section, the data collection methods used are presented. The dataset includes wind speed data, operational data from the wind farm, and electricity market data.

3.4.1 Wind Speed

As the day-ahead market is based on forecasts from the previous day, a method to replicate forecasted capacity factors is to use archived weather forecast data. The national meteorological institutes of Sweden, Norway, and Finland jointly operate the MetCoOp Ensemble Prediction System (MEPS) [35]. This forecasting model has a horizontal grid spacing of 2.5 km and 65 vertical levels, and a domain of 900 $\times$ 960 grid points covering the region.

The Norwegian Meteorological Institute (MET Norway) provides an open source dataset with inter alia archived forecast data from MEPS reaching back to 2016

[36]. Before the bid at 12:00 CET to the day-ahead market, the most recent update available from the MEPS Model is the 06UTC (Coordinated Universal Time) [35]. This run was hence used to retrieve forecasted wind speed data for each following day-ahead planning.

Within this catalogue, there is also re-analysis data with horizontal grid spacing of 1 km on the surface level only. In this report, the wind speed at hub height was of interest and could be obtained using the log-law (Equation 3.43) [37]. From both the forecast and the re-analysis catalogues, the wind speed at 10 m (U_{10}) and the surface roughness length (z_0) were extracted, respectively, to interpolate the wind speed (U_{hub}) at hub height (z_{hub}) using the log-law.

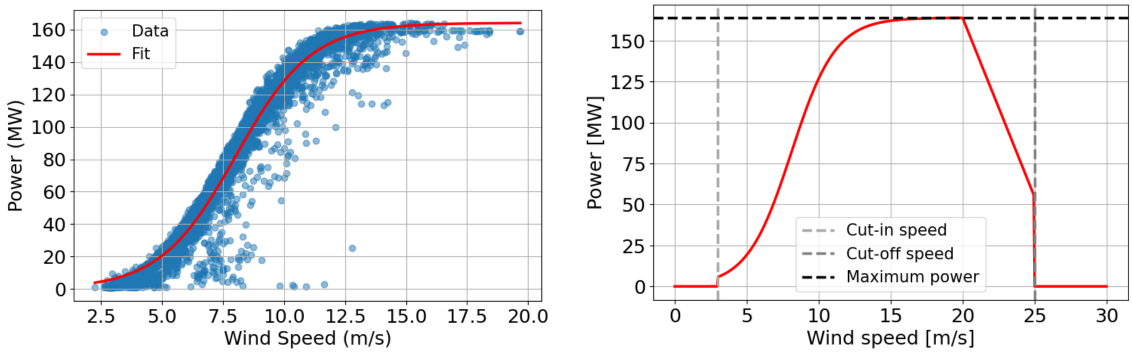
$$U_{hub} = U_{10} \frac{\ln\left(\frac{z_{hub}}{z_0}\right)}{\ln\left(\frac{10}{z_0}\right)} \tag{3.43}$$

There are other methods to extract the wind speed at hub height from MET Norway's catalogue, however, they also contain approximations and interpolations. Furthermore, the methods are limited to the variables available since the catalogue is different for the forecast and re-analysis. By using the same method for both forecast and re-analysis extractions, the limitations were the same for both data series.

The MEPS model has a time step resolution of one hour [35]. To match the change in the electricity market in 2025 to quarters, each time step for both the forecast and re-analysis has been linearly interpolated from one hour to four quarters. The linear interpolation was done on the 10 m wind before the log-law interpolation to hub height.

3.4.2 Turbine Generation

To estimate both the forecasted and actual power production of the wind farm, wind speed data and turbine power curves were required. The power curve was derived from production data collected from the wind farm under investigation for the year 2023, in combination with the manufacturer-provided (warranted) power curves. Both datasets were provided by RES. The S-shaped portion of the curve was fitted using production data and corresponding wind speed measurements, as illustrated in Figure 3.5a. The cut-in and cut-off wind speeds, as well as the linear region of the power curve, were obtained from the warranted turbine specifications. The final power curve used in this study is presented in Figure 3.5b.



(a) Fitted park power curve. **(b)** Power curve used for calculations.

Figure 3.5: Power curves for the wind park.

The forecast errors compared to the actual production are illustrated in Figure 3.6 as a normal distribution. They are divided into two different plots as production changed to a resolution of 15 minutes in 2025. It shows a small bias of overestimation in the forecast and a standard deviation of around 20 MW.

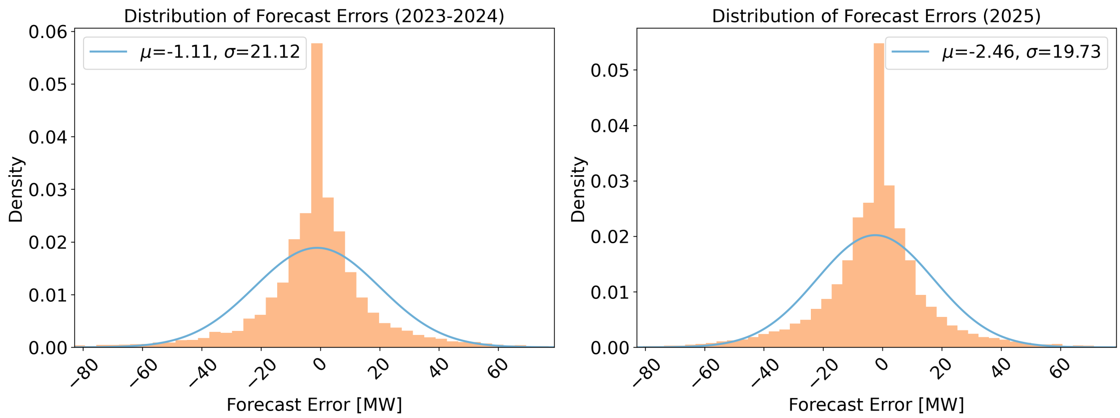


Figure 3.6: Normal distribution of error between forecasted and actual production for 2023, 2024 and 2025. They are divided into two different plots as production changed to a resolution of 15 minutes in 2025.

3.4.3 Day-Ahead and Intraday Prices

To plan the operation in the day-ahead and intraday markets, electricity price data for both markets were required. Additionally, imbalance price data were needed to calculate the actual revenue of the wind farm. Both day-ahead and imbalance price data were retrieved from the ENTSO-E Transparency Platform, while the intraday market price data were provided by Ntricity. In several datasets, missing values were observed for certain hours. To address this, linear interpolation was applied to fill these gaps.

In 2025, the market resolution was changed to a 15-minute interval. Although the transition occurred mid-year, the ENTSO-E Transparency Platform provided data at a 15-minute resolution for the whole year. However, for the periods where the market resolution was still hourly, the same price value was assigned to each 15-minute interval within the corresponding hour. The same approach was applied to both the intraday and imbalance price data.

3.4.4 Imbalance Forecast Data

When planning the operation of the BESS, a forecast of the imbalance price was required. Imbalance costs are difficult to predict, as they depend on several highly stochastic and interrelated factors. Developing a comprehensive forecasting model for these costs were beyond the scope of this study. However, to obtain and utilise representative forecast data, a simple machine learning model was implemented. There are several algorithms for this purpose, including Random Forest Regression, Quantile Regression Forest, and Extreme Gradient Boosting Regression (XGBoost) [38]. Each of these methods has its own strengths and limitations, however, in this study, XGBoost was selected due to its higher accuracy.

Only a simplified model was developed, trained using day-ahead prices and day-ahead load, and evaluated against actual imbalance prices. An example of the forecasted versus actual prices is shown in Figure 3.7. To get a more accurate forecast of the imbalance cost, one could have use even more variables, such as the weather forecast and the breakdown of the sources on which the day-ahead load is based. However, this would significantly increase the complexity of the model and was outside the scope and initial objectives of this study.

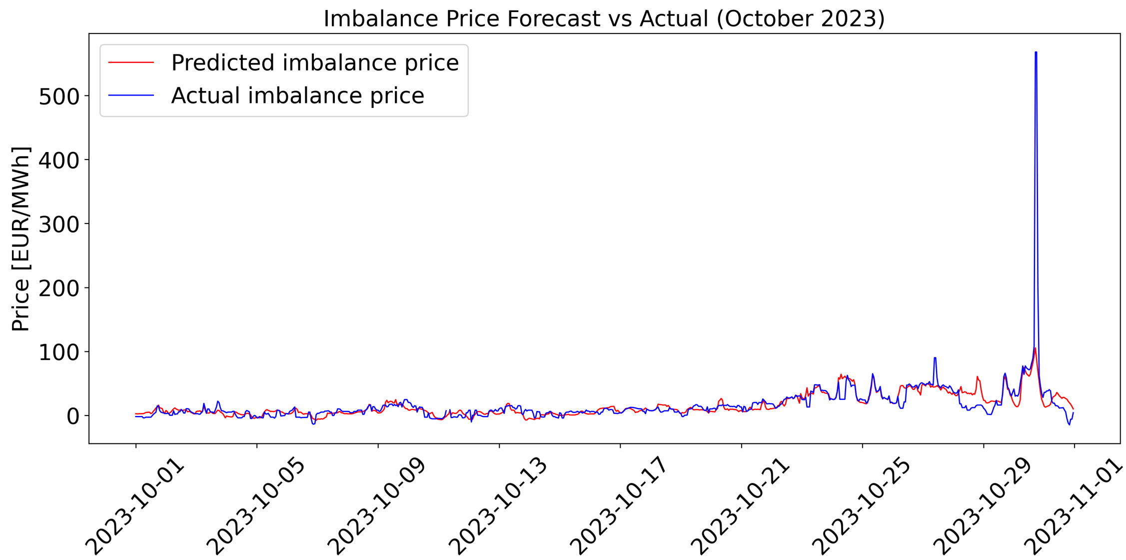


Figure 3.7: Imbalance price forecast and actual imbalance prices for October 2023.

The errors of the imbalance price forecast compared to the real imbalance price are illustrated in Figure 3.8 as a normal distribution. They are divided into two different plots as production changed to a resolution of 15 minutes in 2025. It shows a small bias of overestimation in the forecast and a standard deviation of around 51 EUR/MWh in 2023-2024 and around 160 EUR/MWh in 2025.

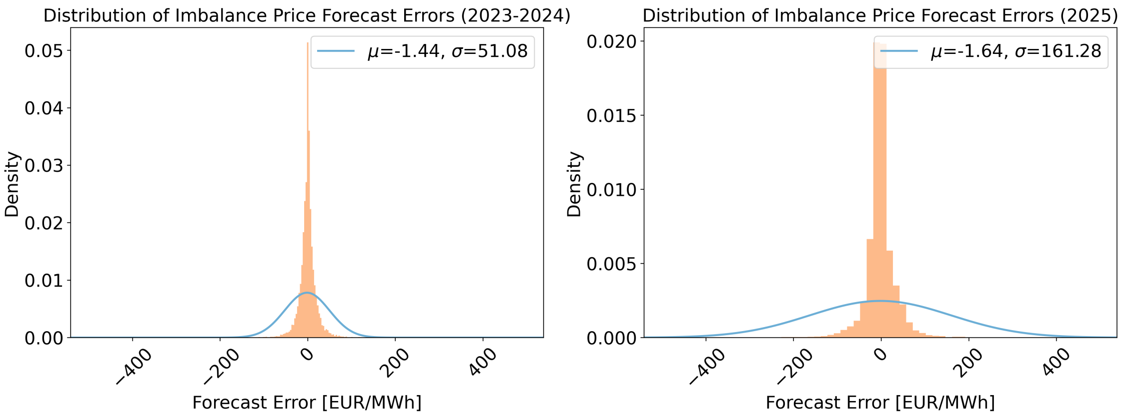


Figure 3.8: Normal distribution of error between forecasted and actual imbalance price for 2023, 2024 and 2025. They are divided into two different plots as the market changed to a resolution of 15 minutes in 2025.

To evaluate the model behaviour, the weekly average difference between the intraday price and the forecasted imbalance price was calculated and presented in Figure 3.9.

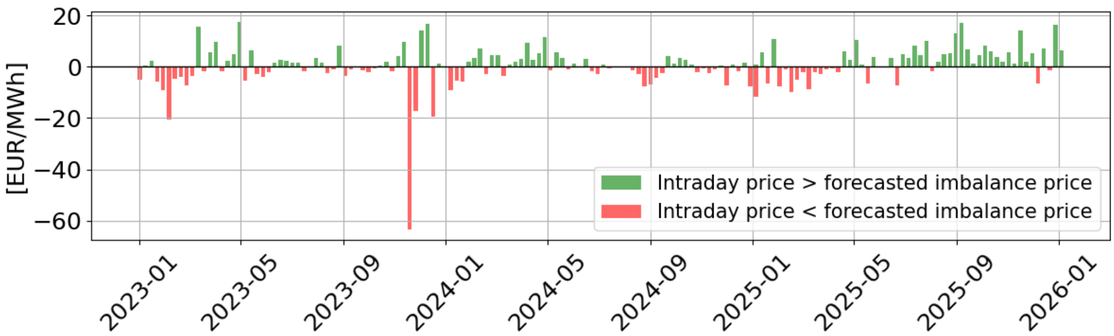


Figure 3.9: Weekly average difference between intraday and forecasted imbalance prices 2023-2025.

Significant price variations was observed throughout the period. However, a clear trend emerged from approximately April 2025 onwards where intraday prices consistently exceed the forecasted imbalance prices.

3.5 Sensitivity Analysis

A sensitivity analysis was conducted to assess the impact of variations in input parameters on the model output and to evaluate the robustness of the results. The parameters investigated were the export capacity of the hybrid park, accuracy of the imbalance price forecast, BESS investment costs and increased intraday market interactions to better compensate imbalances without BESS.

For each year and BESS size, two export capacity cases were evaluated. One case with an expansion and one with a reduction of 20%, respectively. The same economic calculations were performed as for the base case, where the export capacity equals the installed capacity of the wind farm. For each export capacity, the capacity grid tariff varies depending on the size of the grid connection and was calculated according to Equation 3.44, including both export and import tariffs. The import connection capacity was set equal to the BESS capacity.

$$\begin{aligned} OPEX^{grid} = &\text{ Export Capacity} \cdot \text{Capacity Charge}^{Export} \\ &+ \text{Import Capacity} \cdot \text{Capacity Charge}^{Import} \end{aligned} \tag{3.44}$$

Additionally, for each BESS size, a case with perfect imbalance price foresight was evaluated. In these cases, the model was run using the actual historical imbalance prices for the corresponding year. A new reference case without BESS was also simulated and used as a baseline to evaluate the economic performance under this assumption. This was done to evaluate the importance of forecast accuracy for model performance.

Further, the impact of BESS investment costs was evaluated. As described in Section 2.1.2, battery costs are projected to decrease by 20% and 40%, respectively, by 2030. Therefore, these two cost reduction levels were selected for the sensitivity analysis both, for the two-hour and four-hour BESS.

Lastly, a scenario was investigated in which the wind park is permitted to purchase more electricity on the intraday market than the BESS can physically charge. In practice, this may be possible because the purchased electricity does not necessarily need to be physically delivered through the wind park itself. Consequently, intraday market transactions may be used to reduce imbalance costs. Since intraday purchases offset the corresponding day-ahead sales, the overall energy balance remains valid. This scenario was implemented by replacing the import constraints defined in Equations 3.26 and 3.39 with the formulation presented in Equation 3.45.

$$0 \leq p_t^{buy,ID} \leq P^{exp}, \qquad \forall t \in T^{ID} \tag{3.45}$$

Table 3.1 summarises all cases included in the sensitivity analysis, together with the parameter being varied and the corresponding objective.

Table 3.1: Summary of sensitivity analysis cases.

Case	**Variation**	**Objective**
Export capacity size	±20% export capacity	Evaluate the impact of grid connection size
Price forecast accuracy	Historical imbalance prices used	Evaluate the impact of forecast accuracy
Decreased investment costs	20% and 40% reductions in BESS investment costs	Evaluate the sensitivity to future cost reductions
Relaxed intraday import limit	Intraday purchases allowed up to the export capacity	Evaluate imbalance reduction through increased intraday purchases

3.6 Use of AI

Throughout this study, AI-based tools were used to support the research, writing, and coding processes in several ways. They were primarily used as a sounding board for ideas, as well as for brainstorming related to modelling and exploring alternative approaches. AI was also used to identify appropriate sources supporting different modelling methods.

In addition, the tools were used to support the writing process by assisting with proofreading, language refinement, and suggesting alternative phrasings. All suggestions were reviewed and adapted by the authors before being incorporated into the text.

AI was further used as a support tool in coding. Since the authors had no prior experience with Julia, it helped identify potential errors and weaknesses in the model code. It was further used as an assistant in creating the plots for this report. However, no code was entirely generated by AI, instead, it was developed collaboratively by the authors, with AI used only when necessary.

4
Results

This chapter presents the results of the study. The developed model is applied to a specific case but can easily be generalised to other wind farms and price areas as well. The results begin with a presentation of the base case, to which all other cases are compared. This is followed by a presentation of the model performance using the original input assumptions for both two-hour and four-hour storage durations. Finally, the results of the sensitivity analysis are presented.

4.1 Model Performance

This section presents the results used to evaluate the model's performance and its applicability to market conditions. Results are reported for three different years, namely 2023, 2024, and 2025. The results are further presented for both two-hour and four-hour battery configurations. All economic calculations are made in comparison to a base case, with no installed BESS. The export capacity of the park is, in this case, equal to the aggregated power of all wind turbines, which is 164 MW. The quarterly revenues for 2023, 2024, and 2025 are shown in Figure 4.1.

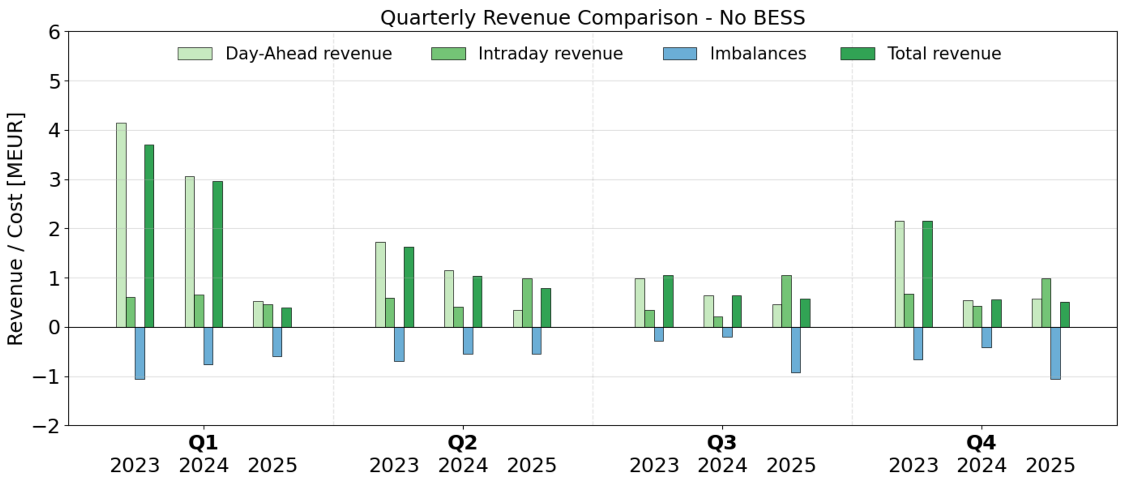


Figure 4.1: Quarterly revenue streams for the base case without BESS, 2023-2025

The total revenues are approximately 8.5 MEUR, 5.2 MEUR, and 2.3 MEUR for the base case in the three respective years. The electricity prices, both day-ahead and intraday, are the highest in 2023 and lowest in 2025, which explains the trend of decreasing income of the park. The majority of the income in 2023 and 2024 originates from the day-ahead market, whereas intraday trading constitutes the largest share in 2025. The model is still able to trade in both the day-ahead and intraday markets without BESS. Imbalance costs are observed during all four quarters in each year. During Q1 2023 and Q4 2025, the imbalance costs exceed 1 MEUR.

When analysing the cumulative revenue for the base case over 2023–2025, it is observed that it reaches approximately 17 MEUR. The total revenue profile closely mirrors that of the day-ahead revenue, while intraday and imbalance revenues tend to offset one another, as can be seen in Figure 4.2.

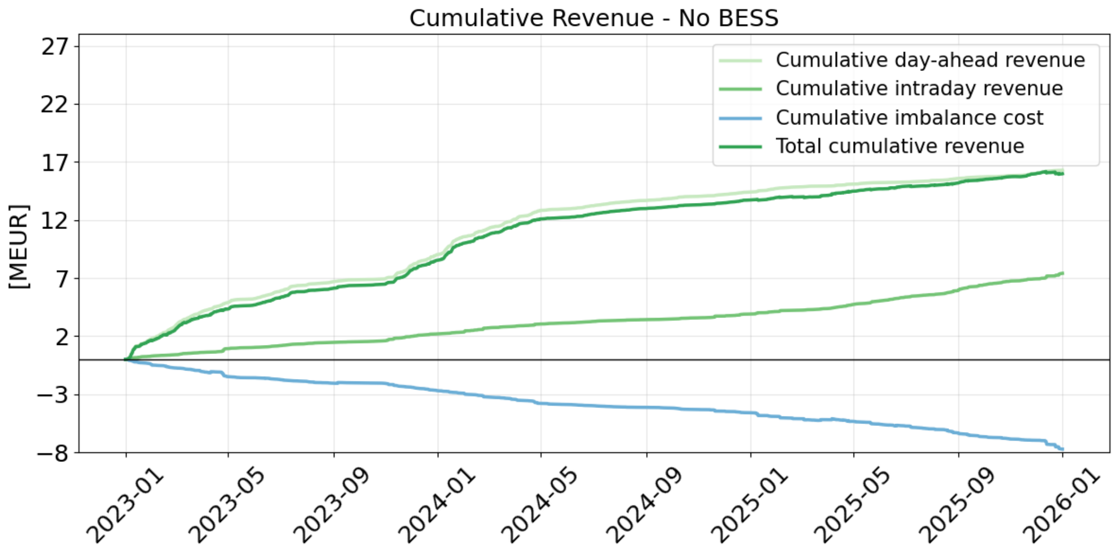


Figure 4.2: Cumulative revenue for the base case without BESS, 2023-2025

4.1.1 Two-Hour Storage Duration Case

This subsection presents the results for the two-hour battery configuration. One way to measure model performance is through its economic results. Therefore, this chapter first examines the economic performance of the model and then investigates the operational behaviour and market strategies applied by the model. Figure 4.3 shows the BESS economics for 2023, 2024, and 2025.

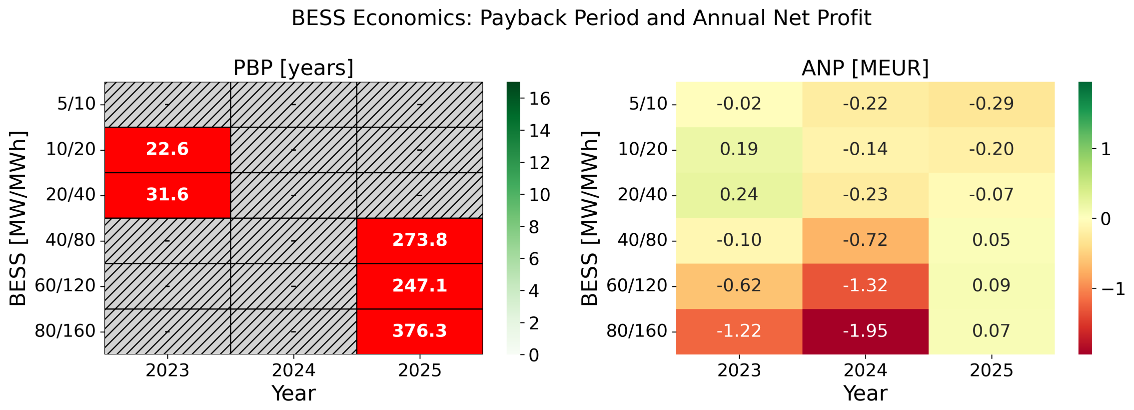


Figure 4.3: Comparison of PBP and ANP for 2023, 2024 and 2025 with different two-hour BESS sizes.

The results show that only the 20/40 MW/MWh and 10/20 MW/MWh BESS configurations generate a positive ANP for 2023. However, neither configuration achieves a PBP within the assumed 17-year battery lifetime. For 2024, all BESS configurations yield negative ANP values, and hence no configuration achieves a PBP. In 2025, the sizes 40/80, 60/120 and 80/160 MW/MWh show positive ANP, however, very low with PBPs of several hundred years.

To further evaluate the model operation, the quarterly revenues for the 20/40 MW/MWh BESS are investigated. The different revenue streams are shown for each quarter of the year in Figure 4.4. Of the delivered electricity, the share sold on the day-ahead market is 79%, 74%, and 58% respectively for the three years.

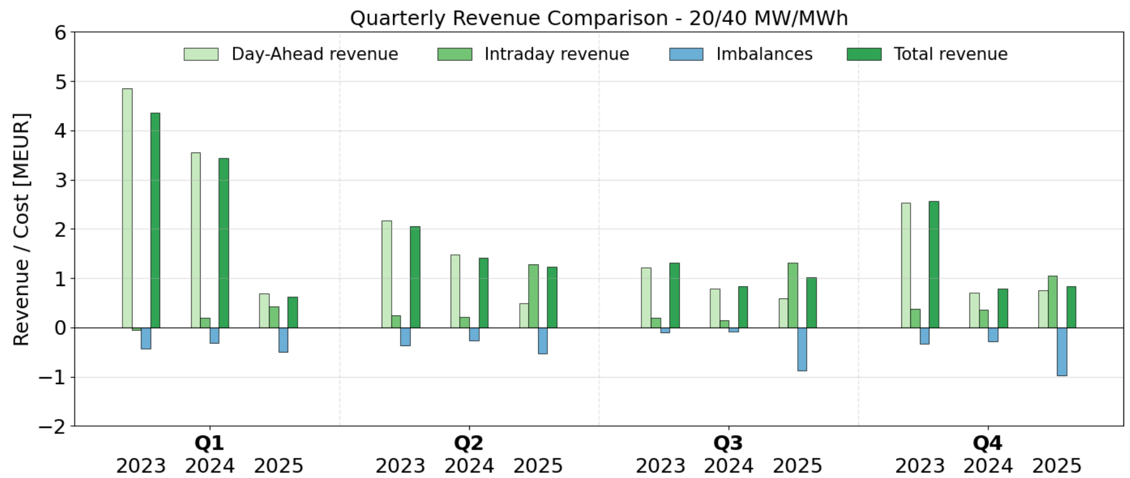


Figure 4.4: Quarterly revenue with a 20/40 MW/MWh BESS, 2023–2025.

For all quarters in both 2023 and 2024, the revenues obtained from the intraday market were lower than those of the reference case without BESS. The largest reductions are observed during the first quarter of each year. At the same time, the inclusion of the BESS reduced the imbalance costs throughout both years. This behaviour is also reflected in the operational results, where the total produced imbalances decreased by approximately 48% and 42% for 2023 and 2024, respectively, compared to the base case without BESS. Furthermore, in addition to the reduction in imbalance costs, the BESS also generated increased revenue in the day-ahead market, resulting in a positive total revenue increase for all quarters.

In 2025, all three revenue streams increase, except during Q1, where the intraday revenue decreases. Nevertheless, the total revenue increase remained positive for all quarters. The reduced imbalance cost in 2025 is due to the BESS resolving circa 16% of the imbalances that occurred in the base case.

When instead considering a larger BESS, namely the 60/120 MW/MWh configuration, the trends remain similar. This can be seen in Figure 4.5. Of the delivered electricity, the share sold on the day-ahead market is 75%, 70%, and 55% respectively for the three years.

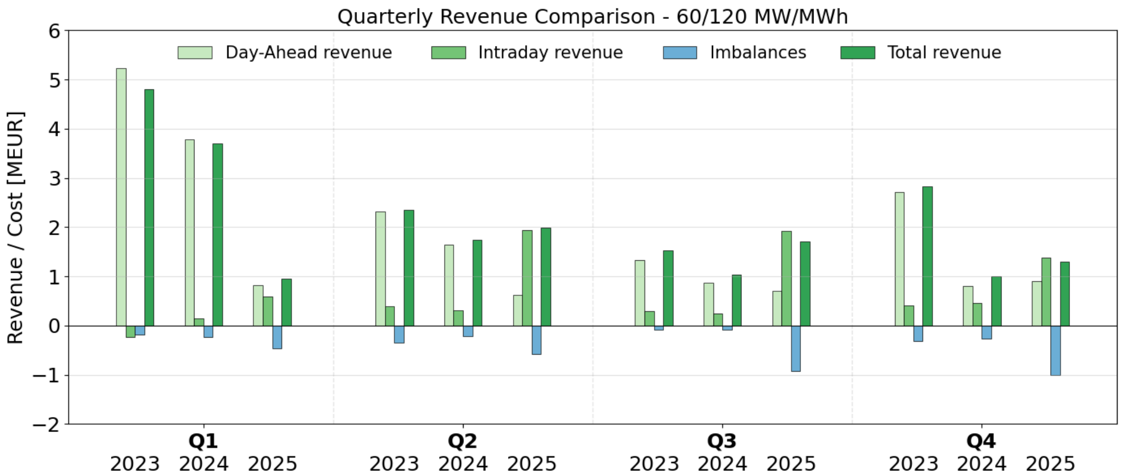


Figure 4.5: Quarterly revenue with a 60/120 MW/MWh BESS, 2023–2025.

For 2023 and 2024, the model continues to reduce revenue from the intraday market while simultaneously increasing both the day-ahead revenue and the avoided imbalance costs. However, the reduction in intraday market revenue is generally lower for both years except for Q1. The pattern for 2025 differs from the previous cases. The intraday market becomes the largest revenue stream for all quarters of the year, except for Q1. In Q2, the imbalance cost increases slightly, whereas a reduction in imbalance costs is observed during the remaining quarters.

In comparison to the base case without BESS, the 60/120 MW/MWh configuration is able to resolve approximately 64%, 56%, and 22% of the produced imbalances during 2023, 2024, and 2025, respectively.

When considering the cumulative revenue for the 60/120 MW/MWh BESS, as shown in Figure 4.6, a shift can be observed in where the model begins generating higher revenues in the intraday market.

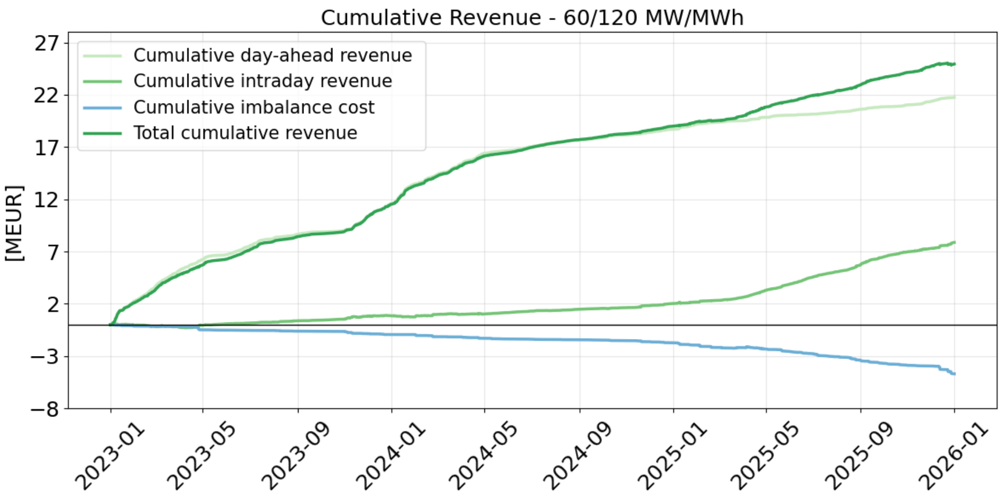


Figure 4.6: Cumulative revenue with a 60/120 MW/MWh BESS, 2023–2025.

Up to March 2025, all revenue curves follow a relatively stable trend, where the total revenue is closely linked to the day-ahead revenue, and the imbalance costs and intraday revenues balance each other out. After this point, the intraday market revenue starts to rise, altering the shape of the total revenue curve. In contrast, the day-ahead and imbalance market revenues maintain approximately the same slope throughout the entire period. The total revenue over the three-year period increases to approximately EUR 25 million compared to the 17 MEUR of the base case.

Other observations from the results are the events occurring on the 10th of April 2023 and the 6th of April 2025. In the first event, an increase in imbalance costs can be seen. For the second event, a large revenue increase can be observed. Both events are due to large errors in the imbalance price forecast, the first resulting in an approximate cost of 22,500 EUR for the wind farm in an hour and the second a profit of around 31,500 EUR in one quarter. To study these events in detail, the decisions made by the model are visualised in Figures 4.7 and 4.8. The first panel shows the model input, the second panel shows the day-ahead decisions, the third panel presents the intraday decisions, and the fourth panel illustrates the economic outcome of the operation.

During the first event, the 10th of April 2023 in Figure 4.7, the day-ahead price is positive but low, and the model buys electricity on the day-ahead market to charge the battery together with its own production. Then, in the intraday market, the model chooses not to buy electricity on the day-ahead market and instead buys it on the intraday market, as the intraday price is negative and would therefore generate a profit. However, this also creates an imbalance of around 11 MWh, resulting in a forecasted imbalance cost of approximately 123 EUR, while the forecasted profit from this strategy change is around 1552 EUR. The forecasted imbalance cost is, however, highly inaccurate. It was predicted to be -26 EUR/MWh, while the actual cost turned out to be -2200 EUR/MWh, resulting in a total cost of around 22,500 EUR instead of the expected revenue of approximately 1429 EUR.

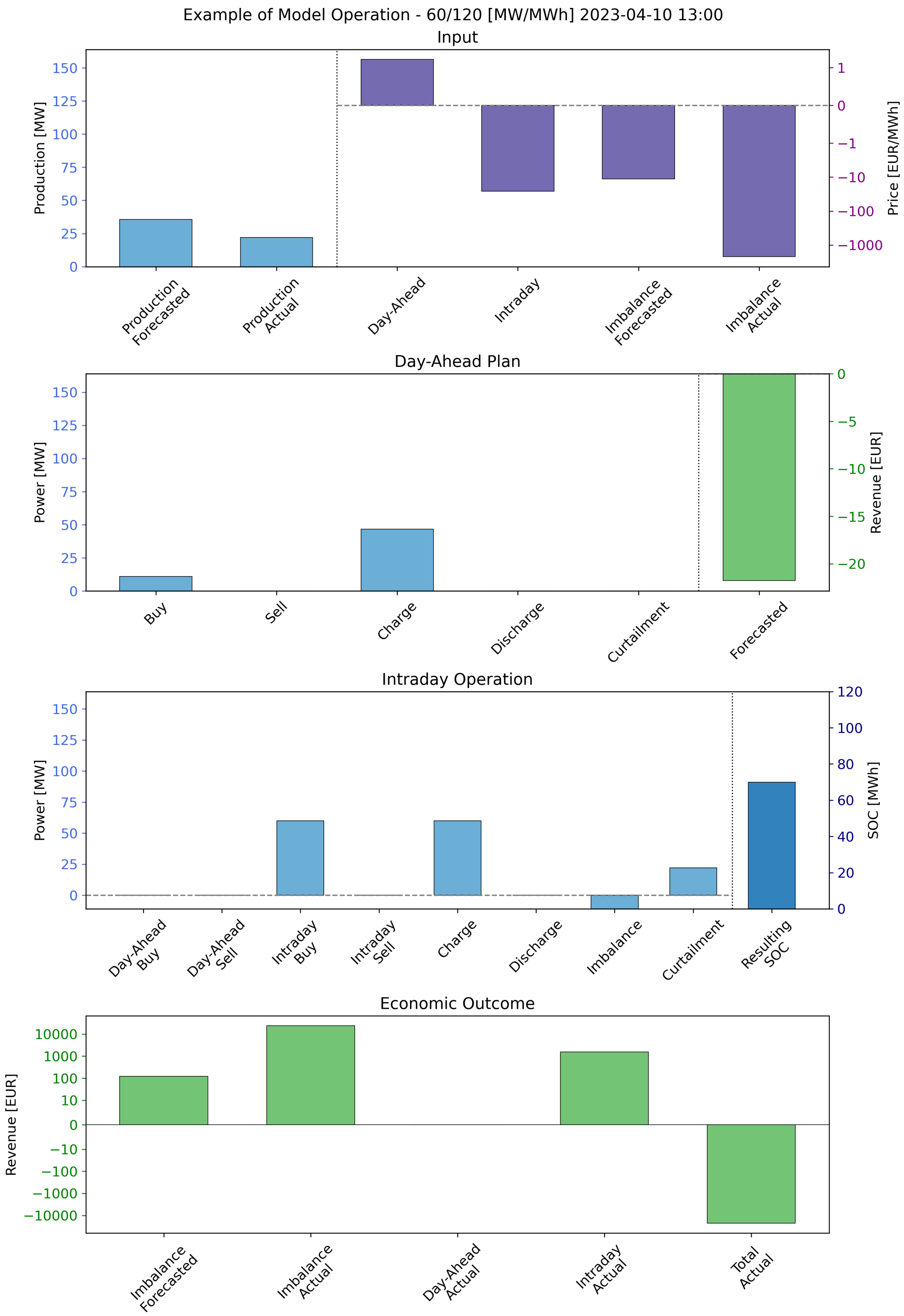


Figure 4.7: Optimal solutions for Day-Ahead and Intraday Model 2023-04-10 13:00–14:00. Note that the scales on the y-axis for the prices in the top panel and then revenue on the lower panel are logarithmic, while the rest are linear.

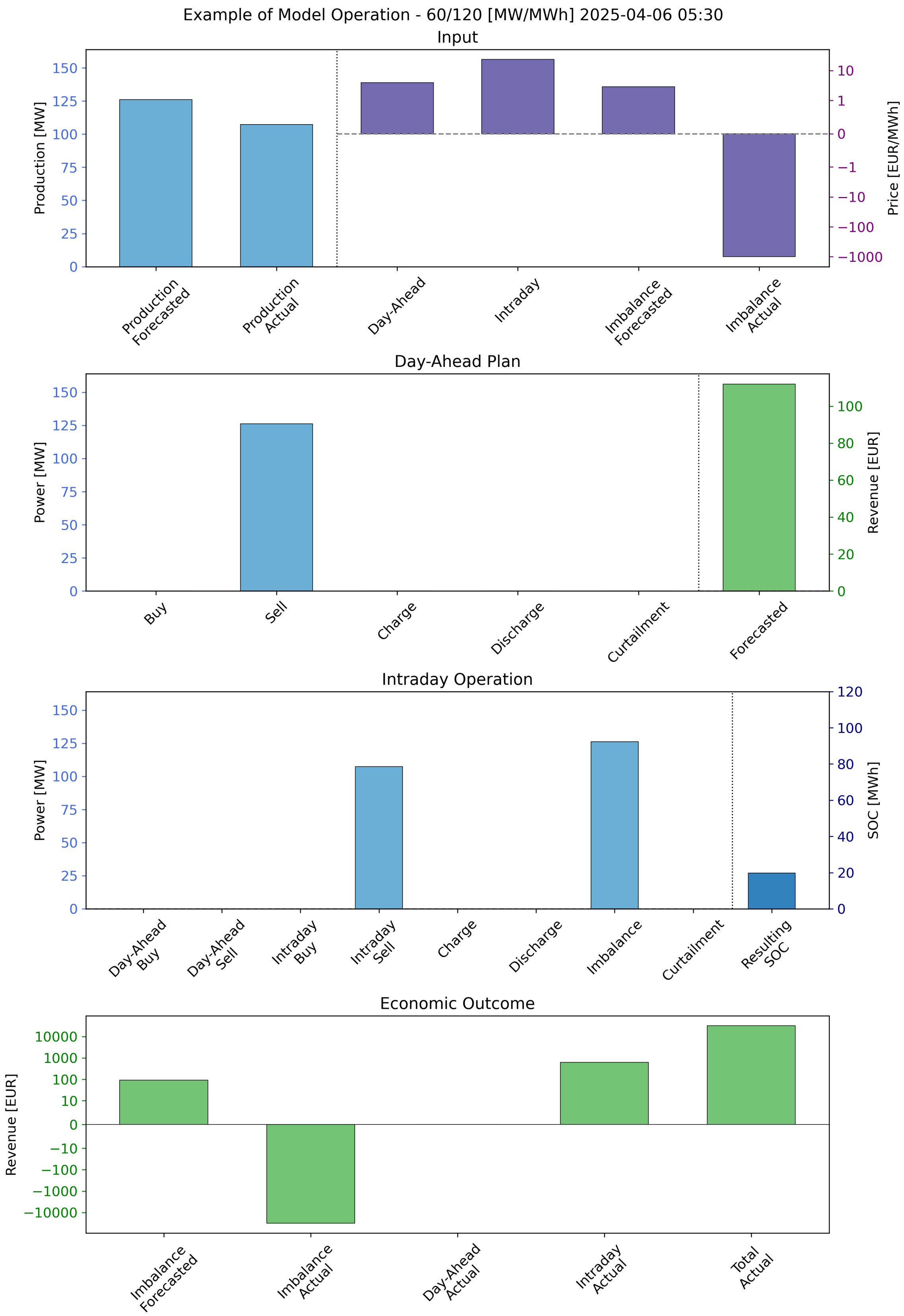


Figure 4.8: Optimal solutions for Day-Ahead and Intraday Model 2025-04-06 05:30–05:45. Note that the scales on the y-axis for prices in the top panel and then revenue on the lower panel are logarithmic, while the rest is linear.

In the second event, the 6th of April 2025 in Figure 4.8, the wind park is forecasted to produce around 126 MWh, which is initially planned to be sold on the day-ahead market at approximately 4 EUR/MWh. The intraday market price, however, is around 24 EUR/MWh, and the model chooses to instead sell the production there. This creates an imbalance, however, as the forecasted imbalance cost is only around 3 EUR/MWh, the expected revenue remains higher, at approximately 535 EUR. It is then shown that the actual imbalance cost is -1000 EUR/MWh. This results in the imbalance created, which was initially assessed as a small cost for a larger profit, instead leading to a substantial profit of around 31,500 EUR.

The two examples above represent extremes in both cost and revenue. A more typical example of the model operation is presented in Figure 4.9. The forecasted production is sold on the day-ahead market, and when the actual production falls short during the intraday period, the BESS is discharged to cover the resulting imbalance. In addition, the BESS is also discharged to sell additional electricity on the intraday. Hence, the model both resolves imbalances and engages in intraday trading in a profitable manner.

The behaviour of the model in addressing imbalances through the intraday market can be observed on the 27th of December 2023 at 15:00, as shown in Figure 4.10. In this case, the model plans to sell at maximum capacity by combining the forecasted wind power production with discharge from the BESS. During the considered hour, the actual production is lower than forecasted, requiring the model to compensate for the deficit. It does so by buying on the intraday since the intraday price is significantly lower than both the day-ahead price and the forecasted imbalance cost. The optimisation strategy prioritises preserving the available BESS capacity for potential future imbalances rather than discharging the battery. However, the realised imbalance cost for the hour turns out to be relatively low and ultimately incurs a loss. If the park had instead accepted the imbalance and not purchased electricity on the intraday market, this loss could have been avoided.

During the same hour, the model also performs arbitrage, which is an intended behaviour. The day-ahead price is high, and the model therefore plans to discharge the battery during that time step in order to maximise revenue. This is successfully achieved. This may further explain why the model chooses to purchase electricity at relatively high intraday prices, as this limits the loss of day-ahead revenue, which is significantly higher than both intraday and imbalance prices.

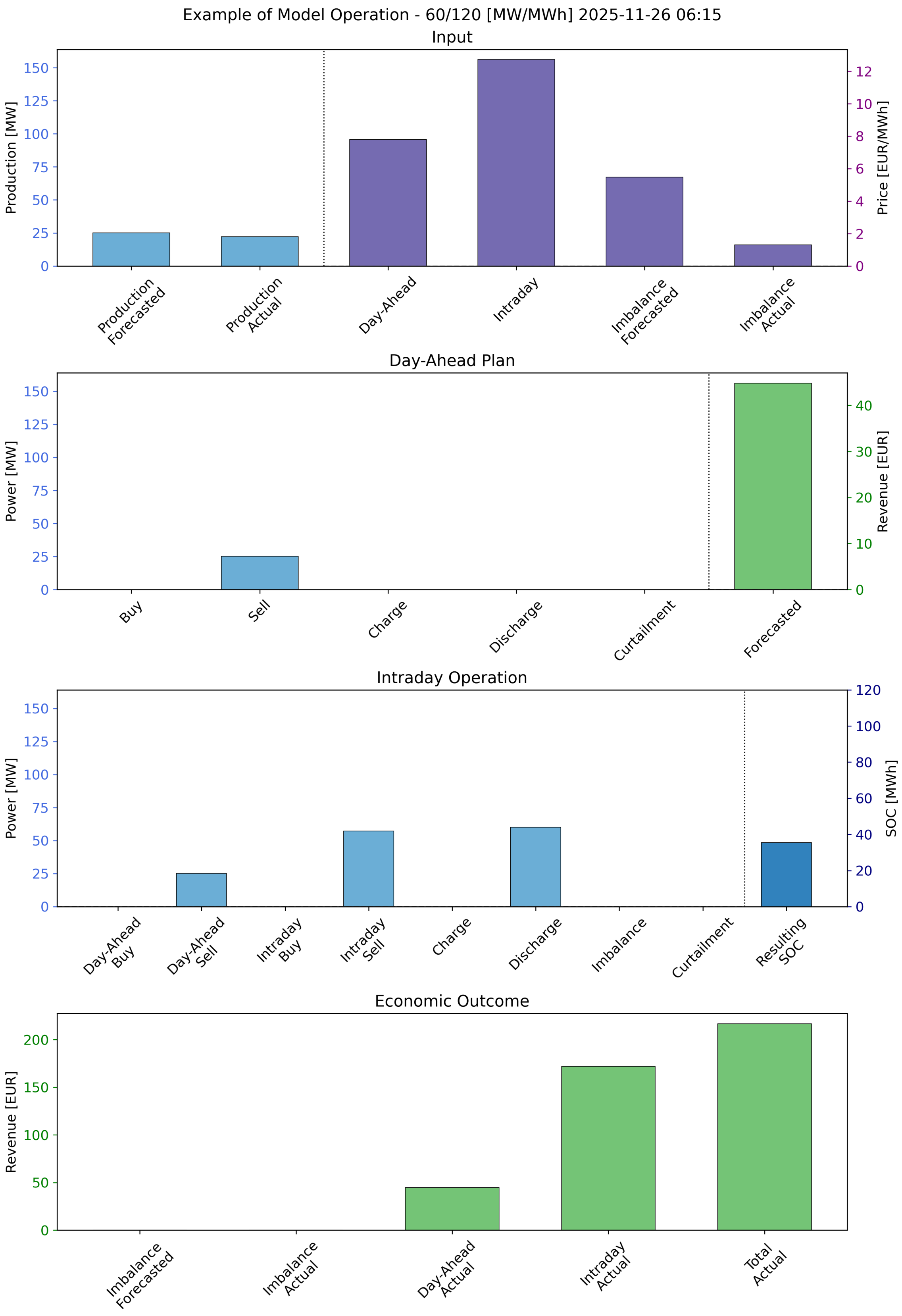


Figure 4.9: Optimal solutions for Day-Ahead and Intraday Model 2025-11-26 06:15–06:30.

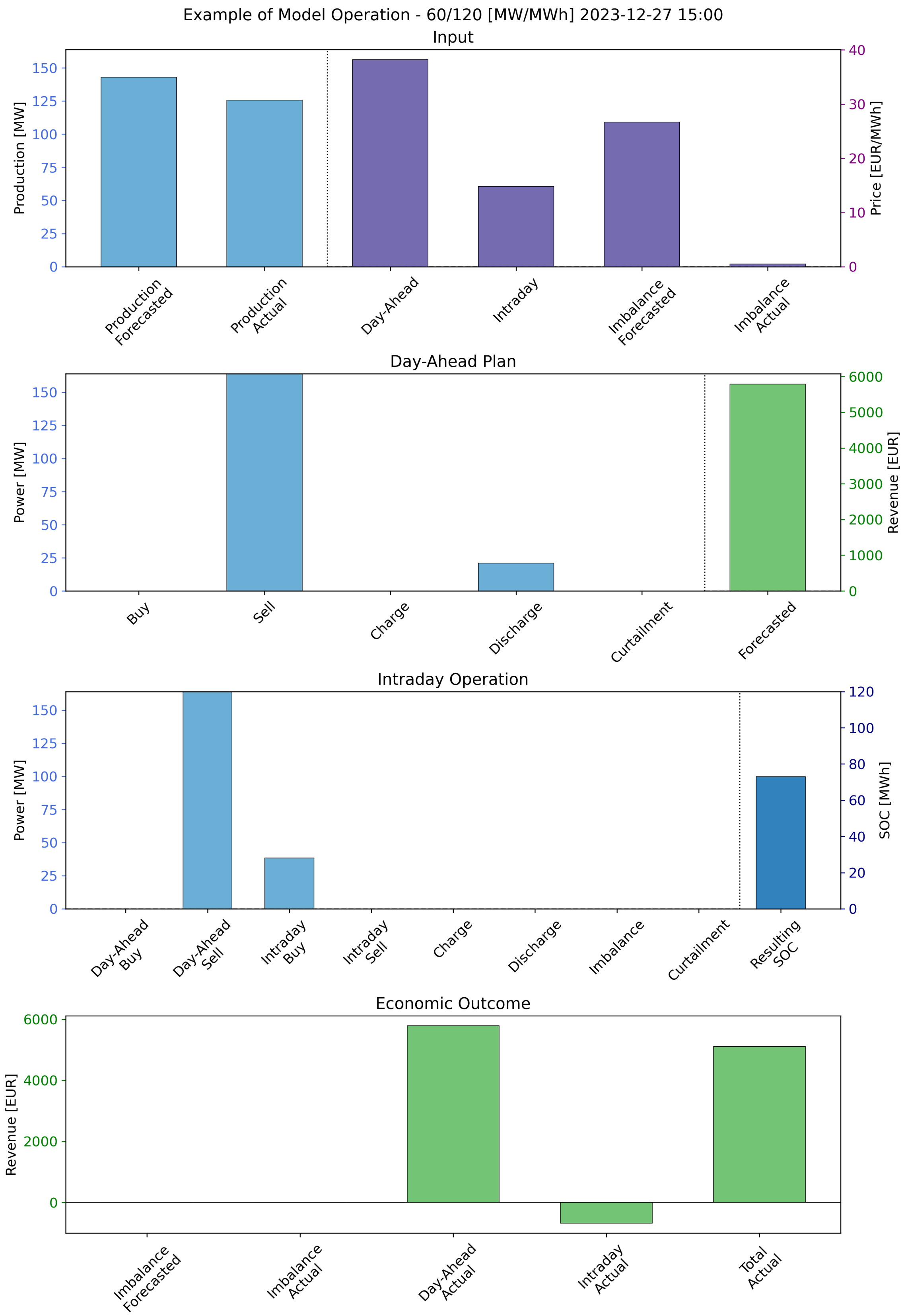


Figure 4.10: Optimal solutions for Day-Ahead and Intraday Model 2023-12-27 15:00–16:00.

4.1.2 Four-Hour Storage Duration Case

This subsection presents the results for the four-hour battery configuration with the economic performance of the model. Figure 4.11 shows the BESS economics for 2023, 2024, and 2025. All of these configurations have the same export capacity as the base case.

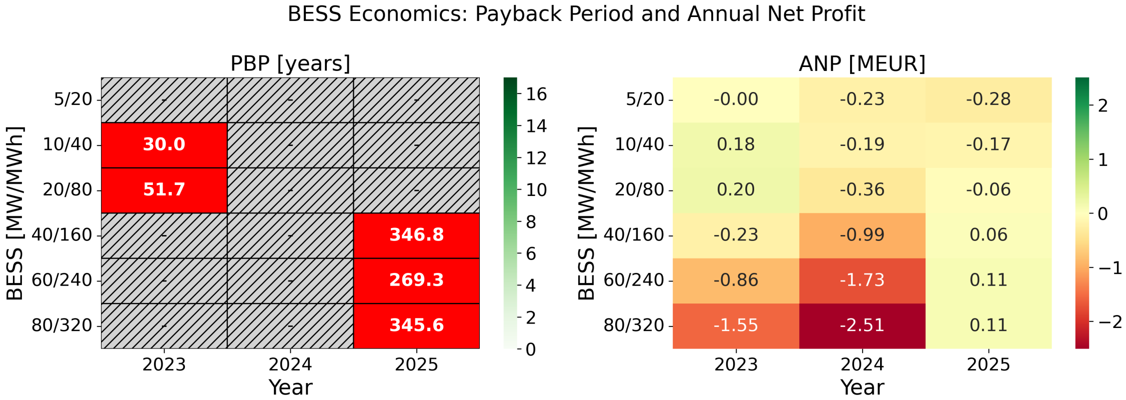


Figure 4.11: Comparison of PBP and ANP for 2023, 2024, 2025 with different four-hour BESS sizes.

Once again, only the 10/40 and 20/80 MW/MWh configurations in 2023 and the 40/120, 60/240, and 80/320 MW/MWh configurations in 2025 result in a positive ANP, which is still low, with the PBP well above the lifetime of the BESS.

The cumulative revenue streams for the 60/240 MW/MWh BESS can be seen in Figure 4.12. The total revenue over the three-year period increases to approximately EUR 27 million.

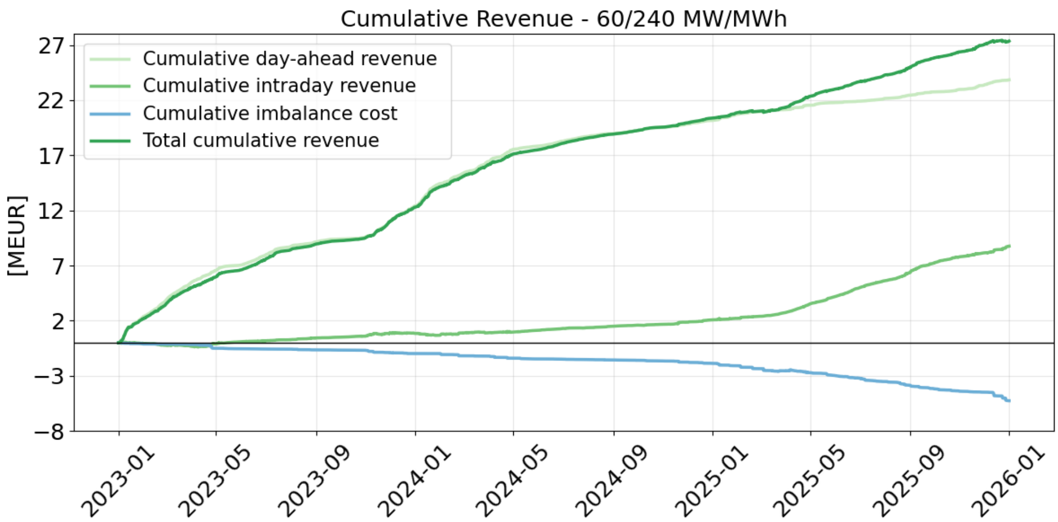


Figure 4.12: Cumulative revenue with a 60/240 MW/MWh BESS, 2023–2025.

Similar trends can be observed with the four-hour system, where the total revenue closely follows the day-ahead revenue up until 2025. Then, in March 2025, the cumulative intraday revenue starts increasing faster and gains a larger impact on the total revenue. Compared to the two-hour system, the four-hour system generates higher total revenue each year.

4.2 Sensitivity Analysis

This section presents the results of the sensitivity analysis. First, the effects of increasing and decreasing the export capacity of the park by 20% are examined for the different cases. Next, the effects of the accuracy of the forecasted imbalance prices on the model results are studied and the effects of reduced investment costs of the BESS are investigated. Lastly, the effects of a relaxed intraday import limit are studied.

4.2.1 Impact of Export Capacity Size

In this section, the results of increasing and decreasing the export capacity will be presented. The original export capacity corresponds to the aggregated power of all wind turbines, and a 20% increase, respectively, decrease of this value are now studied.

With the expanded export capacity, it is still the 10 and 20 MW cases in 2023 and the 40, 60, and 80 MW cases in 2025 that result in a positive ANP. However, only the 80/160, 60/240, and 80/320 MW/MWh configurations in 2025 show an increase in ANP, while the others decrease. The PBP remains well above the lifetime of the BESS. This can be seen in Figures 4.13 and 4.14. However, in 2025, the PBP is reduced compared to the original export capacity case for the 80/160, 60/240, and 80/320 MW/MWh configurations.

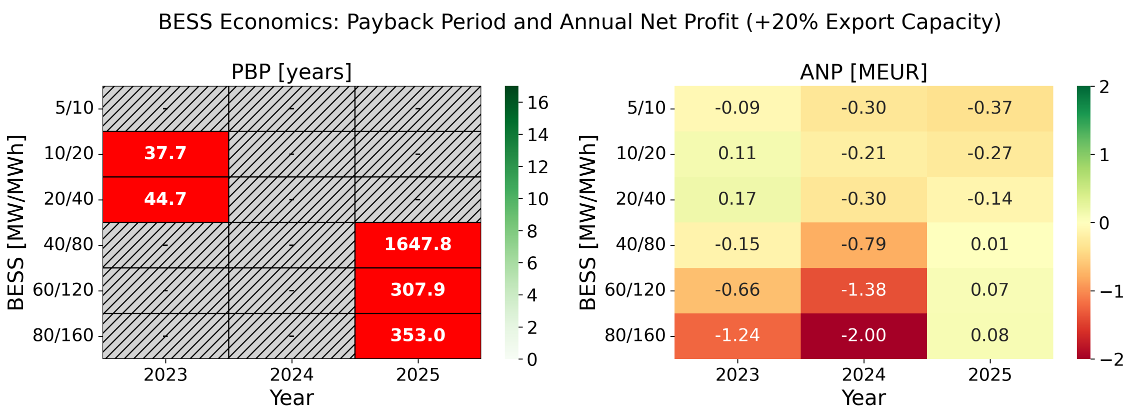


Figure 4.13: Comparison of PBP and ANP for 2023, 2024, 2025 with different two-hour BESS sizes and export capacity of 120%.

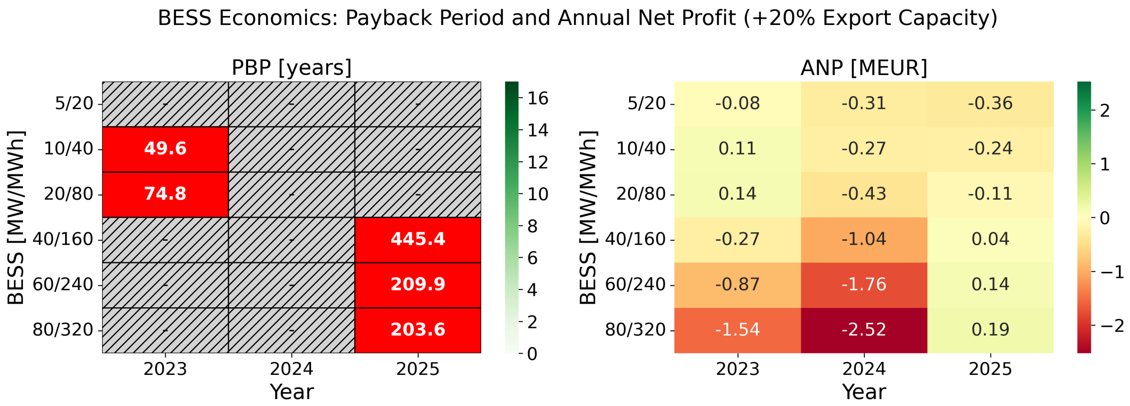


Figure 4.14: Comparison of PBP and ANP for 2023, 2024, 2025 with different four-hour BESS sizes and export capacity of 120%.

When the export capacity is reduced to 80%, the general trend remains, as can be seen in Figures 4.15 and 4.16. It is still the 10 and 20 MW cases in 2023, as well as the 40/80 and 60/120 MW/MWh configurations in 2025, that result in a positive ANP. However, the achieved values are lower, with corresponding PBP extending to several hundred years. It can also be observed that the ANP values for the 5/10 and 10/20 MW/MWh configurations increase slightly, although not sufficiently to achieve positive profitability.

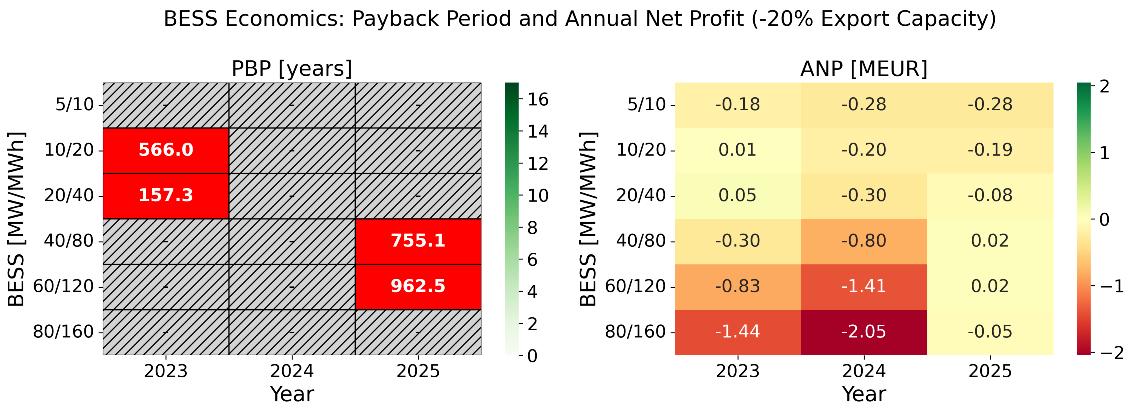


Figure 4.15: Comparison of PBP and ANP for 2023, 2024, 2025 with different two-hour BESS sizes and export capacity of 80%.

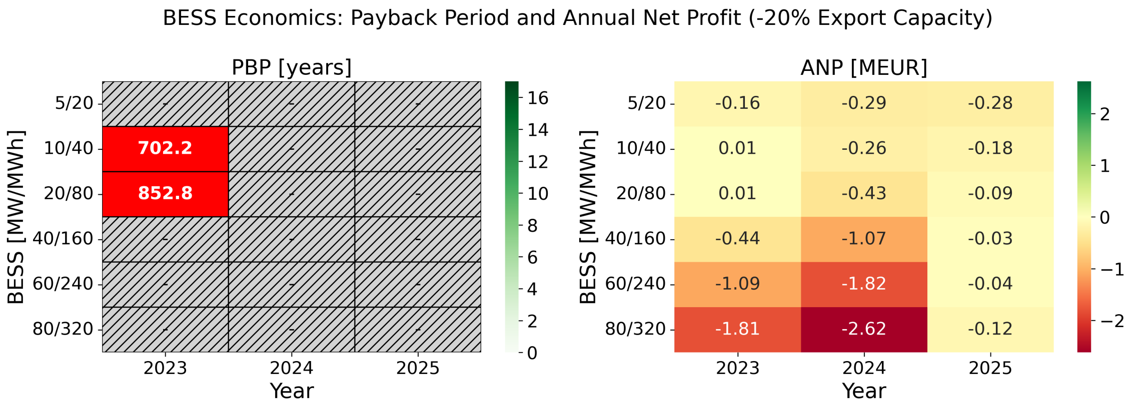


Figure 4.16: Comparison of PBP and ANP for 2023, 2024, 2025 with different four-hour BESS sizes and export capacity of 80%.

4.2.2 Impact of Price Forecast Accuracy

In this section, the results of running the model on historical imbalance prices are compared to those obtained using the forecasted values from the base case.

For the two-hour BESS configuration, all ANP values increase in comparison to the case based on forecasted imbalance prices, as can be seen in Figure 4.17. This increase leads to a reduction in PBP for the cases where a PBP was previously observed, and it also results in new configurations achieving a PBP. Additionally, the 10/20 and 20/40 MW/MWh configurations achieve a PBP shorter than the lifetime for 2023 and 2025, respectively.

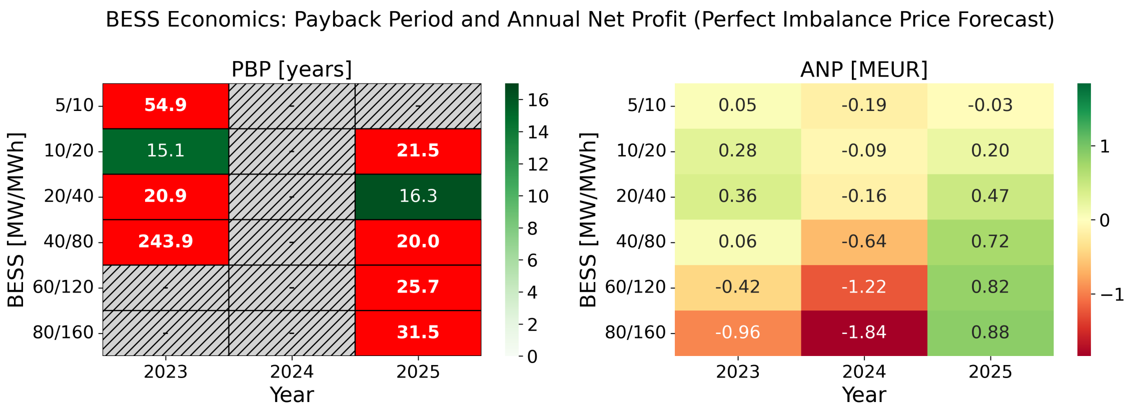


Figure 4.17: Comparison of PBP and ANP for 2023, 2024 and 2025 with different two-hour BESS sizes and perfect imbalance cost forecast.

The four-hour system configurations show similar results in Figure 4.18. The ANP increases for all configurations, resulting in a decrease in PBP for all cases that previously had a PBP. In addition, new configurations achieve a PBP, and several cases obtain a PBP shorter than the lifetime, namely the 10/40, 20/80, and 40/160 MW/MWh configurations in 2025.

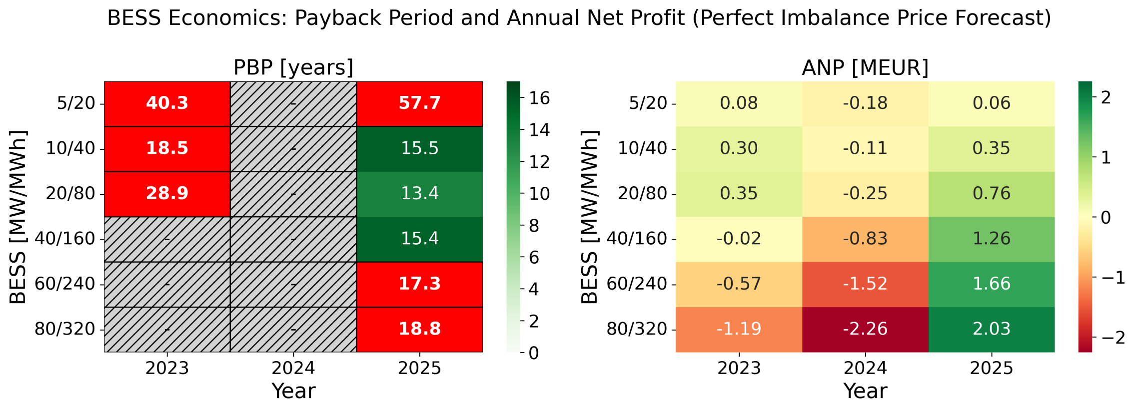


Figure 4.18: Comparison of PBP and ANP for 2023, 2024 and 2025 with different four-hour BESS sizes and perfect imbalance cost forecast.

When examining the imbalances resolved when the model has perfect knowledge of the imbalance prices, the analysis still focuses on the 20/40 and 60/120 MW/MWh configurations. Under these conditions, the smaller BESS configuration resolves 46%, 39%, and 13% of the produced imbalances for the three respective years. The larger configuration resolves 60%, 51%, and 19% of the imbalances.

When the model has access to historical imbalance prices, the utilisation of the BESS changes, with certain charging and discharging actions being shifted in time. This behaviour can be observed in Figure 4.19.

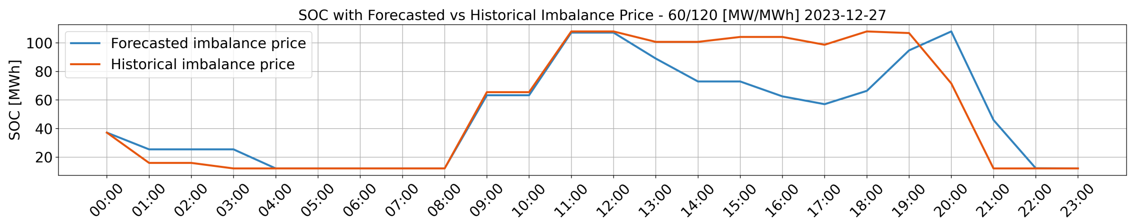


Figure 4.19: SOC with forecasted vs historical imbalance prices for 60/120 MW/MWh BESS in 2023-12-27.

4.2.3 Impact of Decreased Investment Costs

In this section, the impact of decreased investment costs is presented. This is investigated for both two- and four-hour systems, using BESS CAPEX reductions of 20% and 40%. A lower investment cost leads to an increase in ANP for all cases compared to the original configurations.

The two-hour configurations with a 20% cost reduction, shown in Figure 4.20, exhibit a decrease in PBP, and the 10/20 MW/MWh configuration achieves a PBP almost five years shorter than the lifetime of the system.

When the cost is instead decreased by 40%, the PBP decreases further and is up to

10 years shorter than the lifetime, as can be seen in Figure 4.21. In 2025, all BESS sizes from 40/80 MW/MWh and above exhibit a PBP of around 12-13 years.

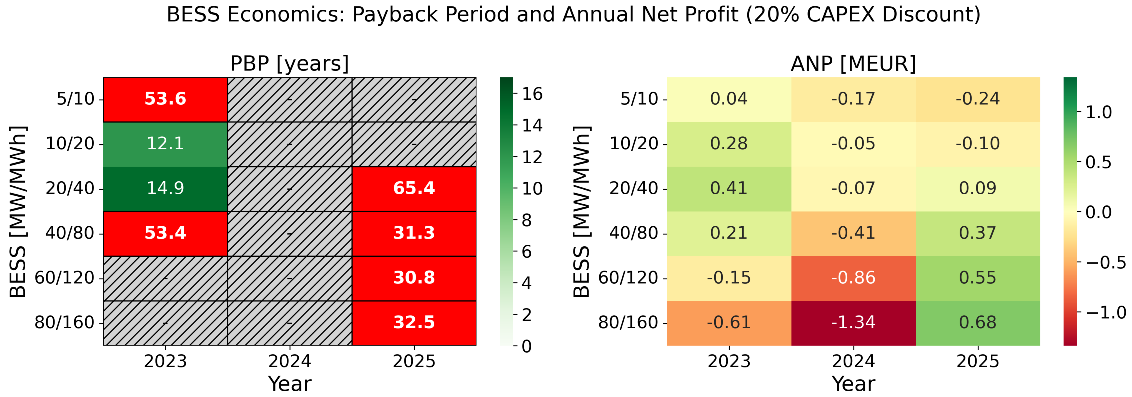


Figure 4.20: Comparison of PBP and ANP for 2023, 2024 and 2025 with different two-hour BESS sizes and when CAPEX has a discount of 20%.

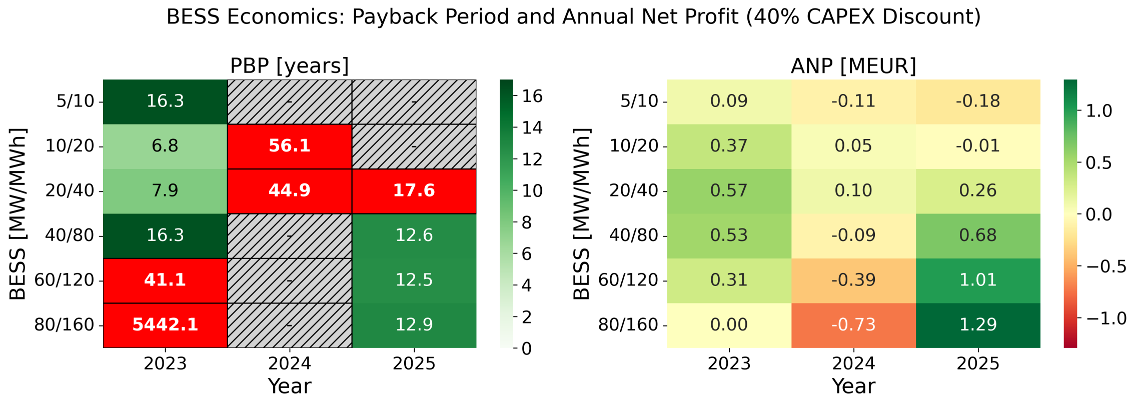


Figure 4.21: Comparison of PBP and ANP for 2023, 2024 and 2025 with different two-hour BESS sizes and when CAPEX has a discount of 40%.

The four-hour configurations show similar results, although only one configuration achieves a PBP below 17 years with the 20% discount, as can be seen in Figure 4.22.

When applying the 40% discount, there are even more cases with a PBP below 17 years. The 20/80 MW/MWh configuration exhibits an acceptable PBP for two of the years, 2023 and 2025. This can be seen in Figure 4.23.

Common to all configurations and discount levels is that the year 2024 never achieves a sufficiently short PBP. The only case in which it achieves a PBP is under the highest discount, and even then the PBP remains above 40 years for all occurrences. This might be explained by the price levels, where the general price level in both the day-ahead and intraday markets are lower in 2024 than in 2023, and the model is able to achieve a better capture price in 2023 with the BESS. As a result, the BESS becomes more profitable in 2023 than in 2024. In 2025, however, the model manages to trade better on the intraday market with the BESS and is thus able to capture a higher intraday price than it does in 2024. This likely explain the behaviour where the year 2024 generates the lowest profitability for BESS.

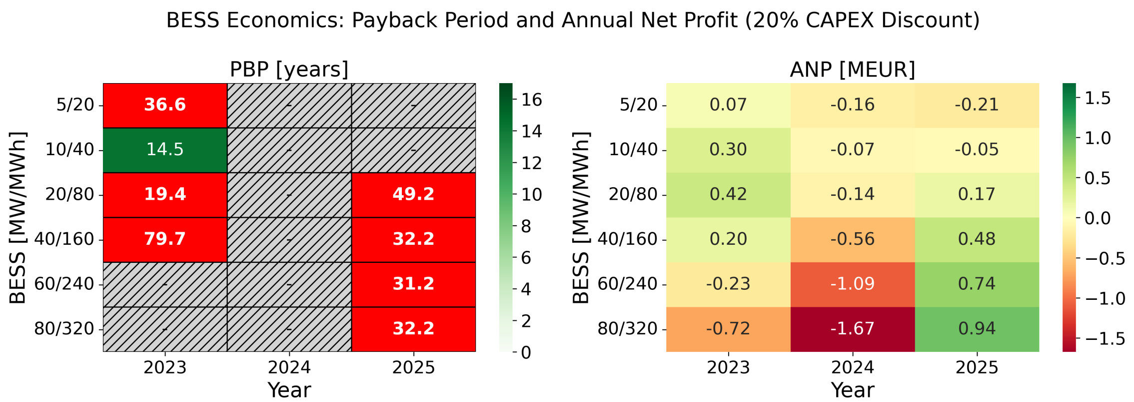


Figure 4.22: Comparison of PBP and ANP for 2023, 2024 and 2025 with different four-hour BESS sizes and when CAPEX has a discount of 20%.

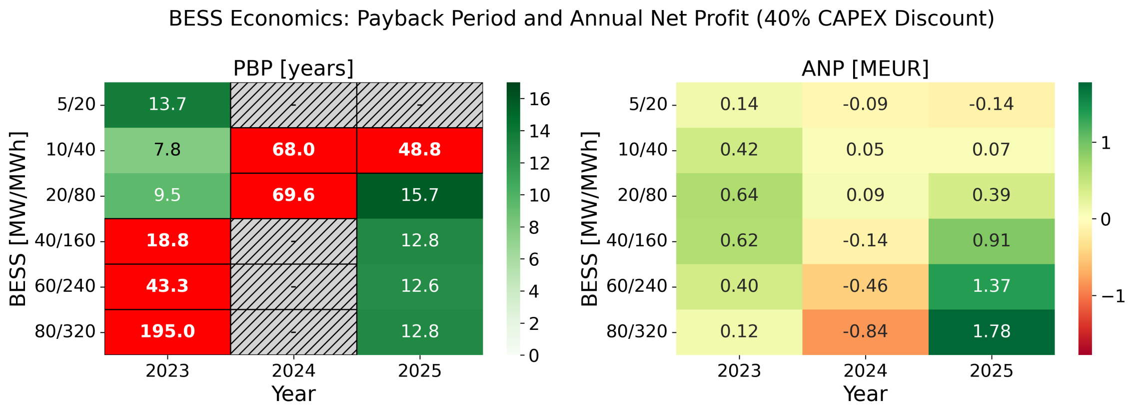


Figure 4.23: Comparison of PBP and ANP for 2023, 2024 and 2025 with different four-hour BESS sizes and when CAPEX has a discount of 40%.

4.2.4 Impact of Relaxed Intraday Import Limit

This section investigates the impact of allowing the model to purchase electricity on the intraday market, either to compensate for production deficits or to increase profits through market interactions.

When the model is allowed more trading on the intraday market, it can solve more of the imbalances on the intraday market, and the total revenues for the case without BESS become 10.3 MEUR, 6.5 MEUR, and 3.6 MEUR. These are increases compared to the base case, which means that the increase in revenue when the BESS is introduced is reduced, and thus the value of the BESS investment decreases. This can be seen for the two BESS sizes of interest in Figure 4.24.

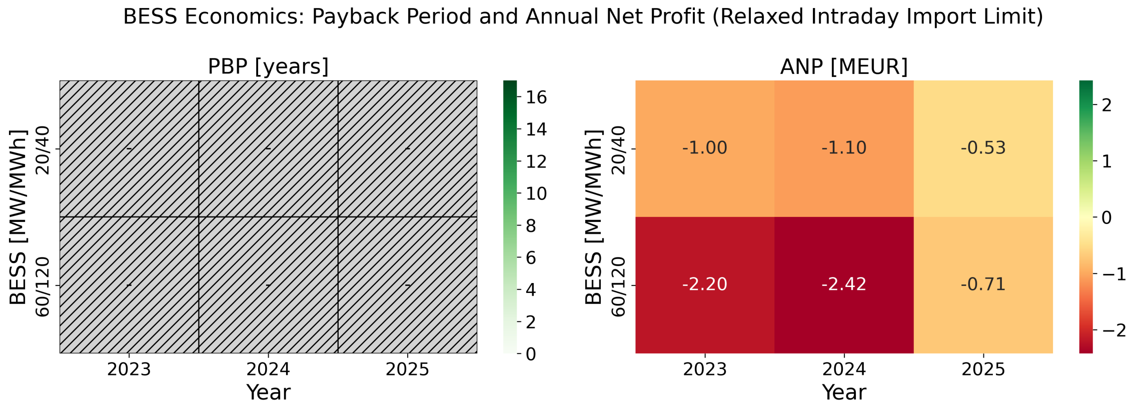


Figure 4.24: Comparison of PBP and ANP for 2023, 2024 and 2025 with 20/40 and 60/120 MW/MWh BESS with relaxed intraday import limit.

In the case without BESS, the model is no longer restricted to accepting imbalance costs when a production deficit occurs. Instead, it can choose to purchase electricity on the intraday market if this is expected to be more profitable. An example of this behaviour can be observed on 1 January 2023.

In the original case shown in Figure 4.25 below, the model sells electricity on the day-ahead market. However, when intraday purchases are allowed, the model instead buys back the entire previously sold volume on the intraday market and curtails all wind production during the same time step, as can be seen in Figure 4.26 below. This behaviour occurs because the intraday price is negative, allowing the model to profit from purchasing electricity while still retaining the revenue obtained from the day-ahead market.

Examining the same time step for the 60/120 MW/MWh BESS configuration, where purchasing is limited to the battery's charging capacity, as shown in Figure 4.27, a similar behaviour is observed. The model chooses to sell all forecasted production on the day-ahead market. Subsequently, in the intraday market, it both purchases electricity, sells electricity from its own production, and discharges the battery.

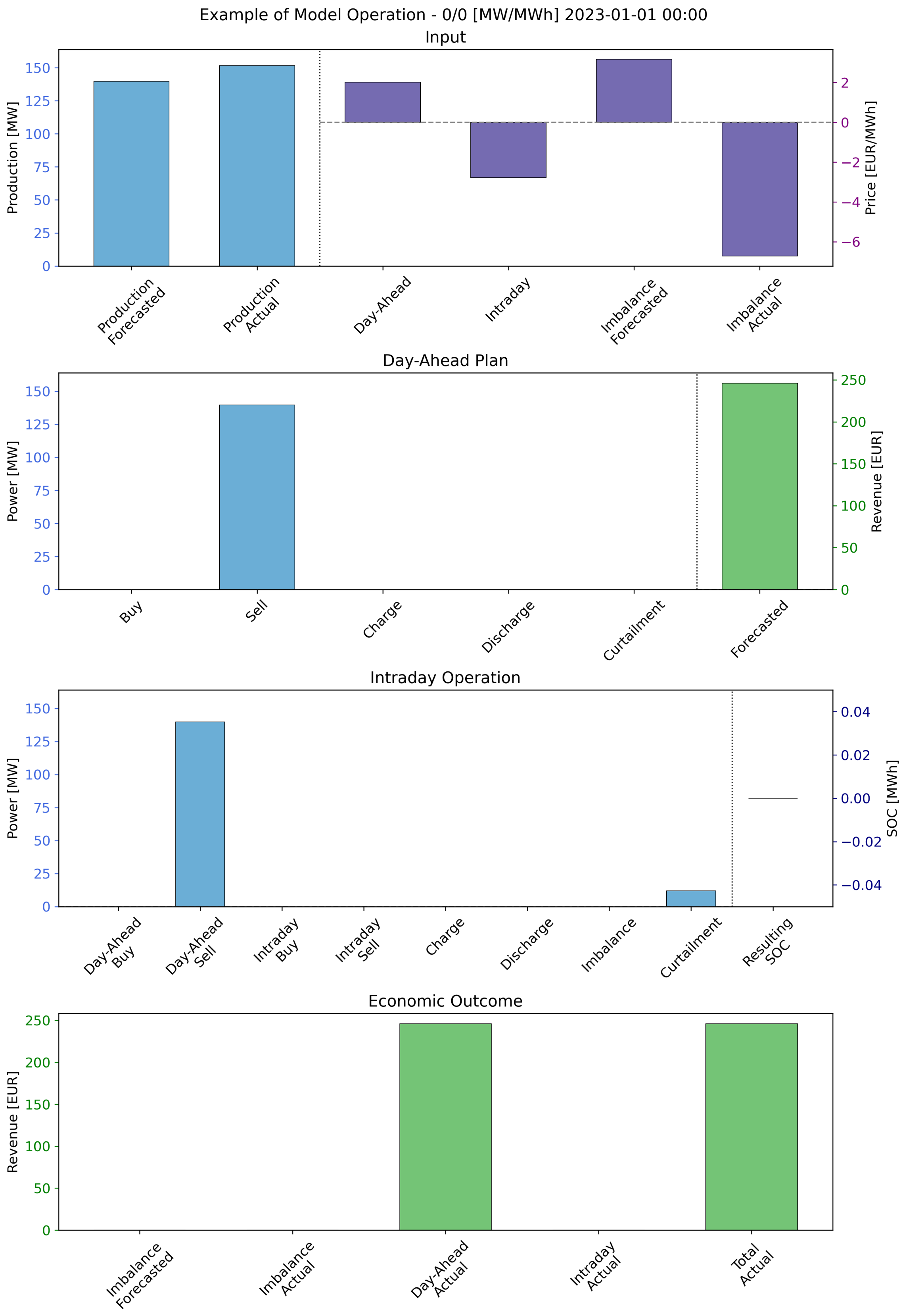


Figure 4.25: Optimal solutions for Day-Ahead and Intraday Model 2023-01-01 00:00–01:00 with no BESS, original case.

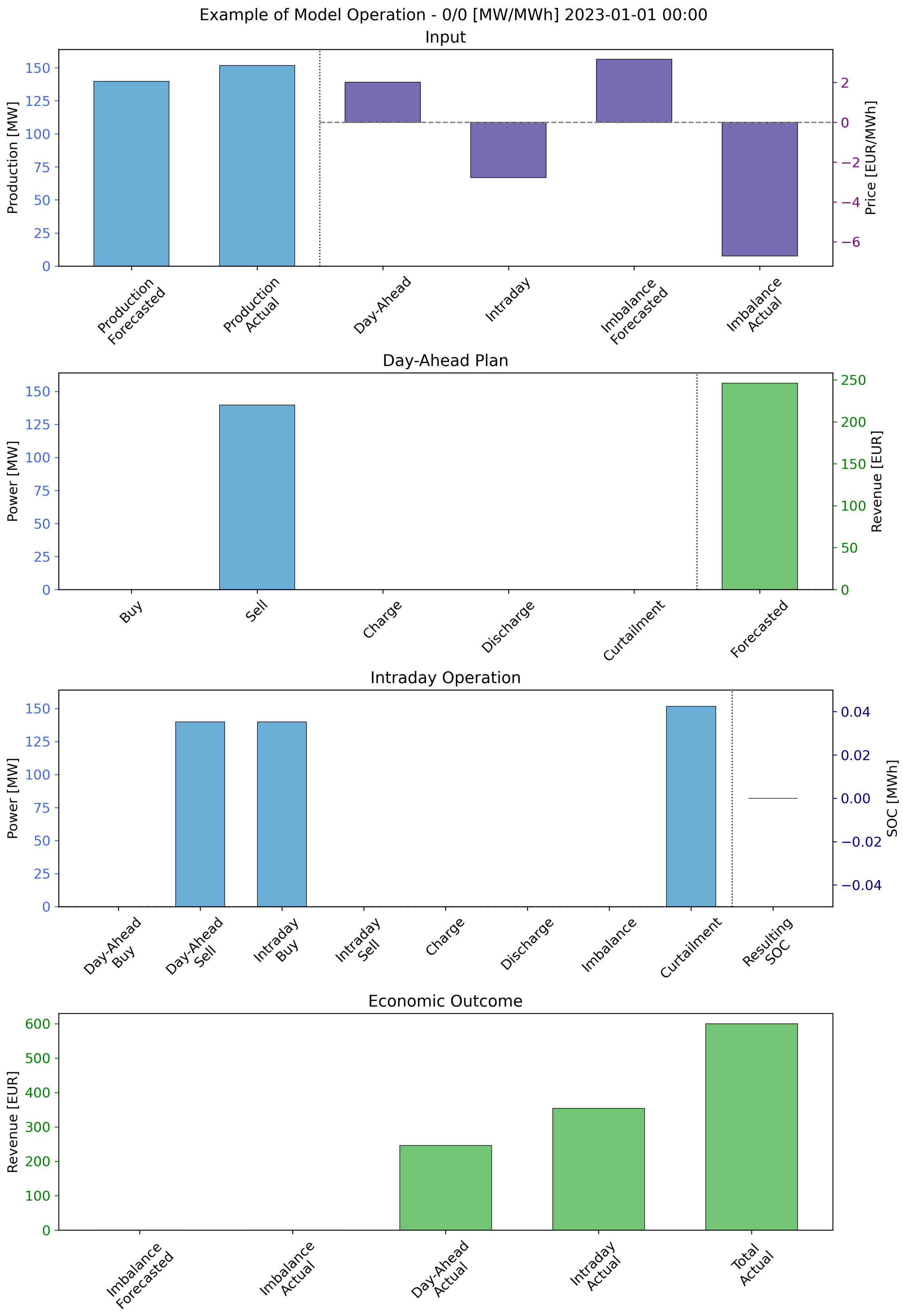


Figure 4.26: Optimal solutions for Day-Ahead and Intraday Model 2023-01-01 00:00–01:00 with no BESS and allowing intraday purchases.

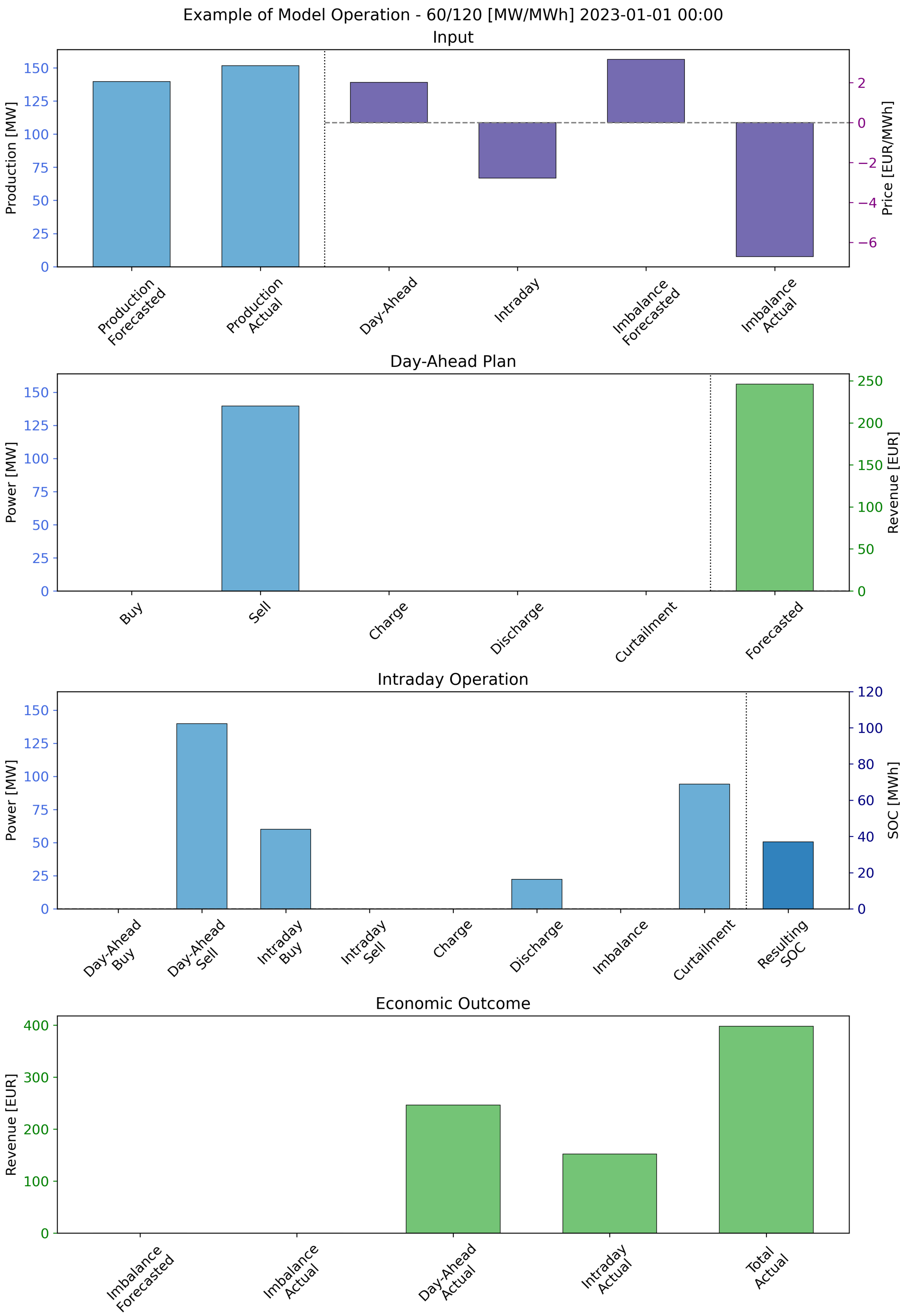


Figure 4.27: Optimal solutions for Day-Ahead and Intraday Model 2023-01-01 00:00–01:00 with 60/120 MW/MWh BESS, original case.

5

Discussion

This chapter discusses the results presented in Chapter 4 with the focus of analysing model performance as well as the implications of the results from a broader perspective. The section is structured as follows: model performance is presented first, followed by the data collection method, the sensitivity analysis, and finally method improvements and future work.

5.1 Model Performance

This section discusses the results related to the model's performance, specifically those presented in Section 4.1. The model is run using both two-hour and four-hour BESS configurations, both of which are discussed in this section.

The main findings indicate that the installation of BESS increases the total revenue of the wind park, but at the same time none of the evaluated BESS capacities have high enough revenue to make the investment profitable. However, on average, the smaller battery systems with a two-hour duration achieve higher profitability and PBP in 2023 compared with the other systems. By contrast, the larger systems perform better in terms of profitability and PBP in 2025 than the other configurations. Despite the low profitability of the system, several important observations can still be drawn from the obtained results.

Large differences can be observed between the studied years, raising questions about future operational and market conditions. The 2023 market is not considered representative of future market conditions due to, as mentioned in Section 2.2, two major developments have occurred in the Swedish electricity market since then. First of all, in October 2024, flow-based capacity calculations were introduced, and second, in March 2025, the market resolution was reduced to 15 minutes. This makes the 2025 market conditions the most representative of future scenarios since this year captures both of these developments. However, since the developments are relatively new, the new market is still immature, which introduces a certain volatility to prices. Intraday prices in 2025 exhibit differences of up to nearly 400 EUR between consecutive 15-minute periods, compared to approximately 150 EUR and 200 EUR between hourly periods in 2023 and 2024, respectively. Furthermore, the electricity market remains highly dependent on political decisions, regulatory developments, and market reforms, all of which remain uncertain going forward.

In general, the BESS is primarily utilised to increase revenue in the day-ahead market, although during 2025 its operation increasingly shifts towards the intraday market. After the transition to a 15-minute market resolution in March 2025, a clear change in optimisation behaviour can be observed. The model prioritises intraday trading over both imbalance cost reduction and additional day-ahead revenue in Q2 and Q3. This shift may be explained by the relative price structure, as intraday prices on average become higher than the forecasted imbalance prices after this point, as illustrated in Figure 3.9.

Before this transition, the model uses the intraday market to resolve imbalances and therefore incurs losses there. This can be explained by the varying relationship between intraday and imbalance prices, where either market may be more favourable depending on the time step. However, after the identified breakpoint, the intraday prices are predominantly higher than forecasted imbalance prices, which changes the economic incentives. The model increasingly prioritises the intraday market by selling a larger share of the electricity there, which can be seen from the results in Section 4.1.1.

Consequently, the intraday market evolves from being the smallest to being the largest contributor to revenue growth. This represents a substantial change, as in significant portions of 2023 and 2024 intraday trading instead contributes negatively to overall revenue. During these periods, this behaviour is primarily driven by the model's use of the intraday market to resolve imbalances, which can be seen in the example in Figure 4.10.

The optimisation strategy assumes the forecasts to be fully accurate. Such a complete reliance on a single forecast and its accuracy is unlikely to be realistic in practical applications. A more conservative optimisation strategy could potentially reduce a significant portion of these losses. Another behaviour of the model is that it occasionally creates deliberate imbalances when the forecasted imbalance price is negative, since this may result in increased profit. Such behaviour introduces considerable economic risks and would likely not be considered a realistic strategy in real-world operations.

5.2 Data Collection

The following section discusses the accuracy and limitations of the data collection methodology presented in Chapter 3.4. Both the forecasted and actual production datasets were constructed using wind data obtained from MEPS together with a power curve developed for the wind park.

The power curve was constructed using operational data from 2023, as this was the only complete dataset available at the time of the study. It was assumed that the relationship between wind speed and production would remain relatively stable across the remaining years, particularly since the derived curve showed good agreement with the warranted power curve of the park. Nevertheless, the methodology introduces uncertainty, as turbine performance may vary between years due to factors such as degradation, maintenance, and changing environmental conditions. Another approach could therefore have been to construct a separate power curve for each year of analysis.

Measured production data from the wind park were available, together with a dataset describing the expected power output based on observed wind conditions for each turbine. However, this expected production data was not considered suitable as forecast data, since it was generated using measured wind speeds rather than meteorological forecast wind. Consequently, it does not represent the uncertainty present in real forecasting situations and would therefore underestimate imbalance effects.

The measured production output from the park was also challenging to use directly. Several periods showed production different from the expected output, but the dataset did not indicate whether these reductions were known in advance by the park operator. In practice, some of these events may have been known by the operator in advance and therefore would not necessarily have resulted in imbalance costs. Since this information was unavailable, the measured production data could not reliably be used as a representation of actual forecast deviations. Instead, forecast data extracted one day in advance was used to maintain consistency with realistic market conditions.

However, this methodology also has limitations. Production scheduling for wind parks depends on more than just average wind speed. Factors such as turbine wake effects, park layout, icing conditions, turbine maintenance, turbulence intensity, and operator forecasting adjustments can all influence forecasted production. These effects are not fully captured by the simplified wind-to-power conversion used in this study.

To obtain wind speeds at hub height, wind data from MEPS was extracted at 10 metres and subsequently interpolated using the logarithmic wind profile law. This interpolation method introduces additional uncertainty, as the logarithmic profile represents an idealised approximation of atmospheric conditions. A more accurate approach would have been to extract wind data closer to the actual turbine hub height, thereby reducing the need for extrapolation over more than 100 metres. However, this was not possible for the re-analysis dataset. To ensure methodological consistency between forecast and reanalysis data, the same interpolation approach was therefore applied to both datasets. For practical reasons, the logarithmic wind profile law was selected instead of the power-law method. The required variables for the logarithmic formulation were available in both datasets, which simplified the data collection and processing workflow considerably. While the power-law approach may in some cases provide improved accuracy, maintaining a consistent interpolation methodology across all datasets was considered more important for the comparability of results.

The temporal resolution of the MEPS datasets is one hour, which was sufficient for the analyses conducted for both 2023 and 2024. However, due to the transition to a 15-minute market resolution in 2025, additional processing of the data was required. Linear interpolation was used to generate 15-minute values within each hour. This approach was chosen instead of assuming constant wind conditions throughout the hour, as it better captures gradual variations in wind speed. Nevertheless, the interpolation cannot fully represent the short-term variability of wind conditions within each quarter-hour period. Access to true 15-minute meteorological data would therefore likely have improved the accuracy of the results.

5.3 Sensitivity Analysis

This section discusses the results of the sensitivity analysis, specifically those presented in Section 4.2. The analysis evaluates how different assumptions and modelling choices influence the economic performance and operational behaviour of the system. In particular, the effects of increased export capacity, perfect imbalance cost forecasting, reduced CAPEX, and the possibility of compensating imbalances through intraday market purchases are discussed. The purpose of this analysis is to assess the robustness of the proposed optimisation strategy and to identify which parameters have the greatest impact on the overall results.

The model was run with two different export capacity cases, one with a 20% expansion and one with a 20% reduction. The expansion results in increased annual costs due to higher capacity charges as well as increased OPEX for the park. However, in the economic calculation it is assumed that the existing infrastructure can accommodate the increased capacity without requiring upgrades, and therefore no additional investment costs are included in the economic assessment. For the larger BESS size in 2025, the increased export capacity contributes to a reduction in the PBP, while a lower export capacity resulted in a higher PBP. This is likely due to the fact that a larger battery enables more effective energy arbitrage, allowing greater energy to be sold during periods of high production while prices remain elevated.

Another topic investigated in the sensitivity analysis is the impact of imbalance cost forecast accuracy on the results. The forecast model exhibits a systematic bias towards overestimation across all three years. For 2023–2024, the standard deviation is approximately 50 EUR/MWh, while for 2025 it increases to approximately 160 EUR/MWh, which indicates a relatively high level of uncertainty. A forecast error of 160 EUR/MWh can lead the model to make suboptimal decisions in several situations, occasionally resulting in either large unintended profits or significant losses. This increase in standard deviation may be explained by the drastic change in market structure during 2025, as the model has not previously been exposed to similar conditions and therefore may struggle to generate accurate predictions. Furthermore, market prices appear to be highly volatile during the transition phase, which may further contribute to the observed behaviour. Such cases are illustrated in Figure 4.8 and Figure 4.7. The model was also run using historical prices to evaluate the impact of forecast accuracy on economic performance. As shown in

Figures 4.17 and 4.18, improved price information enables the model to make better decisions, thereby increasing revenue. However, this increase is not sufficient to justify any of the evaluated BESS sizes across all years. In particular, for 2024, the investment remains unprofitable and results in a net loss for the park.

When analysing the imbalances resolved using historical imbalance prices as input to the model, the share of resolved imbalances decreases for all investigated cases, both for the 20/40 and 60/120 MW/MWh BESS configurations. This is likely because the model can make more informed decisions regarding which imbalances are economically beneficial to resolve, while also allocating battery capacity more effectively towards arbitrage and intraday trading. Additionally, when the model has prior knowledge of the imbalance prices, it may intentionally allow imbalances to occur during periods where being imbalanced is expected to be profitable. In practice, this would constitute a highly risky strategy, as it relies heavily on accurate price forecasts. However, if the forecasts are sufficiently accurate, such a strategy could potentially generate substantial profits for the park.

Comparing the SOC profiles for the cases using forecasted and historical imbalance prices, it can be observed that the BESS changes its behaviour when it has more accurate information about future market conditions. The model addresses future imbalances by assuming that the remaining hours of the day will exhibit the same average forecast error as the hours that have already passed. This assumption arises from the rolling horizon structure of the model, where the model receives updated information every three hours. This enables the model to reserve battery capacity for future imbalances if it expects resolving those to be more profitable than addressing the current imbalance. This behaviour can be observed in Figure 4.19. For example, between 12:00 and 13:00 on 27 December 2023, the model using forecasted imbalance prices discharges the battery to help compensate for an imbalance. However, when historical imbalance prices are known, the model instead chooses to preserve battery capacity for later use and discharges the battery during periods with higher prices. Consequently, the impact of better forecasts can be observed as time shifts in the SOC profile.

Next, the impact of reduced investment costs is investigated. The selected cost reductions are motivated by projected future reductions in BESS costs, as described in Section 2.1.2. These reductions in investment costs increase the ANP for all configurations, which is expected since no other parameters are changed. The results further indicate that, under these reduced cost assumptions, the larger systems become profitable with a 40% discount under the 2025 market conditions and achieve PBPs that make them more attractive for investment. The results for 2025 are of particular interest, as the market conditions after 2024 differ from those in 2023 and 2024, and are therefore considered more representative of future market behaviour.

When examining the effects of allowing the model to purchase larger volumes of electricity on the intraday market, a behaviour can be observed in which the model curtails its own production and instead fulfils its day-ahead sales using electricity purchased on the intraday market. The model also increasingly resolves imbalances through intraday market purchases used to compensate for production deficits. This type of operation becomes possible in the updated version of the model. However, such behaviour may be limited in reality for a wind park operator, as intentionally curtailing production while purchasing electricity from the market could be constrained by operational practices. Nevertheless, the result highlights how negative intraday prices can create strong economic incentives that alter the optimisation behaviour of the model. At the same time, negative intraday prices may reflect periods of system-wide surplus generation, in which case such behaviour could, in principle, contribute to system balancing by absorbing excess electricity.

5.4 Method Improvement and Future Studies

This section discusses possible improvements to the method used in this thesis and possible areas of future studies.

One potential improvement of the method would be to increase the accuracy of the forecasting models. As both the production forecast and the imbalance price forecast were simplified, the accuracy of the optimisation is inevitably affected. By implementing more advanced forecasting methods, the predicted power production could potentially account for additional factors such as icing conditions, turbine availability, and maintenance schedules. This would allow the forecasted production to be compared more accurately with the measured production of the wind park, thereby providing a more realistic representation of the resulting imbalances. However, introducing more detailed forecasting models would also reduce the general applicability of the model, as additional site-specific data and modelling assumptions would likely be required.

The handling of forecast errors could be further investigated. At present, an averaged value from the past hours of the day is used. However, this is the only method implemented, and it could be further analysed how alternative approaches might affect the model results.

Another possible improvement would be to modify the optimisation strategy so that it does not rely entirely on forecasted values. By reducing the dependence on perfect forecasts, the model could become more robust to forecasting errors and unexpected market behaviour. As discussed earlier, forecasting errors, particularly in the imbalance prices, can have significant effects on the results. If the model makes an incorrect decision during a time step with very high prices, this can result in substantial financial losses for the park owner. Additionally, the behaviour in which the park puts itself in a large imbalance and takes a risk could be studied further along with the implications of either taking that risk or not taking that risk.

Another area for further investigation is the horizon length of the model. At present, a three-hour horizon is used, but extending this horizon could potentially improve model revenue. However, this introduces a trade-off, as longer horizons increase exposure to uncertainty in weather and operational forecasts, which are typically more accurate closer to the time of delivery. This trade-off could be further studied in future work, particularly in terms of determining how far the horizon can be extended without significantly reducing forecast accuracy and overall model performance.

A possible improvement relates to how the SOC is calculated. At present, the SOC at 11:00, together with the day-ahead schedule, is used to estimate the initial SOC for the next optimisation window. However, since the schedule may change between optimisation steps, it may be more appropriate to use the most recent schedule for charging and discharging decisions when estimating the SOC in the subsequent window.

Future studies could further investigate improvements to the variable p_t^{res}, which represents the reserved capacity for imbalance management. In the current implementation of the model, this variable could allow the BESS to simultaneously charge and discharge, which may not accurately reflect realistic operational behaviour. Modifying the associated constraints to prevent such behaviour could potentially improve the realism and quality of the day-ahead scheduling strategy. However, since the variable is only included in the Day-Ahead Model, such modifications are not expected to significantly influence the intraday market operation.

6
Conclusion

This thesis aimed to develop and evaluate a techno-economic optimisation model for a hybrid park, as well as to address the main research question of how the profitability of the hybrid park depends on its operational strategy. In this context, factors such as participation in different electricity markets, the avoidance of imbalance costs, and variations across operational years were investigated.

The optimisation model did not identify any operational strategy capable of generating sufficient revenue to fully cover the investment and operational costs associated with the BESS installation over the investment lifetime. However, the results showed that the smaller battery sizes generated a positive ANP in 2023 for both the two-hour and four-hour configurations. In contrast, in 2025, the larger BESS configurations achieved positive ANP values for both two-hour and four-hour systems. No configuration generated a positive profit in 2024.

The larger BESS configurations provided greater operational flexibility, enabling the wind park to perform more arbitrage operations and resolve a larger share of imbalances, which may also provide benefits to the overall electricity system. The results indicate that more imbalances were resolved during the earlier years, whereas in 2025 the model relied more heavily on intraday market trading. This suggests that the difference between intraday and imbalance prices plays an important role in determining the model's operational behaviour and the dominant revenue stream. Furthermore, the results showed that inaccurate imbalance forecasts occasionally caused the model to make operational decisions that unintentionally resulted in either substantial losses or substantial profits.

The sensitivity analysis showed that increasing the export capacity of the park, from being the same as the installed wind farm capacity of 164 MW to 197 MW, can be beneficial primarily for the larger four-hour BESS configurations. At the same time, a decreased export capacity to 131 MW showed no benefit. The analysis also demonstrated that using historical electricity prices resulted in higher economic profits and made certain BESS sizes profitable investments during specific years. In specific, the 10/20 MW/MWh for the 2023 scenario, and 20/40, 10/40, 20/80, and 40/160 MW/MWh in 2025, approached a PBP within the investment lifetime. When investment cost reductions of 20% were applied to the economic calculations, the smaller BESS configurations, 10/20, 20/40 and 10/40 MW/MWh became profitable in the 2023 scenario. Furthermore, the 40% cost reductions also made all of the larger BESS configurations, namely 40/80, 60/120, 80/160, 40/160, 60/240 and 80/320 MW/MWh profitable under the 2025 conditions. Similarly, all of these sizes failed to generate profitable operation during the years 2023 and 2024, except for 40/80 MW/MWh in 2023. Consequently, larger BESS installations only appear economically favourable under the market conditions observed in 2025. Lastly, the sensitivity analysis showed that the intraday trading constraints are significant, as the model was able to increase its revenue even without BESS installation when greater participation in the intraday market was allowed. Overall, the sensitivity analysis suggests that profitability mainly depends on reduced investment costs, improved imbalance forecast accuracy, and increased intraday market participation, while export capacity is primarily important for the largest four-hour BESS configurations.

The results also demonstrate substantial variations between the studied years, indicating that the revenue potential of hybrid parks is highly dependent on market conditions and the cost of BESS. This suggests that dimensioning an optimal BESS configuration based solely on the results from a single year may lead to misleading conclusions regarding long-term profitability and system performance.

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